University of KwaZulu-Natal

A conceptual framework for factors that influence willingness of low-income farmers to pay for weather index insurance in South Africa

by

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DECLARATION

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Psalm 91:2

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ABSTRACT

Weather index insurance is an emerging risk management instrument in the African agricultural landscape designed for low-income farmers that are perpetually vulnerable to weather-related production hazards due to unprecedented intensification in climate variability, particularly in the era of climate change and increasing drought events. Research on weather index insurance in South Africa is still at an embryonic stage, partly attributable to very limited market-based climate risk transfer solutions in the country. However, interest from government and the insurance industry demonstrates a focused approach towards creating more inclusive insurance markets. The purpose of this study was to develop a critical understanding from a behavioural and economic perspective of low-income farmers' willingness-to-pay for weather index insurance, and to develop a conceptual framework grounded on the Theory of Planned Behaviour for factors that influence these purchase decisions. Quantitative research methods were followed, using a probability sample of 326, from a target population of 1774 low-income maize farmers in the Free State, North West, and Mpumalanga provinces of South Africa. Following stratified random sampling, structured questionnaires were used to collect primary data based on telephonic interactions. From the surveys conducted, a 68.7% response rate was obtained. The data were analyzed using an integrated approach of structural equation modelling and logistic regression to evaluate variables that influence low-income farmers' willingness to pay for weather index insurance. The study reported that 86% of farmers were willing to purchase the insurance for security reasons to protect their respective businesses and their welfare. The findings revealed that while insurance culture and risk perception were found to have a direct effect on willingness-to-pay, financial capability was not related to purchase intentions. From a socio-economic perspective, access to credit and group membership were significant factors found to have a positive influence on willingness-to-pay. The study advances the understanding of an underserved market and assists in framing future weather index insurance products in the country. One of the main recommendations is that it is important for policymakers to adopt a systemic approach to agricultural financing where insurance plays a critical risk mitigating role in the broader context of agricultural development.

Keywords: low-income farmers, South Africa, weather index insurance, willingness-to-pay.

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GLOSSARY OF ACRONYMS

AFASA	African Farmers’ Association of South Africa
AMOS	Analysis Moment of Structure
BFAP	Bureau for Food and Agricultural Policy
CASP	Comprehensive Agricultural Support Programme
CCAFS	Climate Change, Agriculture and Food Security
DAFF	Department of Agriculture, Forestry and Fisheries
DALRRD	Department of Agriculture, Land Reform and Rural Development
DEA	Department of Environmental Affairs
DEFF	Department of Environment, Forestry and Fisheries
DLA	Department of Land Affairs
FAO	Food and Agricultural Organization of the United Nations
FSCA	Financial Sector Conduct Authority
GCIS	Government Communication Information Services
GDP	Gross Domestic Product
NCP	National Planning Commission
NDP	National Development Plan
NGO	Non-Government Organization
NGPF	National Gender Policy Framework
OECD	Organization for Economic Co-operation and Development
SADC	Southern African Development Community
SAIA	South African Insurance Association
SMS	Short Message Service
SPSS	Statistical Package for the Social Sciences
TPB	Theory of Planned Behaviour
WFP	World Food Programme
WTP	Willingness-to-pay

CHAPTER ONE: INTRODUCTION

1.1 Introduction

Weather index insurance is an emerging concept in South Africa in the field of agricultural risk transfer. Although new to South Africa, the insurance has been piloted and implemented in most agricultural-based economies in Africa and the rest of the developing countries.

> “The insurance is seen as increasingly important as farmers in South Africa face increasing adverse climate-related weather events, especially drought, for which insurances are increasingly becoming unaffordable” (National Treasury, 2020:47).

Chapter One provides an overarching introduction and background to what necessitated the study. It sets out the research problem under investigation, along with the objectives of the research. Following that, a synopsis is presented of the research methodology and data analysis techniques that the researcher regarded as the best way to address the research problem. A brief overview of key terms and concepts as applied in this study is also put forward. Thereafter the chapter concludes with setting out the framework for the structure of the research.

1.2 Background of the Study

Crop production in South Africa commonly takes place under rainfed conditions, where aberrations in rainfall have the potential to affect crop yield adversely (GCIS, 2017:2). In addition, climate change is shifting agricultural production patterns as increases in temperature, and unpredictable rainfall severely affect farmers’ ability to continue crop cultivation in a feasible and sustainable manner. It is against this backdrop that agricultural insurance, in particular, crop insurance plays a pivotal role in securing livelihoods and farmer welfare. It is recognized as a precondition for strengthening the sector’s contribution to economic growth, increasing productivity, maintaining food security and stabilizing farming income while building the financial resilience of farmers (Karekezi, 2017:36; Roznik, Porth, Porth, Boyd & Roznik, 2019:447). Crop insurance is a tool used to manage agricultural production risk as a result of weather-related perils such as drought, floods, low rainfall, hail, and so forth. It protects agricultural producers (insured) against financial losses by transferring agricultural risk to a third party (insurer) in return for an insurance premium (Reyes, 2015:7), making it one of the most important risk management strategies available to farmers (Aditya, Khan & Kishore, 2018:2).

Crop insurance can take the form of indemnity or index-based insurance, with 96 per cent of all crop insurance products being indemnity-based (IAIS, 2017:1). Traditional indemnity insurance functions on the basis of actual crop loss and serves to restore the insured to the financial position they were in prior to suffering loss or damage. Indemnity-based crop insurance products require expert product distribution intermediaries, sophisticated underwriting, farm-level inspections, as well as substantial skills and dedicated resources for loss verification and quantification (Hohl, 2019:191). This highly specialized interaction of activities makes crop insurance prohibitively expensive (Accenture, 2018:37; GreenCape, 2018:37; Gunjal, 2016:39; Lansigan, 2015:17; Weber, Fecke, Moeller & Musshoff, 2015:32) and not well suited to the risk transfer needs of low-income farmers (Barnett, 2014:211; Carter, Janzen & Stoeffler, 2018:209; World Bank, 2015:11). Crop insurance is characterized by high administrative costs, expensive on-field farm verifications, as well as problems of asymmetric information between the insurer and insured resulting in moral hazard and adverse selection (Castellani & Vigano, 2017:517; Hellin, Hansen, Rose & Braun, 2017:3; Pu, Chen & Pan, 2018:35). Moral hazard occurs when insured individuals modify their farming practices and behaviour in response to having insurance, thus increasing the probability of an adverse outcome. Adverse selection occurs when farmers with higher than average risk seek insurance and those with lower than average risk find it uneconomical (Bastagli & Harman, 2015:5). Both conditions of moral hazard and adverse selection are drivers of insurance premiums and, in most cases, contribute to the exclusion of low-income farmers who often lack the financial capability to adopt effective risk management tools.

Weather index insurance is an alternative to indemnity-based insurance (Choudhury, Jones, Okine & Choudhury, 2016:171). It aims to protect farmers against inherent production risks arising from adverse, unpredictable and variable weather without many of the constraints of indemnity-based crop insurance (Ceballos & Robles, 2020:3; Ward, Makhija & Spielman, 2019:7). Policymakers have heralded it as a panacea to provide farmers in developing countries with insurance at an affordable price (Ehrlinspiel, 2017:3). Index-based insurance schemes have been introduced in developing countries as an innovative way of managing climate risk (Wairimu, Obare & Odendo, 2016), adapting to climate change (Abebe & Bogale, 2015; Adiku, Debrah-Afanyede, Greatrex, Zougmore & MacCarthy, 2017), reducing poverty, improving access to credit (Raju et al., 2016; Mirandu & Mulangu, 2016), and providing relief assistance for catastrophic disaster (Hess & Hazel, 2016), especially for low-income farmers. South Africa is a notable exception among developing countries for its lack of index insurance options (Born, Spillane & Murray, 2018:6; den Hartigh, 2016:2). In fact, there are little to no commercially available insurance products in the country designed for low-income farmers (World Bank, 2016:13). The lack of adequate insurance solutions threatens the livelihoods of around 20 million people that are directly and indirectly dependent on small-scale agriculture in the country (GreenCape, 2021:44).

Where index insurance products are lacking, as in the case in South Africa or where uptake is low, studies have found that a knowledge gap exists about understanding factors influencing farmers' participation in and uptake of weather index insurance contracts (Daninga & Qiao, 2014:20; Njue, Kirimi & Mathenge, 2018:4). It is in this context that this study advances a conceptual framework for factors that influence low-income maize farmers' willingness-to-pay for a hypothetical weather index insurance scheme in key production areas of the Free State, North West and Mpumalanga provinces of South Africa. Globally, there is insufficient knowledge about farmer demand and preference for market-priced, commercially driven weather index insurance (Vasilaky, Doro, Norton, McCarney & Osgood, 2019:1). Moreover, South Africa, has little transactional and market information available regarding the low-income farmer segment. This segment is traditionally excluded from credit, capital and food value chains markets (von Loeper, Drimie & Blignaut 2018:162). This study has the potential to assist financial institutions, multilateral organisations and the government to identify challenges and opportunities in structuring potential insurance solutions for the low-income sector in South Africa in response to climate change, low agricultural productivity, and strategic development of rural agriculture.

1.3 Rationale of the Study

Empirical studies on factors that influence low-income or smallholder farmers' willingness to participate in insurance schemes and subsequent intentions to purchase related insurance products are rare and preliminary within the South African context. A systematic literature review of willingness-to-pay studies in the developing economy shows 44 studies on agricultural innovation uptake, and only three in South Africa, none of which are in the field of crop or index insurance (Olum, Gellynck, Ongeng & De Steur, 2020:8). This is because agricultural innovation, in particular, index insurance is at a developmental stage in the country as National Treasury, the Department of Agriculture, Land Reform and Rural Development (DALRRD), and the insurance industry are in early stages of structuring a public-private partnership (PPP) to provide innovative index-based insurance to protect farmers against climate risk (National Treasury, 2020:47). The PPP approach has been proved to be the most successful method of agricultural insurance delivery across the world (Herbold, 2014:199), leading to better accountability and improved financial performance of agricultural insurance schemes (Reyes, Agbon, Mina & Gloria, 2017:29). The insurance industry in South Africa is showing interest in researching and introducing index insurance because of its many direct and indirect economic benefits that emanate from accessing a vastly underserviced market. To this end, the South African Insurance Association (SAIA) representing the interest of insurance providers submitted an application to the regulatory authorities (Prudential Authority and Financial Services Conduct Authority) for industry-wide approval to open the market for index insurance as a class of business (SAIA, 2019:31).

Prompted by the need to minimize the empirical knowledge gap in this evolving dimension of risk mitigating research, this study sought to make a practical contribution towards the development of a conceptual framework for factors that influence willingness-to-pay for weather index insurance in South Africa. The framework may assist in the introduction of innovative, flexible and affordable agricultural insurance solutions attractive to low-income farmers in the country. Furthermore, considerable literature exists on farmers in other developing countries; however, this research has largely concentrated on economic variables, with little focus on psychological and behavioural factors influencing willingness-to-pay intentions (King & Singh, 2018:2). To address these shortcomings, this study incorporates behavioural intentions as part of the analysis to expand the scope of existing literature. The focus of the study is on maize producers because maize is the pre-eminent grain crop in Africa; a staple food for most South Africans and, in addition, it is a primary feed and industrial crop which is critical to food security (DAFF, 2020:9).

1.4 Problem Statement

Research has been conducted in many developing countries on weather index insurance, farmers' willingness-to-pay for it and on socio-economic factors influencing this willingness (Abebe & Bogale, 2015; Abugri, Amikuzuno & Daadi, 2017; Ahmed, McIntosh & Sarris, 2017; Ali, Egbendewe, Abdoulaye & Sarpong, 2020; Balmalssaka, Wumbei, Buckner & Nartey, 2016; Ellis, 2017; Fonta, Sanfo, Kedir & Thiam, 2018; Sibiko, Veettil & Qaim, 2018). This research forms part of greater efforts to address insurance market failure that has plagued Africa (Shakhovskoy & Mehta 2018:11; Tadesse, Shiferaw & Erenstein, 2015:1). These studies have yielded varied results with willingness-to-pay participation ranging from 41 per cent in some studies to 88 per cent in others. Whilst the insurance premium farmers are willing to pay equals zero is some studies (King & Singh, 2018), it is as much as 12 per cent of income in others (Afriyie, Zabel & Damnyag, 2017). Furthermore, a wide range of factors have been identified as significant determinants of willingness-to-pay in one country whilst in other countries these factors are insignificant (Vasilaky et al., 2019:2). The inconsistency in results indicates that there are various socio-demographic, socio-economic, socio-psychological, environmental and cultural dynamics influencing farmers' perceptions of risk and subsequent participation or lack thereof in insurance schemes (Addey, Jatoe & Kwadzo, 2020:3). It follows that research findings from these various studies cannot be generalized with a high degree of certainty within the developing world, but rather each country appears to be unique in its attributes, attitudes, and preferences (Sulewski & Kłoczko-Gajewska, 2014:140).

The problem identified by this study is that limited empirical research and few academic studies are available on South Africa's low-income farmers' crop insurance purchase decisions. There is further insufficient data on farmers' attitudes and demand for any form of agricultural crop insurance, specifically on the willingness-to-pay for such insurance. To exacerbate the matter, detailed production statistics for smallholders are also not available, which has serious ramifications for the design of agricultural insurance programmes targeting this population (World Bank, 2016:14). According to von Loeper, Musango, Brent and Drimie (2016:74), there appears to be a general lack of knowledge in South Africa on low-income farmers and their overall interaction with financial products. As a result, South Africa is lagging behind other developing countries in establishing agricultural index insurance schemes for its small-scale farmers (GreenCape, 2018:37). The lack of broad research and the knowledge gap in this field has partly contributed to low levels of innovation, product design and the absence of viable alternative microinsurance markets for the underserved low-income farmer (Geyer, 2016:357; Partridge & Wagner, 2016:52).

It is of concern that an estimated 300 000 to 400 000 emerging smallholders (BFAP, 2020:17; National Treasury, 2015:148) remain excluded from formal insurance markets in light of rising exposure to climate change. Insurance penetration is low and is projected to be less than 1 per cent in this segment (de Klerk, Fraser & Fullerton, 2013:11), primarily because of prohibitively expensive traditional crop insurance (National Treasury, 2019:40). The effects of climate change in South Africa have negative impacts on food security, the national economy through reduced export crops and foreign income earning (Schulze, 2016:19) and reductions in government’s tax base as a result of reduced tax collection from the agricultural sector (AgriSA, 2016:16). Climate change is likely to affect low-income farmers disproportionately as they often lack the financial capacity to introduce risk reduction strategies (Ceballos, Ulimwengu, Makombe & Robles, 2017:70; DEA, 2013:45; Mookerjee, 2016:5). They lack access to savings, credit and insurance markets (Moore, Niazi, Rouse & Kramer, 2019:2).

Montmasson-Clair, Mudombi and Patel (2019:3) identify that significant adaptation gaps exist in South Africa, namely the insurance gap, the technology gap, the knowledge gap, and the governance gap. For this reason, the need for viable and affordable insurance for farmers to cover intrinsic weather risk associated with crop production along the primary agricultural value chain has been highlighted by the government as a key driver for sustainable agricultural production (DAFF, 2018b:20).

The question arises as to what the solution is to the problem outlined above. Carter et al. (2014:1) identify that weather index insurance is the ideal solution for the uninsured as it can create access to formal insurance for millions of low-income farmers. Castillo, Boucher and Carter (2016:94) advice that uninsured risk results in under-developed insurance markets, the effects of which are vicious cycles of under-investment, persistently low production patterns and long-lasting poverty traps. This is a view shared by other scholars such as Shee, Turvey and You, (2018:2). It is with this view in mind that Partridge and Wagner (2016:52) pinpoint that there is a clear need in South Africa for innovation that will create access to appropriate and well-designed agricultural insurance products for low-income farmers. Balaban, Simeunovic and Markovic (2018:427) claim that from a broad perspective, a global gap exists for the development of comprehensive insurance for low-income farmers. Zhang, Brown and Waldron (2017:4) acknowledge this gap and assert that farmers represent the demand aspect for weather index insurance contracts and so to narrow the gap, studies on their attitudes, preferences and opinions are critical to understanding how to design and implement appropriate insurance schemes for them.

1.5 Research Objectives

The primary research objective of this study was to develop a conceptual framework of factors that influence the willingness of low-income farmers to pay for weather index insurance in South Africa.

In order to achieve the primary objective, the following empirical research objectives were formulated for the study:

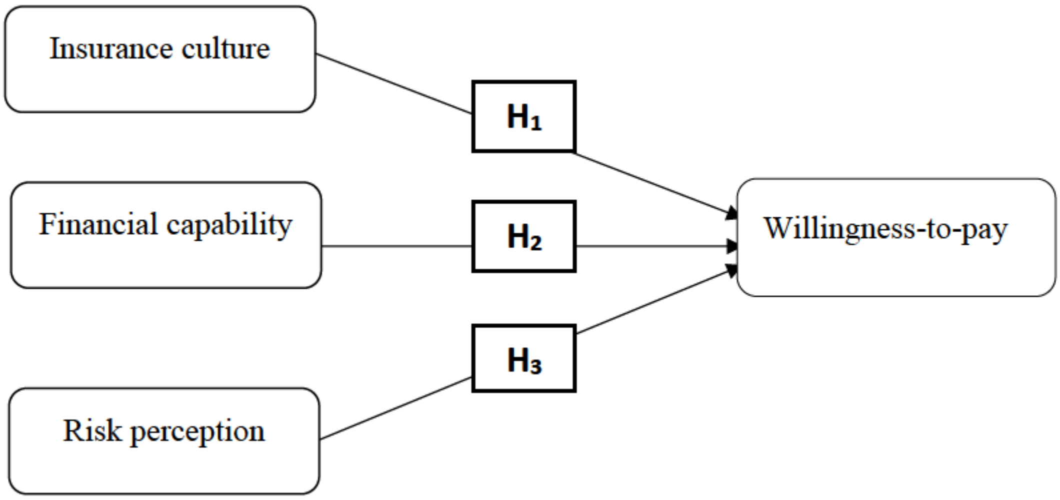
- To investigate low-income farmers willingness-to-pay for weather index insurance;
- To determine the price range low-income farmers are willing to pay for weather index insurance;
- To identify socio-demographic factors that influence willingness-to-pay for weather index insurance;
- To identify socio-economic factors that influence willingness-to-pay for weather index insurance;
- To identify socio-psychological factors that influence willingness-to-pay for weather index insurance; and
- Based on the results of the empirical study, to recommend aspects to include in the product design of weather index insurance solutions in South Africa that may assist relevant stakeholders in implementing such schemes.

1.6 Conceptual Framework and Study Hypotheses

This study applied an integrated approach to develop an understanding of determinants that influence the uptake of weather index insurance. This was achieved through an investigation of socio-psychological, socio-demographic and socio-economic determinants that influence insurance purchase decisions. By means of a conceptual model illustrated in Figure 1.1, the following is proposed: behavioural or socio-psychological unit constructs of insurance culture, financial capability, and risk perception represent the predictor variables, with willingness-to-pay as the outcome variable. These variables are essential because from a behavioural finance perspective, not all economic agents are rational in their considerations, thence behavioural consideration have the potential to enhance market understanding (Nanziri & Leibbrandt, 2018:1).

Jin, Wang and Wang (2016:367) state that studies that examine risk perceptions of farmers when it comes to purchase considerations of weather index insurance are very few. Moreover, the impact of culture on insurance demand is a relatively new area of study (Chitiyo, 2018:32). As such, studies that consider the effects of all three psychological variables are uncommon. The variables are modelled on the Theory of Planned Behaviour (TPB), which is a socio-psychological model for understanding and predicting human behaviour. The TPB is widely used in various disciplines to better understand human behaviour, areas of application include: healthcare (Al Hasan, Muzumdar, Nayak & Wu, 2019), information systems (Jokonya, 2017), agriculture (Akyüz & Theuvsen, 2020), including agricultural insurance (Abd Aziz, Abd Aziz, Aris & Abd Aziz, 2015). TPB is well-researched through meta-analysis for its efficacy as a predictor of intentions and subsequent behaviour (Jalili & Ghaleh, 2019, Hirschey et al., 2020).

Figure 1.1: Conceptual framework



Source: Author's compilation

In the TPB, there are three determinants of an individual's intentions: attitude, subjective norm, and perceived behavioural control. Attitude refers to a person's favourable or unfavourable assessment towards acting out the behaviour based on the outcomes that the behaviour produces. Subjective norm is the person's opinion formed on the basis of social and cultural influences on the enactment of the behaviour. Perceived behavioural control is the ability represented by resources and opportunities to perform the behaviour (Ajzen, 2020:315). These three determinants were adapted in this study in line with insurance market terminology under the TPB where insurance culture is the equivalent of subjective norms, and financial capability and risk perception is the equivalent of behavioural control and attitude, respectively. TPB has been used in various studies to explain an individual's willingness-to-pay for non-market goods and services (Grill & Notaro, 2019:903), but limited research exists in applying TPB to investigate crop demand in order to model appropriate response actions to remove barriers that may hinder insurance purchase considerations (Ibrahim, Nunung, Bustanul & Toni, 2020:52).

Based on the theoretical background, the following three hypotheses were formulated to highlight the various dimensions and relationships under investigation in this study:

H_1- Insurance culture has a positive significant relationship with willingness-to-pay.
H_2- Financial capability has a positive significant relationship with willingness-to-pay.
H_3- Risk perception has a positive significant relationship with willingness-to-pay.

As part of developing a comprehensive framework, it is important to recognize the role of demographic and economic variables that influence willingness-to-pay intentions. Limitations of the TPB are that these aspects are not directly considered in behavioural intentions. For this reason, this study further investigates which significant demographic and economic factors as identified from a wide range of other similar enquiries (Abugri, Amikuzuno & Daadi, 2017; Ellis, 2017; Fonta et al., 2018; Sibiko, Veettil & Qaim, 2018) in different developing countries influence willingness-to-pay for weather index insurance in South Africa. The prevalent explanatory variables tested in this study, as deduced from the literature, were:

- Socio-demographic variables: age, gender, marital status, education, experience and household size; and
- Socio-economic variables: access to credit, turnover, farm size, group membership and risk coping strategies.

1.7 Research Design and Methodology

The focus of research design is on producing knowledge required to address the overall research objectives (Tobi & Kampen, 2018:1212). It is a crucial systematic process that, when followed, produces comparable, valid and reliable results, and conclusions (Kumar, 2011:41). The research design process consists of data collection, research instrument development and sampling (Bhattacherjee, 2012:35). The study followed a descriptive research design. This design approach is based on observation as a method of collecting data as it aims to analyze the state of affairs by defining features and by setting criteria that describe the characteristics of people, organisations or objects to enable predictions to take place under similar circumstances (Walliman, 2011:10). The goal of such research is to explain a participant's attitudes or preferences related to some phenomenon under investigation (Dubey, Kothari & Awari, 2017:380).

The post-positivist research philosophy was used, supporting methods which are aimed at theory testing. Post-positivist research methods are deductive and quantitative in nature. The epistemology proposes that research can be tested scientifically and measured. The ontology suggests that there is a single objective reality that can be proven (Longbottom & Lawson, 2019:124). Post-positivism, which is a variation of positivism seeks to generalize patterns on an objective view of reality (Bhattacherjee, 2012:35). As the post-positivist paradigm traditionally supports a quantitative research method, this was the technique adopted in this study for gathering primary data to respond to the research objectives and to generalize results of the findings to populations that share similar characteristics to those in this study. Quantitative approaches can uncover underlying relationships within the data that contain a deep understanding of the overall complexities of the situation under investigation (Albers, 2017:15).

1.7.1 Unit of analysis and sampling

The study was conducted in the central to eastern regions of South Africa where most of the maize cropping activities take place. The Free State, North West, and Mpumalanga provinces collectively contribute 80 per cent of the countries maize production (DAFF, 2020:9). The study employed probability sampling using a stratified sampling method, in which respondents were randomly selected on a proportional basis across the three provinces. Provinces in South Africa have different topographies which may influence weather patterns and subsequently, the extent and degree of willingness-to-pay for insurance. Hence micro-climatic variables were factored into the sampling process by obtaining diverse representation.

Sampling frame statistics showing a population of 1 774 low-income farmers were obtained from the Land and Agricultural Development Bank of South Africa (Land Bank), a state-owned development finance institution with a core mandate for the promotion, facilitation and support of agriculture by providing financial services. The sampling listing consisted of farmers that applied for loans or grant funding over the last four years between 2015 and 2019. A sample size of 326 was established based on the Taro Yamane sample size calculator.

1.7.2 Data collection

Descriptive research depends on surveys as a tool for gathering data (Edmonds & Kennedy, 2017:27). On this basis, primary data were collected using a structured questionnaire in the form of a survey. Typical study designs for descriptive research also apply a cross-sectional study design (Tobi & Kampen, 2018:1213). Accordingly, a cross-sectional design was used because of its ability to allow for the collection of the same data from multiple units at the same time, while capturing the variation between respondents (Bukve, 2019:111). The survey questionnaire featured demographic, economic, farm-specific closed-ended questions and five-point Likert scale type questions formed and guided on the basis of the literature review. These questions were formulated to obtain a comprehensive and proper understanding of various variables that influence insurance purchase decisions. Surveys were conducted telephonically as this method elicits the highest response rate, typically ranging from 60 and 90 per cent (Gray, 2017:339). Telephonic interviews are cheap, fast to administer, and the remoteness of the interviewer reduces potential response bias (Bryman, 2014:214). The choice of survey method was further influenced by national lockdown restrictions imposed from 27 March 2020 as a result of the global Coronavirus disease (Covid-19). The restrictions necessitate social distancing measures, limiting face-to-face contact, and adherence to health protocols (Stats SA, 2020a:8). In this regard, telephonic interviews represented the ideal method of data collection both with respect to efficiency and adherence to government restrictions on travel and social distancing interventions to curb the spread of Covid-19.

1.8 Data Analysis

Following data collection, numerical data were analyzed using descriptive and inferential statistics; the latter included parametric and non-parametric statistical tests. As a starting point, descriptive statistics which comprise the mean, median, range, and standard deviation were computed. Descriptive statistics are used to represent basic features of data in a study and involve grouping and summarizing sets of data in a simplified manner to obtain better information (Dubey, Kothari & Awari, 2017:7). Beyond descriptive statistics, other statistical methods such as correlation analysis were used to examine relationships between variables under investigation. Structural Equation Modelling (SEM) was applied to investigate the direction and impact of factors that influence willingness-to-pay for weather index insurance. SEM uses various models to describe complex relationships between latent constructs and observed variables. A model is considered an integral part of scientific inference and deduction. It is a theoretical construct that represents quantifiable and rational relationships between a set of variables (Westland, 2015:141). Prior to conducting SEM analysis, Cronbach's Alpha and Composite Reliability were used to test the reliability of the measurement instrument while the validity of the structural model was tested by determining convergent and discriminant validity. Lastly, logistic regression based on the maximum likelihood method was used to identify demographic and economic factors that are associated with willingness-to-pay. Data were analyzed using SPSS and AMOS version 26 for windows. The integrated approach of SEM and regression models that was used by Mutyasira, Hoag and Pendel (2018) to investigate behavioural and economic drivers of purchase intentions was followed in this study.

1.9 Operationalization of Key Terms

Several interpretations in the literature exist for different concepts. The concepts and definitions listed below underpin the study and their contextual interpretation forms the basis of the various chapters, sections and sub-sections that constitute this study.

Adaptation – this refers to "the process of adjustment to actual or expected climate and its effects" (DEFF, 2019:2). Adaptation entails increasing the ability of farmers to withstand catastrophic loss by reducing exposure to weather-related vulnerabilities and promoting financial resilience (Jarzabkowski, Chalkias, Clarke, Iyahen, Stadtmueller, & Zwick, 2019:1). Adaptation alternatives such as index-based insurance schemes can reduce vulnerability to weather risk, leading to sustained agricultural development (Apostolakis, Dijk & Drakos, 2015:149).

Agriculture - entails the sustainable and productive use of natural resources and other inputs by individuals for purposes of plant and/or animal production, either for own consumption or for markets. Considering its comprehensive ties to the rest of the economy and its significance in preventing food insecurity, the agricultural sector plays an important economic and social role (National Treasury, 2019:40).

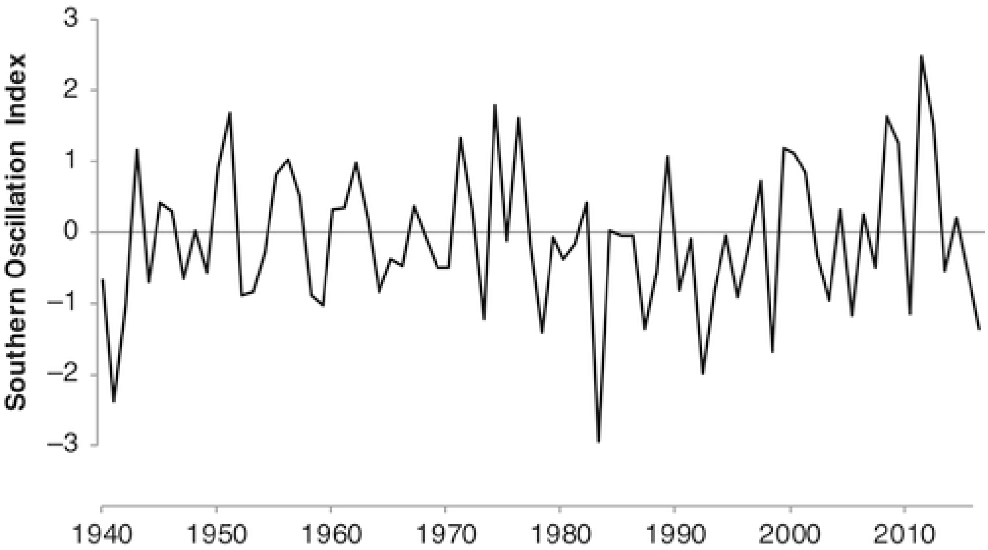
Agricultural Insurance – insurance is a legally binding contract between an insurer and insured that acts as an economic device which transfers risk to a third party, that is, the insurer in exchange for a premium agrees to cover large uncertain financial losses (Atsiaya, Wati, Ingasia & Lagat, 2018:52). Insurance is formulated on the principle of risk pooling such that accurate projections of potential loss are estimates to create a model where the losses of a few are covered by contributions of the entire pool. Risk pooling is most effective when insured risks are relatively independent (idiosyncratic), which means the risk events will not all occur concurrently (Mapfumo, Groenendaal & Dugger, 2017:7). Agricultural insurance is a mechanism primarily used by farmers to cope with farm production losses caused by single or multi-peril events, thus helping to smooth farm income over a period of time (Gunjal, 2016:37).

Agricultural insurance can be an effective instrument for ensuring business continuity, and for maintaining food security on the one hand and fostering rural economic development and modernizing the agricultural sector on the other (National Treasury, 2019:40).

Drought - Climatologists, scientists, and politicians have ongoing discussions on the definition of drought; this classification affects how, if and when appropriate authorities respond to it (Manderson, Kubayi & Drimie, 2016:6). The definitions of drought depend either on technical viewpoints such as meteorology, hydrology or on the economic activity affected such as agriculture. From a meteorological viewpoint, drought exists when cumulative rainfall is abnormally low when compared to the long-term historical average. Hydrological drought happens when there are shortages in water supply, not just limited to rainfall deficits but also to runoff from the land surface and accumulation of surface and subsurface water. Conversely, agricultural drought is a condition that reflects the deterioration of soil moisture over time the extent to which adversely affects crop and pasture yields (Hazelton, Pearson & Kariuki, 1994:3). Drought in the context of this study refers to meteorological drought, that is, below normal precipitation which subsequently leads to agricultural drought.

El Niño – El Niño-Southern Oscillation (ENSO) is one of the most significant factors in the earth's climate cycle that influences weather patterns on a world scale (Klingaman & Keat, 2018:3). El Niño refers to a recurring global atmospheric-oceanic anomaly correlated with sea surface temperature increases in the central tropical Pacific Ocean. These changes mostly occur within a two-to-seven-year period and could persists for up to 24 months. In some parts of the world, the El Niño phenomenon increases the risk of excessive rainfall usually leading to flooding, in other regions, it increases the risk of drought events through severe rainfall deficits (FAO, 2018:1). El Niño events tend to develop between May and August and usually reach their maximum strength from December to February (Klingaman & Keat, 2018:3). Figure 1.2, demonstrates El Niño events in South Africa over the summer period from 1940 – 2016 ranging from mild to very strong El Niño as shown by a sharp spike in 1983, 2010 and 2016 respectively.

Figure 1.2: Effects of El Niño on South African temperatures during austral summer



Source: Lakhraj-Govenver and Grab (2018:146)

Food security - a condition that "exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996:30). Food security is a strategic priority of the South African government (BFAP, 2018:26). In terms of food supply, the country is currently food secure at an aggregate national level. Although adequate food is available to everyone in South Africa though domestic food production and food imports, the means of obtaining food at household level remain an obstacle, underpinned by the high level of income inequality in the country (Stats SA, 2019:6).

Low-income farmer - frequently, the term low-income farmer is used interchangeably with smallholder, small-scale and resource-poor farmer. These terms refer to farmers' limited resource endowment relative to other farmers (Senyolo, Long, Blok & Omta, 2017:3826). Low-income farmers are part of a mixed society that ranges from a broad group of subsistence farmers on one end of the continuum to a smaller community of smallholder farmers with a commercial orientation on the other (Zantsi, Greyling & Vink, 2019:81). For this study, low-income farmers exclude subsistence farmers; these are farmers who farm for household consumption and do not produce for markets.

Resilience - the ability of a societal, economic or ecological system to absorb climate shocks while preserving the same basic structure and methods of functioning. This refers to the ability to respond to stress and change in respect of the climate (DEFF, 2019:4).

Vulnerability - Vulnerability is the extent to which farm revenue is affected by variations in weather patterns. Vulnerable farmers are usually those who are marginalized institutionally, geographically, politically, socially, culturally and economically (Flatø, Muttarak & Pelser, 2017:41). Vulnerability is therefore the capacity to respond to, recover from or to adapt to climatic pressures placed on individuals or groups' livelihoods and well-being (Schulze, 2016:19).

1.10 Contribution of the Study

Weather index insurance has been attracting much attention from academics, policymakers, governments, and non-government organizations across Africa because of its effectiveness in promoting agricultural and rural development (Choudhury et al., 2016:173). The study is expected to assist in providing a better understanding of low-income maize farmers in South Africa, for which publicly available evidence is limited because of their restricted integration in the agricultural value chain as well as formal financial services. The study is expected to add to the contextual knowledge of farmer's need for weather index insurance, which is an aspects that is under-researched currently, and how this insurance solution can play a broader role in financial inclusion, climate change adaptation and agricultural productivity; all of which provide significant benefits in terms of economic development, job creation and poverty alleviation. It is expected that this research might make a practical contribution to policymakers and financial institutions in the planning and development of policies including product design, product pricing and product channel distribution of index-based insurance solutions in the country. Further, this study is expected to make contributions in expanding weather index insurance literature with regard to consideration of socio-psychological factors that influence farmers purchase decisions, in addition to socio-economic considerations that are unique to the South African context. Finally the study presents a conceptual framework for factors that drive low-income farmers' willingness-to-pay for weather index insurance to improve future market participation in these type of insurance schemes.

1.11 Structure of the Thesis

The thesis is structured in seven chapters, each with its sections and sub-sections. Each chapter is outlined as follows:

Chapter One: The first chapter provides an introduction and background, highlighting the research problem under investigation and the various research objectives of the study.

Chapter Two: The second chapter provides an analysis of the agricultural landscape as well as contextualisation of weather index insurance and its variables through a literature review. The role of various stakeholders in insurance is analyzed, with particular reference to the role of the government as an enabler and provider of index insurance.

Chapter Three: The third chapter outlines empirical evidence from other research studies on willingness-to-pay for weather index insurance, the various prices involved and the factors influencing participation.

Chapter Four: The fourth chapter considers the research design and methodological approach in response to the research objectives, underlining the philosophical paradigm and broad research plan to collect sufficient data to solve the research problem.

Chapter Five: The fifth chapter constitutes research findings and analysis of data using descriptive and inferential statistical procedures. In this chapter, the conceptual framework is modelled and validated using SEM.

Chapter Six: The sixth chapter offers a critical discussion of the research findings as aligned to the research objectives and additionally provides an interpretation of results compared to interpretations in the literature review and existing research.

Chapter Seven: Lastly, the seventh chapter documents recommendations made by academic scholars, practitioners and institutions interested in the subject under study. Limitations of the study and implications for further research are also discussed and concluding remarks are made relative to the entire study.

1.12 Conclusion

This chapter provided the introduction and background to the research study. The research problem and study objectives were identified with the remainder of the dissertation structured in a manner that sets out the path to address the research objectives. It was noted that a number of research investigations have attempted to understand the factors that impede or promote the penetration of index insurance in Africa. In this study, a unique three-pronged approach was followed, which included analysis of demographic, economic and psychological drivers of insurance uptake intentions. It was expected that this study should make theoretical contributions to expand index insurance literature and could make a practical contribution to weather index insurance development and successful implementation in South Africa. Lastly, Chapter One outlines key terms as used in the rest of the thesis, concluding with providing a broad framework of the structure of the thesis.

The next chapter provides an analysis of the agricultural landscape in South Africa, followed by the literature review which undertakes an in-depth study of the concept of weather index insurance, its application, and its challenges and opportunities.

CHAPTER TWO: AGRICULTURAL LANDSCAPE AND CONTEXUALIZATION OF WEATHER INDEX INSURANCE

2.1 Introduction

Chapter Two contains an overview of the agricultural environment and landscape within which farmers in South Africa operate as it pertains to political, socio-economic and agro-economic dynamics. Referred to as the breadbasket of the southern African region (DAFF, 2020:11), South Africa has a dual agricultural economy where well-capitalized commercial farmers control the primary food supply value chain and operate in parallel with resource-constrained, low-income farmers who face a myriad of structural challenges (GreenCape, 2021:10). Critically, the chapter addresses how resource-strapped farmers apply risk management practices to reduce inherent production risks attributable to adverse weather and how the risk management environment is increasingly becoming complex to navigate because of the effects of global warming and climate change. Conceivably the most pressing issue of our time is climate change, demanding appropriate actions from those managing agricultural production systems (Gunjal, 2016:9). Following the background and overview, chapter two closely positions weather index insurance as a potential mitigating solution for low-income farmers, setting out how the insurance has been integrated in other developing countries as part of a comprehensive farm risk management strategy.

Detailed in this chapter are benefits and limitations of weather index insurance, particularly as they pertain to increased credit accessibility *vis-à-vis* basis risk, that is, the uninsured portion of index insurance due to technical product design shortcomings. Further, demand for weather index insurance among low-income farmers, mostly in agricultural-based developing economies exposed to the vagaries of the weather, is considered, assessed, and discussed to identify potential impacts in the South African environment. Explanations are drawn from a wide range of views from leading practitioners, authors, and institutions promoting insurance inclusion on the current level of demand and strategies to enhance demand for parametric insurance. Elabed and Carter (2015:151) claim that index insurance contracts would have an enormous developmental impact on poor and rural farming communities in Africa if demand is understood and stimulated in order for these products to reach scale.

2.2 Agricultural Landscape of South Africa

South Africa is an upper middle-income economy that has relatively stable macroeconomic systems and diversified economic activities (World Bank, 2018:1). The country has a vibrant cultural diversity and an incredible variety of agricultural, biodiversity, climate and soil types. The climate-soil composition leaves 12 per cent of the country suitable for the production of rainfed crops, with only 3 per cent considered truly fertile land (DAFF, 2018b:5). Agriculture contributes 3 per cent to the GDP of South Africa and accounts for about 7 per cent of formal employment (GCIS, 2019:2). Elementary work, defined as work which primarily requires physical labour makes up 77 per cent of the agricultural workforce, of those, 22 per cent are considered unskilled (GreenCape, 2017:15). Notwithstanding its moderate contribution to GDP, primary agriculture is the foundation for food provision. It plays a key role in backward and forward linkages to other sectors of the economy, in particular manufacturing where an estimated 70 per cent of agricultural outputs are used as intermediate products.

South Africa is classified as a semi-arid country (CapeGreen, 2021:10) with rainfall generally low and erratic (Schulze, 2016:5). Erratic rainfall is the primary determinant of income variability for farmers, in particular, low-income farmers who are highly susceptible to these fluctuations (Akter et al., 2016:217). Water availability is the single most important factor in crop production in South Africa (du Plessis, 2003:13). Its availability is scarce and the country suffers from poor irrigation systems (Ncube & Shikwambana, 2016:28). The country is notably vulnerable to drought and hailstorms (World Bank, 2016:11), drought being the most prevalent and recurring hazard (Bahta, Jordaan & Muyambo, 2016:40). Drought impacts crop growth in different ways, including, direct effects such as the topsoil layer getting drier, reducing moisture and reducing the plant’s ability to absorb water in its root systems, and indirect effects in that the plant becomes more susceptible to pests and disease through increased stress (Hohl, 2019:52). The monetary effects of drought resulted in an estimated R12 billion loss of revenue for maize farmers in the 2015/16 crop season alone (AgriSa, 2016:20). From 1980 to 2013, drought-related financial losses have accounted for 42 per cent of all agricultural losses in South Africa (Sasria, 2018:29). The impact of drought on crop production and yield is further highlighted in Table 2.1 below:

Table 2.1: Five-year history of maize production in South Africa

Season	**2013/14**	**2014/15**	**2015/16**	**2016/17**	**2017/18**
Planting (ha)	2 688 200	2 652 850	1 946 750	2 628 600	2 318 850
Production (t)	14 250 000	9 955 000	7 778 500	16 820 000	12 510 000
Yield (t/ha)	5.30	3.75	4.00	6.40	5.39

Source: DAFF (2018a:11; 2020:10)

In the 2016/17 crop season rainfall improved as evidenced by the yield per hectare increase to 6.40 which is a 60 per cent increase from the previous season, underscoring the impact of drought on maize production as the tail end of 2014/15 was generally dry (Manderson, Kubayi & Drimie, 2016:22) and 2015/16 was officially declared as a drought disaster period affecting the Free State, North West, KwaZulu-Natal, Limpopo and Mpumalanga (Davis-Reddy & Vincent, 2017:42). Where an estimated 250 000 farmers were affected and over 6 million people indirectly affected (Ncube & Shikwambana, 2016:2).

Drought has repeatedly been proven to cause a sequence of behavioural reactions that demonstrate that the societal and economic costs of drought are significantly greater than what might have been historically observed immediately following a drought occurrence (Lybbert & Carter, 2014:5). Where food insecurity is assessed to increase by as much as 45 per cent in some regions following extreme drought (Boucher et al., 2020:6). When dry conditions prevail, farmers respond by reducing investment in agricultural production and plant fewer hectares as evidenced by the fact that the planted area in 2015/16 was the lowest in five years. Inevitably this resulted in shortages that placed inflationary pressure on maize as an essential food staple which saw commodity prices increase by up to 37 per cent in 2015/16 (BFAP, 2016:12). Food price increases have been shown to have negative welfare effects of South African households, where 1 percent rise in food prices could reduce household welfare by as much as 21 percent. In general food prices are expected to escalate year on year, thus increasing vulnerability of households to food insecurity (van Wyk & Dlamini, 2018:1).

Maize is a multidisciplinary crop produced by an estimated 6 500 commercial farmers who are responsible for most of South Africa’s crop, and thousands of smallholder and subsistence producers are responsible for the rest (GCIS, 2019:10). South Africa produces 17 per cent of the total maize in Africa (Davis-Reddy & Vincent, 2017:55). Almost 90 per cent of the maize in South Africa is produced under dryland conditions, and the remaining 10 per cent is produced under irrigated land conditions (DAFF, 2020:10). Under irrigation, high yields are produced, resulting in substantially more tons per hectare (Calzadilla, Zhu, Rehdanz, Tol & Ringler, 2014:27). Maize is a warm-weather crop ideally cultivated in regions where the average daily temperature is above 19 degree Celsius or where the average of the summer months is above 23 degree Celsius (du Plessis, 2003:11). The crop requires 450 to 600 mm of rainfall per growing season for optimal growth (Schulze & Durand, 2016:5), with South Africa only experiencing an average rainfall of 464 mm (GCIS, 2017:2), meaning that maize producers are exposed to inherent shortcomings in rainfall. Best crop husbandry practices suggest that maize planting should be planned in a way that avoids midsummer droughts from coinciding with the most vulnerable period of crop development. This is the flowering period when maize is most sensitive to water deficits and heat stress (du Plessis, 2003:19). For this purpose, maize is planted in early summer, with peak planting periods in November and December and harvested from May through to late August (DAFF, 2020:9).

The global covid-19 pandemic that resulted in a national lockdown from the 27 March 2020 has had severe economic implications across the board. Following lockdown restrictions the agricultural sector was one of the few key industries which continued to operate as it was classified as an essential service under the *Disaster Management Act* underscoring the importance of the sector to societal livelihood and sustainability. The agricultural sector was the only industry in South Africa to record impressive fundamental growth during the pandemic, with 27.8% and 15.1% in the first and second quarter of 2020 respectively (Stats SA, 2020a:3), underpinned by increased production of field crops, and increased maize exports which generated much needed foreign currency. The overall increase in agricultural activity is likely to attract future Foreign Direct Investment (FDI) in attempts to recover and rebuild the economy in the midst of the global health crisis. FDI inflows have continued to decrease in South Africa, marked by a 15.1% decline between 2018 and 2019. The country continues to see the largest outflow of FDI in Africa (UNCTAD, 2019:34). The resurgent and central growth in the agricultural sector offers a silver lining to an economic recovery trajectory and has enormous untapped potential for wider scale growth.

2.2.1 Low-income farmers in South Africa

Colonial land dispossession, apartheid, and then post-apartheid deregulation of agriculture have all contributed to the dominance of a highly industrialized and commercial agricultural sector in South Africa (African Centre for Biodiversity, 2017:10). It is estimated that South Africa has approximately 40 000 commercial farming units covering 82 million hectares and between 300 000 and 400 000 predominantly Black low-income farmers covering an estimated 14 million hectares (National Treasury, 2015:148). Low-income or smallholder farmers refers to those that produce at a primary level for household consumption and market supply. In other words, agriculture is deliberately undertaken to satisfy both household sustenance and is a source of revenue generation. Most low-income farmers are emerging entrants aspiring to produce at scale to maximize profit. The typical annual revenue for small-scale farming ranges from R50 000 - R5 million per annum (DAFF, 2018b:12). Production revenue below this level is considered subsistence farming, which is purely a livelihood strategy for own consumption, and anything above the upper threshold is classified as semi-commercial to commercial.

The Department of Agriculture further provides a typology or segmentation of smallholder farmers. Type 1, includes farmers that produce on a part-time basis where farming forms part of a multiple livelihood strategy. Type 2, represents farmers in the middle of the spectrum, relying mainly on their farming enterprise for income generation These farmers can sustain their livelihood but require further assistance both to expand production and access markets. Type 3, are those farmers who operate according to commercial norms. They tend to be capable entrepreneurs and command support from the government due to their upward mobility; they often have the capacity to sustain themselves and to secure loan financing (DAFF, 2013:6). This study is concerned with Type 3 market-producing farmers.

Table 2.2: Summary statistics on farming units in South Africa

Farming unit	No. of farmers	Hectares (Ha)	Average farm size
Commercial Farms	40 000	82 million	2 050 ha per farm
Smallholder Farms	300 000 - 400 000	14 million	35 ha per farm

Source: National Treasury (2015:148)

From a demographic analysis, low-income farmers are mostly Black African males who are 65 years and older who did not finish school, and normally have limited financial literacy lacking awareness of financial products (Accenture, 2018:4). The historical spatial demarcation of South Africa means that most low-income farmers' farm in less productive areas (former homelands) exposed to erratic and unreliable rainfall (Thamaga-Chitja & Morojele, 2014:151), where the production of maize is on average 1 ton per hectare (Bahta, Jordaan & Muyambo, 2016:40), compared to commercial farmers who produce 4 - 6 tons per hectare on dryland and in excess of 10 tons per hectare on irrigated land (BFAP, 2018a:5).

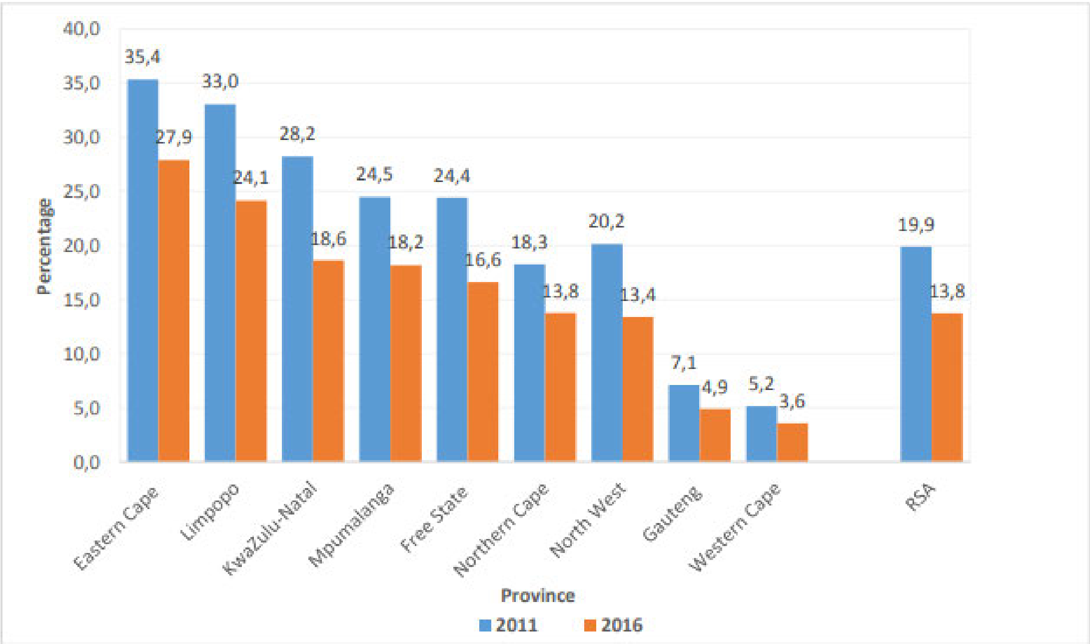
Production risk is rooted in low-income farmers daily farming practices (Belissa, Lensink & van Asseldonk, 2019:1), and it is found that low incomes generated in this segment have a negative effect on proactive measures to manage production risk (Jumare, Visser & Brick, 2018:12), including undesirable long-term consequences on the economic welfare of rural communities (Tolno, Kobayashi, Ichizen, Esham & Balde, 2015:123), where three-quarters of low-income farmers are situated (GCIS, 2020:3). These agricultural producers face a multitude of challenges as a result of economic, political and environmental dynamics such as poor infrastructure, limited arable land, inferior quality inputs, lack of technical training and lack of access to viable markets (GreenCape, 2021:44; von Loeper et al., 2016:748). Market access for low-income farmers entails the ability to operate in, as well as to access opportunities, to produce at a profit for household income and food security needs (Ngqangweni, Mmbengwa, Myeki, Sotsha & Khoza, 2016:2). Typically, information asymmetry on prices, technologies and linkages to established value chain participants limit these market opportunities (Sikwela, Fuyane & Mushunje, 2016:537). Consequently, smallholders currently supply informal markets and loose value chains with less demanding criteria on quality, governance and regulation than formal traders. This often translates into lower revenue because of the fragmented nature of informal markets. It is observed that less than one-fifth of smallholder farmers receive government support in gaining access to formal markets (Okunlola, Ngubane, Cousins & du Toit, 2016:57).

Structurally, low-income farmers have limited access to water resources and rights (DAFF, 2018b:3; Ncube, 2018:94), limited access to information related to farm water and soil management strategies, as well as a limited tradition of long-term planning (Wilk, Andersson & Warburton, 2012:1). The combined effects of identified challenges mean that limited -resourced low-income farmers have little access to credit, with credit accessibility rates in South Africa estimated at only 12 per cent (World Bank, 2016:14). Without access to credit, low-income farmers face working capital restrictions and subsequent barriers to expansion, for example, restrictions on acquiring modern equipment, implements and technologically improved seed varieties to achieve higher productivity. Small-scale farming, as a consequence, remains a survivalist activity exposed to unmitigated weather risk, low rates of technology adoptation, resultant stagnant growth, and perpetually low productivity. Kahan (2013:4) concludes that such a cavalier approach to agriculture is no longer feasible, even if production is for own-consumption given the associated high levels of risk.

Agricultural land access

Water scarcity, production risk, and fluctuating commodity prices make agricultural production in South Africa an expensive economic pursuit, where expert skills, experience and economies of scale are needed to achieve profitability. Furthermore, profit margins are low compared to many other countries because of the high cost of seed input, fuel, and labour. For this reason, many low-income and emerging farmers are gradually shifting to non-agricultural land use or selling their farms and migrating to urban areas. South Africa is one of the most urbanised countries in sub-Saharan Africa, with almost 65 per cent of its population living in towns and cities (PWC, 2018:25). With repurposed land use, increases in manufacturing, industrialization the number of farms in South Africa has decreased by over two-thirds relative to the early 1990s. Still, average commercial farm sizes have continued to increase as commercial farmers absorb neighbouring low-income farms (NAMC, 2018:7). The decline is further captured in Figure 2.1, which compares the percentage of Agricultural households by province in 2011 and 2016.

Figure 2.1: Comparison of agricultural households by province (2011 and 2016)



Source: Stats SA (2019:7)

Consistent with human capital theory, in choosing to remain in an occupation, the prospective worker evaluates, subject to labour and capital market constraints, possible monetary and non-monetary cost and benefit implications associated with various professions. The profession or trade with the highest value of future potential benefits given the worker's knowledge, skill, interest and experience will be selected (Dzanku, 2018:367). Additionally, research indicates that those who intend abandoning farming use fewer agricultural inputs and their output is substantially lower indicating that this intention is not conducive to improving agricultural production or the conditions of low-income farmers (Guo, Wen & Zhu, 2015:4).

Livelihood status

One of the most important sources of income for the majority of low-income farmers in South Africa stems from social grants, such as a pension, or child support grant or a combination of both and from financial allowances from family members who migrate to urban areas for employment opportunities. Farming usually involves a set of livelihood activities implemented to supplement household income (Okunlola et al., 2016:14). The ancillary activities to farming are in direct response, to the fact that more than half of low-income farming households live below the poverty line (DAFF, 2015:12) which is a disconcerting fact considering their prospective role in food production. But it is a position that sharply points to the difficult conditions in which low-income farmers operate, in addition to being marginalized and excluded by financial institutions because of high transaction costs and perceived low margins in servicing the market (Jarzabkowski et al., 2019:30).

The reality for the non-farming community is also the same; South Africa is one of the most unequal countries in the world with a consumption per capita Gini coefficient of 0.63. At the upper national poverty line of R992 per person per month, half of the population of South Africa is considered chronically poor. A further 27 per cent of the population is vulnerable and has an above-average chance of being in poverty, meaning that approximately 76 per cent of South Africans live in poverty or under the constant threat of poverty (World Bank, 2018:42). Several policies have been promulgated such as land reform and comprehensive agricultural support, to address challenges of poverty, inequality and unemployment precisely, as they pertain to the broader economy and to the agricultural sector. However, policy discourse in agriculture continues to be informed by unexamined assumptions about the nature and needs of low-income farmers (Okunlola et al., 2016:7).

2.2.2 Government support for the agricultural sector

Small-scale farmers produce 70 per cent of all food consumed worldwide (Microinsurance Network, 2017:6). Their role in food security systems, employment creation, economic development and poverty alleviation is gradually taking centre stage, with global evidence derived from empirical studies beginning to advocate support for low-income farmers (Thamaga-Chitja & Morojele, 2014:147). In light of this evidence, the South African government has identified low-income farmers as catalysts for inclusive growth initiatives. Smallholder farmers have been tasked through the government's policy framework with the responsibility of creating over a million employment opportunities by 2030 and to contribute meaningfully to rural economic development (National Planning Commission, 2012:124). Smallholder farming is labour intensive, as opposed to mechanized commercial farming (GCIS, 2019:2). In this way, it has the capacity to create sustainable employment for an economy with one of the highest official unemployment rates at 30.1 per cent (Stats SA, 2020b:2). Smallholder farmers are seen as holding the promise for agrarian transformation in South Africa (Hornby & Cousins, 2016:2) and the government is committed to interventions that assist these producers with technical, infrastructural and financial support, including the recognition that all future support should include insurance (DAFF, 2018b:41).

Agricultural support in South Africa is an area of synchronized national and provincial responsibility. Funds for farmer support programmes come from a combination of Department of Agriculture, Land Reform and Rural Development (DALRRD) conditional grants, and direct projects as well as from the equitable provincial share from National Treasury to provincial treasuries. From 2010 to 2020, the Provincial Departments of Agriculture had a total budgetary expenditure of R104 billion, the bulk of which was allocated to the commercialization of smallholders through two main programmes: Comprehensive Agricultural Support Programme (CASP) and Ilima/Letsema which is more focussed on household food production systems (African Centre for Biodiversity, 2018:4). CASP was established in 2005 based on six key pillars of:

> "on and off farm infrastructure support; knowledge and information management; technical and advisory services; training and capacity building; market and business development support; and financial services" (DAFF, 2019:9).

Since inception CASP has supported close to 700 000 farmer beneficiaries, while Ilima/Letsema has provided support to approximately 200 000 farmers in terms of broader social, economic and environmental benefits (DAFF, 2019:12). In addition to grant funding, government oversees the Micro Agricultural Financial Institution of South Africa (MAFISA), which provides low-interest rate loans to a limit of R500 000 per farmer aimed at assisting low-income farmers, particularly beneficiaries of land reform programmes. In its current form, MAFISA capital reserves are low, and it is in no position to extend further funding (Aliber, 2020:9). Land Bank offers similar agricultural loans and structured finance solutions to the agricultural sector through various programmes tailored for commercial and developmental farmer needs. The bank currently services an estimated 30 per cent of the agricultural credit market, the rest of the funding comes from commercial banks with 56 per cent, agricultural cooperative with 9 per cent and other creditors constituting the remaining portion (GCIS, 2020:6). Land Bank has a stronger focus on commercial and semi-commercial Black farmers as opposed to the various subclasses of smallholder farmers (Okunlola et al., 2016:57). It acknowledges though that much needs to be done to provide access to finance for smallholder farmers (Aliber, 2020:9).

Notwithstanding grant funding and loans, the government manages drought relief grant schemes administered by the Department of Cooperative Governance and Traditional Affairs (COGTA) as part of the national effort to assist affected farmers with disaster drought recovery measures. Drought is common, and it is repeated without any noticeably consistent pattern of occurrence and its characteristics vary from region to region (Žarković, Miloradić & Samardžić, 2016:1297). Budget allocations to the drought relief scheme have increased significantly over the years from R118.1 million in 2016/17 to R423.7 million in 2017/18, and they are expected to increase further at an average annual rate to 5 per cent over the medium term, to R492.4 million in 2020/21 (National Treasury, 2018:3). With various agencies and organs of state responsible for agricultural funding, it is generally agreed among many critics that the policies of different institutions engaging and supporting low-income farmers lack coordination and harmonization (Ncube, 2018:95). There needs to be an alignment and consolidation of the different policies, starting from the term ‘low-income farmers’. While such phrases are used freely in political and policy discourse, they appear to mean very different things to different people and organisations (Okunlola et al., 2016:9). The National Department of Agricultural in its submissions to parliament accepts these policy misalignments and as a way forward calls for the overhaul and restructure of farmer support programmes in the country (DALRRD, 2020:37).

A common metric in measuring the net welfare benefits provided by governments is the Nominal Rate of Assistance (NRA), which calculates the combined effect of subsidies, grants and incentives to farmers, less the compulsory industry levies, taxes, and tariffs. Developed economies have an estimated 10 per cent NRA for the agricultural sector, in comparison to NRA which is at parity for most emerging market economies. South Africa registers below average figures in relation to the rest of the developing world, signalling that the net effect of charges imposed on farmers exceeds the benefits farmers derive from government incentives and programmes (Finmark Trust, 2016:44). Agriculture in South Africa has undergone enormous structural changes, the effects of which have seen the loss of employment at a higher rate than new jobs created (DAFF, 2014:6). Some of the strategic challenges centre on, ineffective disaster relief distribution of funds, inadequate insurance policy framework and land reform considerations, which usually takes front and centre stage in most discussions on agriculture. These strategic challenges are discussed in the sections that follow.

2.2.2.1 Disaster relief

Disaster relief schemes face challenges of poor coordination, limited and untimely reach to farmers. There exist complex bureaucratic hurdles which impede and continue to frustrate effective drought response efforts (Baudoin, Vogel, Nortje & Naik, 2017:128). These include a lack of transparent processes over the selection criteria; an obscure and unscientific basis for allocation of funds to affected farmers; as well as poor governance and oversight with limited accountability, often leading to non-payment to farmers in the most remote areas (Gulati, Terway & Hussain, 2018:3). A case in point is a drought relief scheme which was implemented in the North West province after two consecutive years of below-average rainfall. Ultimately more than 60 per cent of the affected farmers did not receive any assistance from the government (van Niekerk, Wentink & Shoroma, 2018:17). As observed by Aheeyar, de Silva, Senaratna-Sellamuttu and Arulingam (2019:2), within local jurisdictions, vulnerable farmers often lack political capital and knowledge to organize, mobilize and lobby timely government relief effectively. Among other considerations, this may be because, farmers and farmworkers are poorly unionized, and smallholder farmers' interests are often inadequately represented within civil society organizations (Cousins, 2017:144).

According to Castillo, Boucher and Carter (2016:94) the improvement of government participation in formal insurance structures appears to be a more efficient apparatus of responding to climate risk than by providing emergency response finance. This is because insurance has the ability to smooth consumption and to lessen the financial and economic shocks of adverse climate events (Montmasson-Clair, Mudombi & Patel, 2019:4). Insurance could offer a valid, market-based approach to promote agricultural production and intensification, while improving the efficacy of disaster relief financing especially distribution and allocation of funding efforts since insurers keep detailed records of the farm location, commodity insured, and number and value of hectares insured (Binswanger-Mkhize, 2012:189). A number of developed countries such as Canada, France, Italy and the United States support agricultural insurance programmes as a means to reduce reliance on government disaster assistance (Barnett, 2014:202). In these countries, insurance is integrated within a holistic risk management framework which incorporates risk financing mechanisms. Effectively this addresses the protection as well as the financial gap (Weingartner, Simonet & Caravani, 2017:34). It is this sort of environment of integrated risk management where weather index insurance provides its best benefits (Choudhury et al., 2016:173). In additional this holistic approach of supporting insurance schemes contributes to macroeconomic growth by means of freeing capital for investment that government would otherwise have reserved for disaster relief.

2.2.2.2 Insurance framework

It is well publicized that the South African government allocates a vast amount of its budget expenditure towards development, inclusive growth and transformation of agriculture. However, the effectiveness and return on investment remains questionable given the present plight of low-income farmers. For instance, a study in the Eastern Cape revealed that low-income farmers perceive that there is a lack of adequate government support for weather risk reduction (Bahta, Jordaan & Muyambo, 2016:47). Political-will has translated into funding, legislation, policies, and plans, but alongside this there exists a gap involving the lack of a national insurance policy framework in agriculture. It has been proven that such a framework promotes high insurance coverage among individual farmers, subsequently leading to faster response and recovery from disasters, as insurance provision facilitates the flow of capital to support insured individuals.

Worldwide governments are recognizing the role and benefits of insurance as a social safety-net in transferring risk from weather-related shocks and disasters to international markets where risk is pooled and aggregated (Jarzabkowski et al., 2019:1). The South African government is no exception. It acknowledges that one of the key policy levers for sustainable agriculture is the development and introduction of a policy that will address social protection for farmers though insurance (DAFF, 2014:26). Social protection, as empirical evidence suggests, can be an effective instrument to resolve causes of temporary and permanent migration, which are driven by deteriorating livelihoods, income shocks and food insecurity (Schwan & Yu, 2018:51). Food production systems and the insecurity that may emerge from unfavourable production environments is pervasive in developing countries. Food insecurity is often affected to a greater extent by the prevailing political and economic influences than by availability and choice of coping strategies (Finmark Trust, 2016:56).

2.2.2.3 Socio-political dynamics: land reform

An estimated 4 per cent of agricultural land is in the possession of the indigenous Black population (DRDLR, 2017:80). This is a disconcerting situation for a country where 80 per cent of the population is Black African (Stats SA, 2019:8). In recent times these skewed land distribution patterns have heightened debate and policy action around land redistribution in the context of a broader land reform programme. Social divisions and inequalities based on a complex articulation of gender, race and class characteristics underpin the unequal land distribution (Cousins, 2017:135). In response to this complex matrix of forces, land reform in South Africa depends on the policy controls in government's response to deepening inequality, poverty and unemployment. The founding principles of land reform are de-racialization of the rural economy and democratic and equitable land allocation across gender, race and class (DRDLR, 2015:13). As such, land reform is a policy action classified as a moral, social and economic imperative (South African Government, 2019:11). In their Presidential Advisory Panel on Land Reform and Agriculture report, Mahlati et al. (2019:41) articiculate that:

> "The dispossession of the land of native South Africans by European settlers caused devastating poverty and fractured economic well-being for African families and their communities. Centuries later, landlessness, deep structural inequality and poverty remain the everyday reality for the African majority".

Land reform programmes have been instituted by the present-day government since the dawn of democracy in 1994. These programmes aim to address historical injustices of land dispossession through land redistribution, restitution and land tenure (Zantsi, Greyling & Vink, 2019:82). Redistribution aims to assist urban and rural poor, farmworkers, labour tenants, as well as emergent farmers by redistributing commercial land for residential and productive purposes in order to improve their livelihoods. Restitution focusses on restoring land to those previously dispossessed by racially discriminatory laws and practices. Land tenure seeks to secure property rights of persons living under unsecured arrangements; it entails a system of landholding, land rights and forms of ownership (GCIS, 2020:19).

For a variety of reasons, the past two decades of land reform in South Africa have shown little progress in setting up a new generation of Black farmers, ranging from the sluggish pace of government land acquisition programmes to government reluctance to transfer possession of the acquired land to beneficiaries (Mahlati et al., 2019:50). At the same time, low-income farmers remain on the peripheries of mainstream economic activity due to the effects of the slow-moving redress of inequality and the land ownership reform process. Rhetoric about land reform for smallholder farmers has long disguised the complete neglect of these producers, with the most powerful voices being elite capitalist farmers who are often the main beneficiaries of land reform and at the heart of underlying class dynamics that have captured the policy agenda (Cousins, 2017:138). Some scholars like Netshipale, Oosting, Mashiloane, van Reenen, de Boer and Raidimi, (2020:2) argue that it is not only the elite capitalist's capture, rather, economists advocating for efficient use of capital, environmentalists driving conservational use of natural resources, social activists calling for the security of tenure, and lastly, politicians chasing stability while pursuing the agenda of the most influential stakeholder. It is estimated that South Africa has a total land area of 122 million hectares, of which 25 per cent is owned by the state. Approximately 7.4 million hectares of land has been transferred to previously disadvantaged South Africans for sustainable agricultural development through land and agrarian reform programmes. This is far below the target of 24.6 million hectares or 30 per cent initially set to be achieved by 2014 (National Treasury, 2019:39).

The most recent land reform analysis showed that 90 per cent of reform projects were unsuccessful, having spent an estimated R30 billion to acquire and transfer commercial farmlands, which are now operating sub-optimally or are no longer in productive use (Davis-Reddy & Vincent, 2017:59). Lack of adequate post-settlement support in land reform programmes is widely seen as a strategic challenge. This includes access to finance, infrastructure, inputs, markets, extension services, training, and water for irrigation for land reform beneficiaries (Institute for Poverty, Land and Agrarian Studies, 2016:79). Scholars such as Netshipale et al. (2020:8) hypothesize that limited post-settlement support from the state is a direct result of budgetary constraints after significant expenditure on land acquisition costs. Other views are that land is not the main issue, but financing existing agricultural enterprises is the main concern. To support this argument, in October 2020, the government announced that it would be releasing underutilized or vacant agricultural state land of 896 farms measuring 700 000 hectares (DALRRD, 2020:1). The question is, where will financial support to work the land come from as Land Bank announced in the earlier part of the year that the institution is unable to disburse financing due to liquidity constraints, emanating from elevated credit risks due to increased non-performing loans, declining capital reserves resulting in breaches of loan covenants, and effects of the sovereign credit rating downgrade that resulted in all Development Finance Institutions (DFI) in the country including Land Bank being downgraded as well, implications of which triggered disinvestments from funders. Further to these factors, the bank remains on negative outlook because of it intrinsic ties to the agricultural sector and the potential downward risk of the impact of land reform programmes (Land Bank, 2020:15). With respect to land reform, Cousins (2017:148) offers a diagnosis of failures, that includes insufficient political-will for reform and he suggests a new narrative for land reform, which offers thought-provoking alternatives. In his paper, he argues that land reform as a whole should be reconfigured, to a point where 80 per cent of commercial farming units should be subdivided among Black smallholder farmers who already produce crops and livestock.

Land reform is perhaps the most divisive topic in contemporary South African politics (Voster, 2019:1). The current political discourse on land reform, in particular, the expanded use of expropriation and specifically, expropriation of land without compensation, has affected investment in the agricultural sector significantly. In February 2018, the National Assembly of the Parliament of South Africa adopted a motion to amend the Constitution so as to allow for the expropriation of land without compensation (South African Government, 2019:11). Section 25 of the constitution provides for expropriation of land "for a public purpose or in the public interest" at levels of compensation that must be "just and equitable". Thus far, compensation for land acquired for restitution purposes has mostly taken place at or above market value, and constitutional powers of expropriation have not been used in pursuit of land redistribution; instead, a policy choice has been made to follow a 'willing buyer, willing seller' approach based on voluntary sales (Kepe & Hall, 2016:4). It remains to be seen whether or not the current administration will amend the property clause section of the constitution following widespread public consultation on the matter. Current surveys show that a significant number of commercial farmers are reconsidering future investment until the expropriation issue has been tested and resolved. This decision has a direct impact on the future productivity of the agricultural sector with long-term growth declining by 40 per cent and 30 per cent of farm jobs lost (BFAP, 2018:7).

2.2.3 Agricultural insurance market

Agricultural insurance interlinks financial service and the agricultural sector. The former is the largest contributor to South Africa's GDP at 21 per cent (Stats SA, 2020a:10), where the non-life insurance industry contributes approximately R150 billion in annual gross written premiums (Madlala & Luyaba, 2019:6). From this amount the crop insurance industry represents an estimated R1.5 billion which equates to 30 per cent of the value of all crops in the country, highlighting the overall low level of agricultural insurance penetration (Wiese, 2019:30). It is generally agreed that financial services in emerging market economies are marked by weak competitive environments owing to high concentrations of market dominance (Alhassan & Biekpe, 2019:1371). Low competition capacity leaves very few alternatives for consumers in terms of products and price. As a result, the use of substitute and often less effective non-market risk management solutions have become prevalent, which restricts the growth potential of agriculture. South Africa is no exception with an oligopolistic crop insurance market where two large insurers from a total of 74 non-life insurers (Madlala & Luyaba, 2019:3) dominate the market. These are Santam with a market share of 59 per cent indicated by a gross written premium of R886 million (Santam, 2019:112), and Land Bank Insurance with a market share of 34 per cent indicates by a gross written premium of R504 million (Land Bank Insurance, 2018:16) and they are the principle providers of traditional named peril and multi-peril crop insurance (GreenCape, 2018:36; Sasria, 2018:29).

Named peril insurance, typically known as hail insurance in South Africa emerged in Europe more than two centuries ago, the policy provides cover against crop damage caused by hail. It may feature extended coverage for frost, fire and wind damage (Weber, 2019:1). Named peril insurance gradually developed in the 1960s to encompass Multi-peril crop insurance (MPCI) for systemic risk. MPCI covers farmers from a wide range of progressive perils, including drought, high temperatures, excessive rain, flooding, pests and disease in addition to responding to hail damage with its various extensions, making MPCI a more comprehensive and all-encompassing insurance solution (Barnett, 2014:200). MPCI schemes worldwide usually supplement or substitute government disaster funding programmes, with the exception of South Africa, which is the only MPCI market not subsidized by the government (Hohl, 2019:215).

Hail losses are compensated based on damaged insured yield. Physical on-field assessments are conducted to verify and quantify the extent of crop damage, for which the farmer will be compensated according to the units damaged. Usually, hail damage results in plant stand reduction, stem damage, leaf defoliation and grain losses which can all lead to sharp yield loss (Hohl, 2019:199). MPCI compensates based on an agreed percentage (coverage), typically 50 to 70 per cent of the individual farmer's actual production history (for example, 10-year average yield). MPCI losses are adjusted by an expert in the specific type of crop, and its valuation takes place immediately after harvest, with the basis of indemnity determined as the difference between the historical average yield and the actual yield multiplied by the agreed guarantee percentage of coverage (Adiku et al., 2017:39).

Hail and MPCI carry different risk attributes; hail is a localized weather event by nature. The isolated events allow for a structured insurance model focusing on spatial and temporal spread to diversify insured risk geographically, minimize correlated events, and manage a profitable portfolio through pooling premiums that allow the insurer to accumulate enough capital reserves to offset large claim payments. Geographically diversified risk requires less capital to cover expected losses than a concentrated portfolio (OECD, 2018:27). This is more in line with conventional insurance theory and application. On the other hand, MPCI is exposed to a wide-ranging number of factors which can result in an insurance claim, for instance, farmers adopt difference production techniques, expertise, machinery implements, and are exposed to different environments impacting soil moisture and quality, together these variables may influence actual yield and increase risk (Barnett, 2014:209).

MPCI outcomes have long incurred negative underwriting results because of the systemic drought risk in South Africa. From 2004/5 to 2014/15, the long-term loss ratio (claims paid over premium received) is 114 per cent (World Bank, 2016:43), making the cover economically unsustainable for insurers. MPCI is a product under considerable debate likely to be withdrawn from the market in the next few years unless results can be improved (Sasria, 2018:29). A realistic option considering that, for example, no insurer provides MPCI in Zimbabwe (Tsikirayi, Makoni & Matiza, 2016:5). From a global perspective, actuarial experience on MPCI products shows a trend of under-performance where enormous premium subsidies are needed to encourage uptake (Barnett, 2014:200). This crucial market failure has persisted even in countries with sophisticated financial markets such as the United States, which has the most extensive MPCI programme in the world as well as advanced insurance markets in Australia

(Weber, 2019:1). By its nature, agricultural insurance is volatile and requires highly specialized skills to manage and stabilize; a widely distributed crop insurance portfolio can attract up to 20 times more risk than an equally valued property and casualty portfolio (Balaban, Simeunovic & Markovic, 2014:420). Nonetheless, crop insurance is deemed critical for long –term sustainability of food security.

The increased prevalence of hail and drought means that South Africa's leading crop insurance companies are facing considerable business strain. The response has been to de-risk and reduce exposure in MPCI, which is more systemic than hail. In addition, the crop insurance market is contracting due to among other factors; expensive insurance premiums and high MPCI premiums in particular (Stoppa & Dick, 2018:18; Tang, Yang, Ge & Chen, 2019:623). Commercial farmers are also increasingly becoming larger, with strong balance sheets, hence have a better ability to absorb more risk. The level of diversification is becoming more sophisticated among farmers though diversifying by crop type, livestock and establishing operations in other 'less risky' geographical areas. In diversifying by crop type, farmers plant different crops that are negatively correlated to each other in response to a particular weather hazard. The crop that is most sensitive or affected by the hazard is the one insured translating into risk management at a portfolio level. While livestock diversification, with respect to income generated from reproduction sales, forms an integral part of farmer's livelihood strategy which is less vulnerable to climate shocks (Stoeffler, Carter, Guirkinger & Gelade, 2020:5). Economic conditions driven by low commodity prices resulting in lower profit margins also fuel the reduction in crop insurance demand in South Africa.

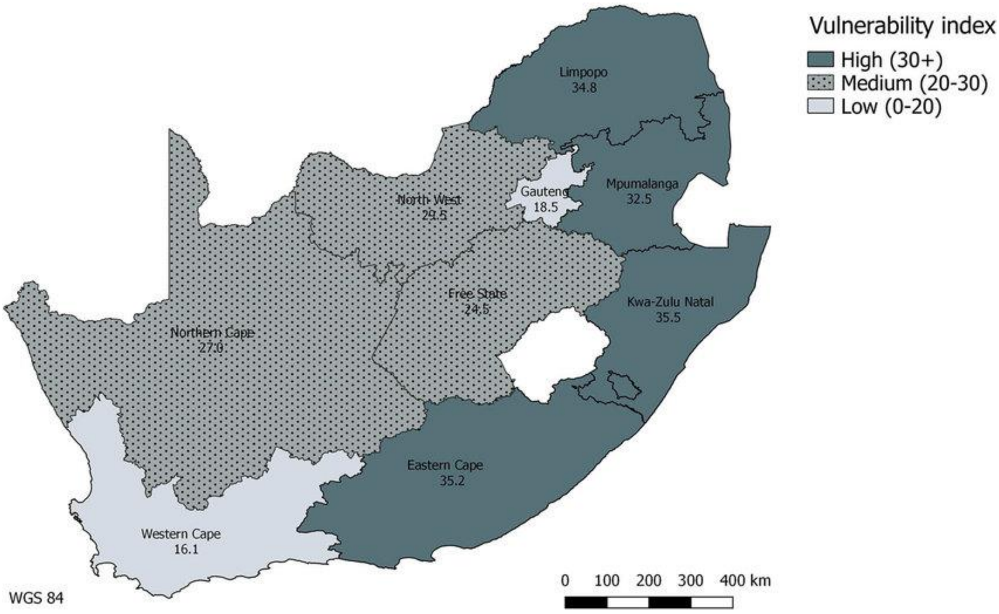
Hail and MPCI products have failed to expand successfully in developing countries, particularly for reasons of accessibility and affordability (Ceballos et al., 2017:73). Invariably, there is a lack of or insufficient insurance markets for low-income farmers in South Africa, and Africa as a whole (Farrin, Miranda & O'Donoghue, 2016:2; Ogunmefun & Achike, 2015:412; Sandmark, Debar & Tatin-Jaleran, 2013:9). According to Meyer, Hazell and Varangis (2017:32) if left to market forces alone insurance may not develop at a sufficient pace and scale to meet low-income farmers or societal needs. In this case, government intervention, both in terms of policy and wider economic and human development objectives, is required in identifying effective climate risk adaptation strategies especially in the context of rapid climate change (Ward & Makhija, 2018:164).

2.2.4 Climate change and agricultural insurance

Developing countries are especially vulnerable to climate change impacts due to inadequate institutional support structures and high reliance on rainfall for crop water supply. Agriculture in South Africa is no exception and faces a variety of risks associated with climate change, such as changes in rainfall distribution, pests and plant disease proliferation, higher evaporation rates, increased temperatures, reduced crop yields, and spatial adjustments in optimal cropping areas, which all affect sustainable agricultural development (Zwane & Montmasson-Clair, 2016:2). These climatic variations affecting agricultural operations and productivity are expected to change without uniformity in frequency, scale, and direction over the next few decades (Schulze, 2016:5). A projected 120 million individuals will face the risk of undernourishment by 2050, most of them in sub-Saharan Africa, due to compromised food security systems as a direct result of climate change (Hohl, 2019:5).

There is mounting evidence that extreme weather events are becoming a frequent reality in South Africa as evidenced by a severe drought in 2015 attributed to the El Niño cycle which resulted in the lowest annual rainfall since 1904 (Partridge & Wagner, 2016:50). As a direct consequence, major crop losses, death or forced sale of livestock at marked down prices and food price escalations were experienced (GreenCape, 2017:16). El Niño events usually result in an irregular drop in precipitation between November and March in most of Southern Africa, coinciding with the maize crop growing season (FAO, 2018:4). Moreover, Southern Africa has been undergoing significant warming over the last century. Temperatures over the region have increased at a rate of 0.4 degree Celsius per decade from 1961 to 2014 (Davis-Reddy & Vincent, 2017:6). It is now well documented that climate change in South Africa is expected to disrupt all sectors of the economy, including having adverse effects of human settlement and human health (DEA, 2017:77). Moreover, increasing vulnerability to food insecurity and poverty (Awondo, Kostandini, Setimela & Erenstein, 2019:4). Authors Born, Spillane and Murray (2018:6) developed a vulnerability index, as shown in Figure 2.2, premised on factors in smallholder farmers livelihoods in order to assess their capacity to adapt to climate change. Among the factors considered is the degree of reliance on rainfall for agricultural purposes. This index shows that small-scale farmers in Mpumalanga are highly vulnerable with moderate levels of vulnerability in North West and in the Free State.

Figure 2.2: Vulnerability index of South African provinces



Source: Born, Spillane and Murray (2018:6)

Deficits in rainfall, even at a small-scale have a disproportionate effect on livelihoods, for instance, in Cameroon, a 14 per cent reduction in rainfall is estimated to result in USD 4.65 billion worth of economic losses (IAIS, 2017:1). Findings by (Flatø, Muttarak & Pelser, 2017:52) show that low rainfall levels over one season can trigger complex processes which have multi-year effects on farm revenue for at least two subsequent cycles. From an environmental perspective, agriculture is the largest water user in South Africa (Montmasson-Clair, Mudombi & Patel, 2019:4). Declining rainfall, coupled with an increase in the number of hot days (>35°C), can add a minimum of 10 per cent to current water requirements for crops (GreenCape, 2017:19). Given the current water scarcity and forecasting over the next thirty years and afar, climate impact on the production of maize is expected to be mostly negative (NAMC, 2018:8).

Choudhury et al. (2016:170) are of the view that without adequate coping mechanisms, the cycle of poverty, inequality and unemployment is likely to be perpetuated. As the impact of climate change escalates, the ability to implement adaptation strategies, the capacity to mitigate, deal with, rebound and build resilience to shocks and stresses has become essential for poverty reduction (Moore et al., 2019:3). Increased agricultural risk fuelled by climate change implies that farmers face new realities that cannot be addressed comprehensively by their indigenous knowledge and informal risk mitigating techniques alone (Adiku et al., 2017:16). In the face of unprecedented challenges posed by climate change, the need for effective risk management in the agricultural sector has never been greater (Ehrlinspiel, 2017:4). It is within this context that there is a burgeoning interest in weather index insurance as an affordable microinsurance solution within the development, finance and agricultural space (Jensen, Barrett & Mude, 2016:26), which has seen Africa being the vanguard of index insurance growth during the past decade (Ceballos et al., 2017:78), as it offers a promising avenue for climate risk management (Pacheco, Santos & Levin, 2015:998).

The general consensus among experts is that mitigation efforts alone will not be adequate to prevent the harmful effects of climate change and that adaptation strategies are essential for increasing resilience to future changes (Clarke & Kumar, 2016:219). Methods such as conservation agriculture, sustainable agricultural practices, rainwater harvesting, adopting drought-resistant and early maturity seed varieties could be suitable alternatives for South Africa. Conservation agriculture entails strategies aimed at reducing soil erosion, improving water retention and soil structure, as well as fertility to increase crop yields sustainably and building the resilience of farm systems (Gunjal, 2016:11). Experimental trials in Malawi find that conservative agriculture substantially increases maize yields, reporting 11 to 70 per cent improvements specifically in years of low rainfall (Nyasimi, Amwata, Hove, Kinyangi & Wamukoya, 2014:17). The challenge is that such adaptation strategies are capital intensive and may prove too expensive for low-income farmers to adopt successfully (Senyolo et al., 2017:3825). This is especially true considering the fact that drought-tolerant seeds have been found in Lybbert and Carter (2014:8) to provide no benefit whatsoever in severe and extreme drought conditions. This is confirmed in a study where Boucher et al. (2020) performed a randomized control trial between 2014 and 2019 collecting date from over 3 000 farmers on the performance of drought resilient maize seed varieties. In periods of mid-season drought, yield from the drought-tolerant maize seeds outperformed other types of cultivars by almost 50 per cent. In years with no drought, drought-tolerant maize yields were still around 12 per cent higher than other varieties. While in periods of extreme drought, the performance of drought resilient varieties drops to a level where the advantages over other varieties are nullified. According to Ward, Makhija and Spielman, (2019:6) the relative benefits of drought-resilient seeds might not be realized in any given year, because droughts are erratic and intermittent (Ward, Makhija & Spielman, 2019:6). It is, therefore, in consideration of some of these restrictions that the United Nations has endorsed weather index insurance as a climate change adaptation measure for low and middle-income countries (Hohl, 2019:249).

2.3 Risk Management Strategies of Low-income Farmers

Risk management in agriculture is concerned with reducing the possibility of unfavourable outcomes (Kumari, Singh, Mishra, Sinha & Ahmad, 2017:361) and has historically formed a large part of agricultural industrialization (Hohl, 2019:6). The nature of agricultural production makes risk management a vital tool for the sustainability of farming enterprises (Mbonane & Makhura, 2018:2). However, the subject of risk management as it pertains to crop production, and sustainability therefore, remains to be fully addressed, as there is a continuing need to establish new models of market-based risk transfer through insurance and alternative risk transfer markets (Kokot, Marković & Pajić, 2017:13).

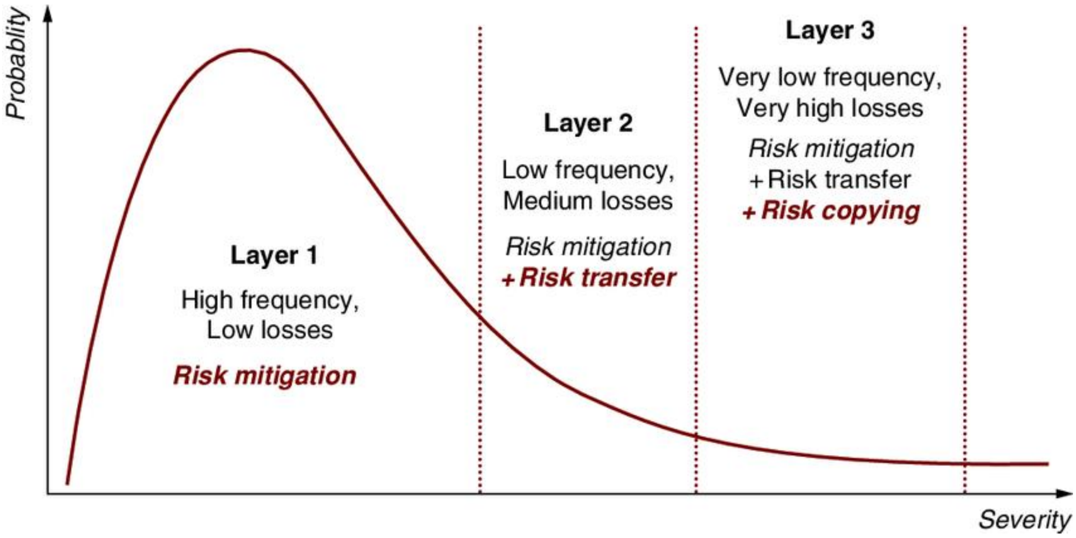
One of the critical reasons advanced for the perpetual challenges of South Africa's low-income farmers is their inability to manage climate risk effectively though insurance (Partridge & Wagner, 2016:49). In the absence of risk transfer markets, most low-income practitioners respond by altering their economic behaviour and risk management decisions (Haile, Nillesen & Tirivayi, 2019:1). Considerable empirical evidence continues to mount that insurance conduct is guided by individuals' misunderstanding of risk, and the use of inappropriate but straightforward heuristic decision guidelines (Kunreuther & Pauly, 2014:2).

Agricultural risk management entails a basket of ex-ante (planned) and ex-post (reactive) strategies employed by farmers, which involve risk reduction, risk avoidance, risk transfer and risk retention, all in efforts to smooth income effects of weather-related shocks. Low-income farmers primarily employ informal ex-ante risk management techniques which involve changes in the production strategy (Wairimu, Obare & Odendo, 2016:111), such as low risk, low return approach (Ward, 2017:1), shifting production patterns by adopting early planting dates, planting on different plots of land to spread the risk (land defragmentation), generating off-farm income, diversifying crops and following a mixed farming methodology (Abugri, Amikuzuno & Daadi, 2017:5; Ntukamazina et al., 2017:171; Zhang, Brown & Waldron, 2017:12).

Mookerjee, Clarke, Grenham, Sharpe and Stein (2014:253) maintain that these identified ex-ante strategies are potentially ineffective and exaggeratedly conservative in reducing and avoiding risk. Ward (2017:1) further voices that such policies curtail crop production and profit in a manner that inhibits long-term growth. For example, land defragmentation reduces agricultural productivity levels (Guo, Wen & Zhu, 2015:7), and crop diversification has been shown to reduce average farming income (Wairimu, Obare and Odendo, 2016:111) while increasing operational costs due to skills and equipment required to produce different crops (Sulewski, Sulewski, Was, Kobus, Pogodzinska, Szymanska & Sosulski, 2020:10). In order to be successful, risk management needs to be in accordance with active considerations around interchanges and opportunities for efficiencies (Jarzabkowski et al., 2019:29), and no one strategy should result in significantly curtailed production.

Substantial evidence from other studies shows that diversification is the most practised form of crop risk management (Hosu, Cishe & Luswazi, 2016:135; Ogunmefun & Achike, 2015:417). These authors indicate that, among other factors, revenue growth in the agricultural sector is limited by precautionary risk management approaches. In response, Giertz et al. (2015:39) propose a risk layering approach illustrated in Figure 2.3, as a guide for when low-income farmers should use a blend of available risk management tools. Risk layering is the segmentation of the risk levels that the farmer may or should retain, handle by informal techniques, or transfer through insurance (World Bank, 2011:5). A proficient risk management system involves assigning a device or collection of tools to each risk level, consistent with the designated approach of either retention, reduction or transfer. Financial instruments, in combination with risk prevention and reduction measures, should be selected based on the frequency and severity of weather-related risks and potential catastrophic disasters (Schäfer, Warner & Kreft, 2019:328).

Figure 2.3: Risk layering for low-income farmers



Source: (Giertz et al., 2015:39)

For recurrent weather events where the financial loss is low as captured in layer 1, Romero and Molina (2015:3) suggest that ex-ante strategies may be most appropriate. As the frequency of risk becomes lower (1 in 5 years) and financial losses begin to increase, a combination of risk mitigation and risk transfer measures is advised. Risk transfer refers to mechanisms such as insurance, coinsurance, or financial hedging, in which a willing third party(s) assumes all or part of the risk in return for a premium. Layer 3 reflects events where the risk is infrequent (1 in 10 years) but has potentially enormous financial implications, in such a case, risk mitigation, risk transfer, and coping mechanisms may be required to insure the recovery of low-income farmers from a loss event. Risk coping includes ex-post mechanisms such as public assistance to farmers and scalable social safety nets (Braimoh et al., 2018:18).

Social safety nets are a response to market failure, that is, absent or poorly developed risk transfer markets. They are informal mutual insurance arrangement by social networks (Helamo, 2018:26). Social networks being structures constituting persons that are connected by socially meaningful relations such as family, friends, and trust-based relations found in local communities. In times of crisis, these networks extend financial and non-financial support in the form of borrowings, labour resources transfer and food-sharing (Mbugua, Nzuma & Muange, 2019:31). In agriculture, the typical spatial proximity of social networks exposes the arrangement to systemic shocks because of highly concentrated risks rendering the structure imperfect, leading to inherent shortcomings as covariate shocks have a broad coverage affecting farmers simultaneously (Pradhan & Mukherjee, 2018:103). Positively though, social network arrangements are indicative of potential latent demand for microinsurance. It, therefore, comes as little surprise that where weather index insurance is offered, a decline is noted in informal social safety nets, indicating that insurance is a substitute for informal risk sharing (Tobacman, Stein, Shah, Litvine, Cole & Chattopadhyay, 2017:2).

In the absence of government and social network ex-post interventions, following covariate shocks low-income farmers resort to prematurely liquidating productive assets (Hellin et al., 2017:5), such as selling livestock to survive (Abebe & Bogale, 2015:2742), reducing consumption and labour resources. Janzen and Carter (2019:651) believe that this contributes to the intergenerational transmission of poverty among low-income farmers. These last resort ex-post disaster risk management actions emanate from insufficient risk retention capacity, which is the inability to cope under risk layer 1 as shown in Figure 2.3. Risk retention refers to the use of precautionary savings, including access to credit (Carter et al., 2014:3). Both savings and credit have been found to be incompatible in smoothing the effects of weather shocks, particularly for timing reasons. When unexpected events occur, credit may be in high demand or simply unavailable when the farmer is most vulnerable, and savings may not yet be sufficient to reduce the shock (Ceballos et al., 2017:72).

Isaboke et al. (2016:72) found that where weather index insurance is offered, especially without subsidization, the target population by no means considers it to be the most preferred risk coping strategy. The reason is modelled under the expected utility framework generally adopted in studies on farmers choices, which reveals that farmers will, given their level of risk preference under uncertainty conditions, select the technology that offers the maximum expected utility (Barham, Chavas, Fitz, Ríos-Salas & Schechter, 2015:16). For low-income farmers, there is an opportunity cost to insurance which has to be balanced with current consumption needs. In the course of balancing consumption needs farmers have been observed to exhibit 'cognitive failure,' that is, they underestimate the severity of catastrophic events in the face of competing priorities as a psychological coping strategy (Romero & Molina, 2015:20). Illustratively, cognitive failure has been identified further in a household survey in Kenya, where a majority of low-income farmers were found not to consider fully losses in sales, own-consumption and crop inputs following weather-related shocks. Psychologically this approach makes it easier to recover; however, from an economic and commercial point of view, it makes the provision of insurance and microinsurance a challenging proposition (Zollmann, 2015:13).

2.4 Index-Based Insurance

To frame the discussion of index insurance solutions, organizations such as World Bank, United Nations World Food Program (FAO), and the United Kingdom Department for International Development have since the late 1990s conducted feasibility studies and pilot projects in African developing countries that are predominantly agriculture-based such as Burkina Faso, Ethiopia, Ghana, Kenya, Malawi, Morocco, Rwanda, Senegal and Tanzania (Farrin, Miranda & O'Donoghue, 2016:3). These initiatives have been rooted in social imperatives of poverty reduction, employment creation, food provision, and security. It is an established fact that poverty discriminates against those living in rural areas, particularly those in sub-Saharan Africa mostly due to catastrophic weather phenomena which threaten livelihoods and which lead to an unending poverty trap (Dzanku, 2018:365).

Between 1961 and 2016 global agricultural output has more than tripled, crop yields for key staple foods such as maize increased by more than 200 per cent between 1960 – 2016 but average increases have sharply declined to an average of 1 per cent per annum since the 1990s (Hohl, 2019:189). The risk related to crop production has substantially increased over that period due to climate change, the effects of which result in demand for insurance solutions. With index insurance, a distinction is necessary between initiatives aimed at developing and encouraging ex-ante risk management, particularly insurance, savings, and credit and the management of risks on an ex-post basis, particularly government intervention in emergency disaster response and humanitarian relief (World Bank, 2011:5). Index insurance, be it as a programme for commercial insurance or social protection, takes various forms: Weather Index Insurance, Area Yield Index Insurance (AYII), and Normalized Difference Vegetation Index (NDVI).

AYII indemnifies the insured according to current yield losses against an historical average yield in a defined geographical area (Ntukamazina et al., 2017:176). It requires the collection of yield samples and surveys data by field agents from farmers within a defined homogenous grouping to determine actual yield for the area. Much like MPCI, accurate long-term average historical data is a prerequisite (Microinsurance Network, 2017:18). The difficulty rests in the lack of high-quality historical yield data for small-scale farmers covering adequate time series at the necessary disaggregated level (Coleman, Dick, Gilliams, Piccard, Rispoli & Stoppa, 2017:18). South Africa's historic yield records are only up to provincial level, with limited or no data available at district level (Wang, Karuaihe, Young & Zhang, 2013:95). Where provincial data are available, they are usually from samples gathered from commercial farms with little or no data available on smallholder farmers.

NDVI employs satellite remote sensing to measure the level of greenness of vegetation by quantifying the total amount of green biomass in each pixel of a satellite image during the measurement period. This vegetation health assessment is used as an insurance proxy that compensates the insured when assessment reports indicate dryness and reduction of vegetation quality. Higher NDVI values indicate lush, well-watered vegetation with sufficient moisture. Low NDVI values point to stressed vegetation deprived of moisture, typical of drought conditions (Bokusheva, Kogan, Vitkovskaya, Conradt & Batyrbayeva, 2016:201). NDVI is most useful in monitoring the quality of pastoral forage and livestock losses but its usefulness for crop assessments is limited (Ntukamazina et al., 2017:180). One of the large-scale NDVI programmes is in Mexico, covering 13 million hectares of pastoral lands in over 20 states (Hohl, 2019:262). The lack of yield data for AYII and unsuitability of NDVI for crop monitoring has led to the prominence, adoptation and piloting of weather index insurance which relies more on readily available weather records from weather stations or by satellite (Gaurav & Chaudhary, 2020:1; Roznik et al., 2019:447).

2.5 Weather Index Insurance

Weather index insurance is a contract between the insurer and the insured under which claim payments are triggered based on the measure of a specific weather parameter such as rainfall, temperature, and moisture at a specific reference weather station or via satellite over a given period of time (Akter et al., 2016:217; WFP, 2017:20). It is founded on the concept of weather derivatives which has been configured for the agricultural sector. A key feature of this contract is that crop yield losses are indirectly assessed by using the weather proxy or index as an estimate of the level of damage rather than direct on-field farm assessments (Ward, 2017:2), this results in significant savings and reduced administration costs (Adegoke et al., 2017:7). Modelled losses are projected premised on the severity of the weather phenomenon (Jarzabkowski et al., 2019:11). Therefore, parameters of the insurance contract are set to correlate as accurately as possible the weather hazards and the reduction of crop yields (Ahmed, McIntosh & Sarris, 2017:3; Castellani & Vigano, 2015:1672).

Carter, de Janvry, Sadoulet and Sarris (2014:3) state that the effectiveness of weather index contracts as a measure of crop loss lies in its objectivity, quantifiability, verifiability, and nonmanipulable nature by either party to the contract. Weather index insurance eliminates much of the fraud, moral hazard, adverse selection, and high administrative costs, which are common in classical indemnity-based insurance (Berg, Blake & Morsink, 2017:16; Bokusheva, 2018:2328; de Leeuw et al., 2014:10892; Matsuda & Kurosaki, 2019:3; Mubhoff, Hirshauer, Gruner & Pielsticker, 2018:117; Ward, 2017:1; Weber, 2019:4). This is precisely because indemnity payments are linked to the independent performance of an underlying index (Roznik et al., 2019:449).

With weather index insurance, farmers are grouped into homogeneous Unit Areas of Insurance (UAI) according to the geographical location within which they pay the same premium amounts, and receive uniform levels of payout when the index is triggered (WFP, 2017:23). What makes the grouping possible is that agricultural producers in an area are exposed to similar risks such as drought, floods and windstorms, causing losses across individual farmers to be significantly correlated (Bokusheva et al., 2016:200; Miranda & Mulangu, 2016:4). The widespread occurrence of risk is referred to as covariate or systemic risk, and such widespread risk cannot be addressed effectively through traditional insurance, which is more suited for idiosyncratic, that is to say, individualized events (Carter et al., 2014:3). Normally, a geographically wider area of insurance will result in more varied individual risk exposure, this leads to greater idiosyncratic variance and the weaker the index will be in predicting individual outcomes (Clement, Botzen, Brouwer & Aerts, 2018:847).

The consensus among scholars and business practitioners is that index-based insurance is an appropriate solution to address covariate shocks since it is the covariate nature of a hazard that improves the ability to forecast and determine the quantum of future claims for a large number of policyholders over a defined geographical area (de Leeuw et al., 2014:10891; Greatrex et al., 2015:6; Jensen & Barrett, 2016:203). In addition, a central advantage of index insurance contracts is effective liquidity relief that enables claims to be processed speedily as there is an elimination of time-consuming on-field verifications resulting from the easily and independently observable nature of indices (Bastagli & Harman, 2015:5; IAIS, 2017:2).

Some of the key features of index-based insurance include (Swiss Re, 2018:3):

- Protection against negative impact following adverse weather conditions;
- The cover is structured using weather parameters impacting crop yield or quality;

- The settlement is based on ground weather stations or satellite data;
- No additional proof of loss or farm visits are needed to verify crop conditions;
- Policies can be renewed annually or signed on a multi-year basis; and
- Policyholders can choose a structure consisting of triggers or risk periods that best suit their needs. Risk periods are specific periods in the crop growing cycle during which the crop is extra sensitive to adverse weather.

Traditional insurance and index insurance are not mutually exclusive. They can co-exist and complement each other since they are designed to target different layers of risk and have different levels of administrative capabilities. Where weather indices and indemnity insurance are used in conjunction, a double trigger exists. The first is the breach of the weather threshold, which then prompts on-field assessment for more accurate loss adjusting (Hohl, 2019:249). Around 70 to 80 per cent of crop losses worldwide are projected to be due to insufficient or excess rainfall (Herbold, 2014:200). In direct response, index insurance solutions are beneficial for protection against progressive perils, where losses gradually accumulate over time through the natural deterioration of plant productive capacity caused by drought, deficit or excess of rainfall (Morsink, Clarke & Mapfumo, 2016:5; Shirsath, Vyas, Aggarwal & Rao, 2019:2). However, indices are less effective in managing localized risk such as hail (Barnett, 2014:211; Insurance Regulatory Authority, 2015:8). Weather index insurance is not intended to cover all risks or the entire livelihood of a farmer, but rather to offer protection against a clearly defined covariate hazard. Extending cover to a single primary hazard leads to more affordable premiums because the risk can be modelled and priced more accurately with less variables that influence claims (Greatrex et al., 2015:6).

Index insurance assumes many roles in the development landscape. Weather index insurance can be applied at a micro level - where the product is sold directly to farmers; at a meso-level - where it is sold to aggregators such as banks, microfinance institutes or input providers either on behalf of farmers or to cover a portfolio from the risk of default due to weather risk or at a macro level - where it is sold to governments in order to stabilize climate-related fluctuation in GDP, provide adequate disaster relief and ensure timely distribution of funds to underlying farmer-beneficiaries (Adiku et al., 2017:18). In the context of this study, weather index insurance is considered at a micro-level.

Micro-level insurance

At a micro-level weather index insurance products are sold directly to individual farmers through a wide range of distribution channels such as insurance companies, agribusinesses, input providers and commercial banks. At this level, the product design requires significant ground-truthing with policyholders to ensure that the policy being sold adequately predicts losses on the ground (Syroka & Reinecke, 2015:3). At this level, insurance has the ability to stabilize farmers' purchasing power, which will improve their capacity to reinvest in the next crop cycle (Sandmark, Debar & Tatin-Jaleran, 2013:7). Agricultural insurance at this level is seen as a guarantee for business survival (Munyoro & Moyo, 2019:28). With insurance coverage, small-scale farmers are less vulnerable to climate hazard, which in turn reduces their default risk when accessing credit (van Asseldonk et al., 2015:4).

Born, Spillane and Murray (2018:3) point to the fact that evidence is emerging of scale-out micro-level insurance for smallholders. The Indian National Index Insurance Programme reaches 30 million farmers; the Agriculture and Climate Risk Enterprise (ACRE) reaches 200,000 farmers in Kenya, Rwanda and Tanzania. The R4 Rural Resilience Initiative (R4) in Ethiopia, Senegal, Malawi, Zambia, Kenya and Zimbabwe reaches over 87,000 farmers, benefitting around 545,000 people (WFP, 2019:6). Agricultural insurance has been present in India since 1972. Hence it comes as little surprise that various indemnity and index-based insurance scheme have matured and are continually improving to serve low-income farmer's needs (Gulati, Terway & Hussain, 2018:3).

From a micro-level perspective, differences between insured and non-insured farmers are statistically significant (Sibiko & Qaim, 2017:11). The impact of R4 micro-level insurance has seen, on average, across all districts, insured farmers increase the amount of savings more than 120 per cent compared to uninsured farmers (Adegoke et al., 2017:20). Further evidence from the ACRE programme shows that insured farmers invest 19 per cent more and earn 16 per cent more than neighbouring uninsured counterparts (World Bank, 2017:2). The success of both ACRE and R4 is credited to a comprehensive risk management approach which complements weather index insurance provision with quality inputs, savings and credit facilities (Awondo et al., 2019:3).

Meso-level insurance

Weber et al. (2015:31) hypothesize that index-based insurance products bear large risk mitigation potential at an aggregate level. Institutions with exposure to systemic production risks that affect a large number of their clients at the same time, often respond to weather shocks by restructuring existing loans to prevent complete default, and even extending further loans at concessionary rates to recover their investment in certain cases (Meyer, Hazell & Varangis, 2017:2). As a tool of last resort, financiers use general provisioning, that is, setting aside capital to cover the income that will potentially be lost due to writing-off non-performing loans. These risk mitigation strategies involve an opportunity cost to the financier in the form of the capital set aside and expenses incurred in attempting to recover the debt (Mapfumo, Groenendaal & Dugger, 2017:84).

The potential of meso-level insurance rests on the promise that it transfers agricultural risk from the balance sheet of lenders to that of the insurer. In doing so, meso-level agricultural insurance allows lenders to absorb unexpected shocks while increasing their exposure to the agricultural sector (Sandmark, Debar & Tatin-Jaleran, 2013:23). At this level, lenders could operate more efficiently by extending their reach and by providing reduced interest rates (Syroka & Reinecke, 2015:4). Lenders often associate credit provision to low-income farmers with high levels of risk and increased cost of administration, thus ration credit supply or extend credit on onerous terms that may very well be too expensive or too demanding on collateral requirements (Ahmed, McIntosh & Sarris, 2017:8). According to Dougherty, Flatnes, Gallenstein, Miranda and Sam (2019:40) selling weather index insurance to meso-level clients that generally have better understanding of risk management, and climate change impacts could be more beneficial than directly marketing the product to individual farmers. Gallenstein, Mishra Sam & Miranda (2018:20) find that there is greater interest in micro-level index insurance among farmers that interest for meso-level insurance linked with loans. Indicating that farmers have a higher preference for liquidity and prefer spending insurance payouts on reasons other than repayment of loans.

Macro-level insurance

At a macro-level, the government acts as the policyholder insured at a national or regional level against catastrophic risk events with farmers as the underlying beneficiaries. Advocates argue that at a macro-level, index insurance is useful to secure timely and adequate policy response in the event of covariate shocks as part of social protection programmes requiring disaster or humanitarian responses (Bastagli & Harman, 2015:3). Most often, low-income farmers in South Africa that are recipients of disaster relief have complained that efforts are introduced too late when significant losses have already been incurred (AgriSa, 2016:19). This type of macro-level intervention is ideally suited to address issues of timely intervention to reduce the impacts on farmers' livelihoods, asset depletion, and prevalence of poverty traps. The argument is that index insurance is best suited when defined on the characteristics of a catastrophic event and not necessarily on actual farm-level loss.

An example of a macro-level scheme is the African Risk Capacity (ARC) initiative which is a specialised agency of the African Union that operates a sovereign catastrophe risk pool, providing index-based insurance to participating countries (Kenya, Mauritania, Niger, Senegal, Gambia, Malawi and Mali) against severe drought events (ARC, 2017:4). The ARC model is calibrated on satellite rainfall estimates, which are used to calculate drought index within each insured country. The satellite rainfall estimates are available across Africa every 10 days at a resolution of approximately 10 kilometre by 10 kilometre (Bastagli & Harman, 2015:10). It is estimated that pooling risk across the continent, within its diverse rainfall patterns, could save countries up to 50 per cent in the cost of emergency contingency funds while reducing dependency on foreign disaster relief funding (ARC, 2016:4).

2.5.1 Product design

A successful insurance programme requires a well-defined and designed product, an acceptable level of demand, financial capability to meet premium obligations by the farmer and capacity by the insurer to administer policies and pay claims (Atsiaya et al., 2018:52). An inadequately structured insurance solution that does not sufficiently covers losses or damages nor provides an incentive for risk reduction behaviour may inadvertently reinforce poverty traps where insurance provides no material value to the farmers in smoothing earnings after experiencing climatic shocks (Schäfer, Warner & Kreft, 2019:328). Most weather index insurance contracts are a function of recorded weather at a contractual weather station (Mookerjee, 2014:254). Recorded data from the reference station is prone to manipulation if the process entails manual logging, and proper safeguards are required to avoid tempering. Preferably, an automated data capturing process is ideal. The degree of data integrity directly impacts on the cost of uncertainty loading that is factored into the final insurance charge (Insurance Regulatory Authority, 2015:16).

It should be recognized that not all farms are close to weather stations, as such for rainfall based indices a 20 kilometre radius is acceptable as the standard distance from the weather station to farm (Mookerjee et al., 2014:264; Stoppa & Manuamorn, 2017:6). Contracts outside the 20 kilometre zone, are found to have high basis risk, that is, low correlation between actual crop yield and the index measure (Bokusheva et al., 2016:200). Hence, weather index insurance demand decreases as the distance from the weather station increases (Würtenberger, 2019:23). Sparse meteorological networks are often considered an impediment to index insurance development. This is because weather station networks are not expressly developed for insurance purposes, and station density is usually not sufficient to provide appropriate broad coverage for risk management applications. However, increasing the density of stations is possible and the cost of new-generation automatic weather stations is becoming progressively more affordable (Stoppa & Dick, 2018:43).

Hansen, Araba, Hellin and Goslinga (2017:25) believe that satellite rainfall estimates can provide an alternative to weather station observations, as complete coverage can be received in terms of space and time. Satellite rainfall estimates showing a 10 kilometre by 10 kilometre resolution provide more confidence and reduce basis risk (Adiku et al., 2017:37). In some cases, satellite data has been found to provide more reliable information about plant growing conditions (Bokusheva et al., 2016:200). Given the credibility and reliability of the data source on plant growth, great progress has been made in developing a range of satellite-based indices, mainly soil moisture driven proxies that measure the extent of moisture in the ground and use the results as a basis for predicting plant health and growth potential. If below expected growth in relation to the long-term historical average is found, then a claim payout is triggered (Hess, Hazell & Kuhn, 2016:21).

According to van Asseldonk et al. (2015:5), satellite-based indices represent a major advancement towards affordable insurance solutions. Although satellite products are increasingly available at low costs and at real-time, home-grown understanding, information and data from ground stations are still critical to design, calibrate, and validate remote sensing indices (Coleman et al., 2017:10). Daron and Stainforth (2014:77) warn that weather index insurance based only on observed data faces the risk of under – or overestimating the likelihood of triggering payments. This means that merging satellite estimates with quality-controlled station data could be a solution to increase the accuracy of an index significantly.

Meteorological services are needed to provide historical data, current season data and seasonal agricultural interpretation and forecasting. Their services to insurers are highly complementary to the existing functions of meteorological departments, such as providing advice to farmers and extension services, along with early warnings and longer-term climate monitoring (Stoppa & Dick, 2018:16). South Africa has adequate supporting institutions to cater for the scaling of index insurance (Born, Spillane & Murray, 2018:11) and infrastructure such as a good network of weather stations and at least 50 years of quality data to scale and support the development of index insurance (Mapfumo, 2007:8).

2.5.2 Contract design

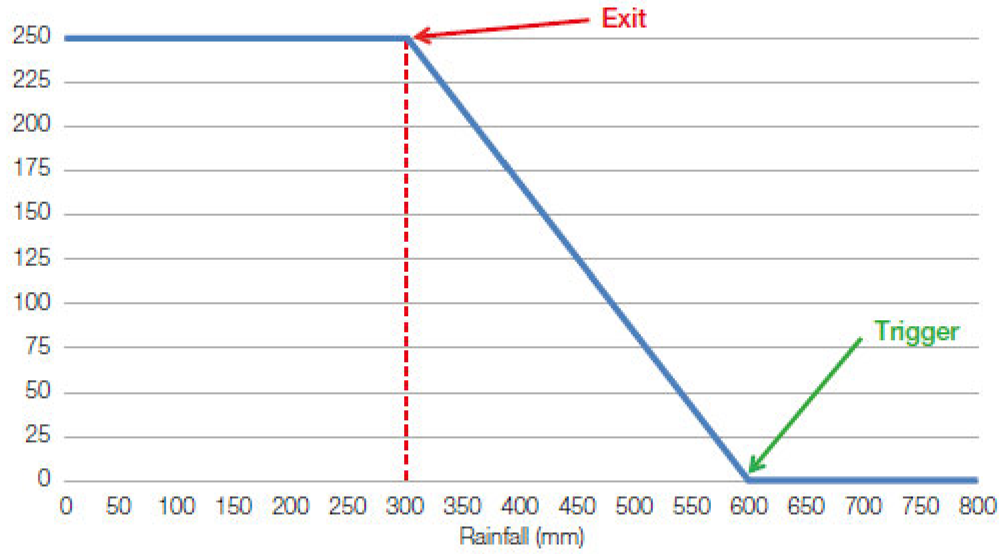
The value at risk under the insurance contract is traditionally calculated as the expected commercial value of the crop for that specific crop cycle, calculated as expected yield multiplied by the commodity price (Hohl, 2019:202). In the conceptualization of an index that fits insurance contract, it is essential to establish guidelines under which claims will be settled. In particular, it is necessary to define (Coleman et al., 2017:56):

- the maximum amount that the insured will be eligible to receive – maximum payout;
- the point at which the contract should start paying out – trigger;
- the point at which the maximum amount should be reached – the exit; and
- the payout rate per index unit between payout point and maximum amount.

Figure 2.4 provides a visual example of the above parameters for a simple drought index-based insurance contract.

- The maximum payout is set at R250 000;
- The trigger is 600 mm, where payouts are made any time cumulative rainfall registers below 600 mm;
- The exit is 300 mm, that is the maximum payout and exit point of the contract;
- Given the maximum payout of R250 000, a trigger of 600 mm and an exit of 300 mm, the monetary value of each deficit mm of rainfall below the trigger is: R250 000/(600 mm – 300 mm) R833,33 per mm.

Figure 2.4: Index insurance payout structure



Source: Coleman et al. (2017:56)

Rainfall timing, distribution as well as the length of planting season are critical variables to crop yield (Stoppa & Dick, 2018:19). Dry spells during the key stages of crop development can contribute to loss of yield, even though the cumulative rainfall for the season is sufficient. In general, the water requirement of maize crops are very minimal at early growth phases; they are at the highest during plant reproductive growth phase, thereafter water requirements are significantly lower during terminal growth phases (Aslam, Maqbool & Cengiz, 2015:5). Therefore, a physiologically mature crop with a well-established root system will likely cope better with a period of drought than would a developing seedling (Shah, Siderius & Hellegers, 2020:1). Thus, index-based insurance contract design should consider multiple measurement stages during the crop season, usually three stages, each with their own thresholds and limits (Mahato & Saha, 2019:552). In Ghana, as an example, maize drought contracts are offered in three stages, which are germination, growing, and flowering where each stage has different minimum levels of measured rainfall requirements as determined from applying a Water Requirement Satisfaction Index (WRSI). When rainfall is below the required minimum level in any of the key phases, the index is immediately triggered, thus incorporating the added benefit of early payments should drought occur in the first phases of the crop growth cycle. Index insurance schemes in Burkina Faso, Kenya, Malawi, Tanzania and India operate on the same three-phase approach (van Asseldonk et al., 2015:3).

2.5.3 Contract pricing

Actuarially fair premium rates on traditional crop insurance policies are determined as a function of claim payments predicated on historical data divided by the sum insured; this ratio is commonly referred to as the expected loss cost. Farmers that plant high risk crops, for example, soya beans, apply high risk production methods, produce in risk-prone regions, that is, dryland instead of irrigated farming will have a higher expected loss cost, hence, higher actuarially fair premiums (Barnett, 2014:203). Once fair premiums are established, marginal costs are loaded on the policy based on operational expenses, cost of capital, risk margin and expected profit. Preliminary assessments by a few academics that index insurance could be provided with loadings of between 2 – 5 per cent now appear very hopeful. For example, an organization offering microinsurance in India was initially willing to provide an index product to low-income farmers with about a 15 per cent loading factor but then estimated that a minimum loading of 25 per cent would be required to cover the company's operations and administration expenses (Smith, 2016:282). From his analysis, Hohl (2019:261) suggests loadings of between 30 – 50 per cent as adequate for weather index insurance products.

Insurers are by law required to hold significant cash reserves in safe financial instruments to meet their capital imperatives of settling claims obligations when they fall due. The capital requirements are contingent on the risk and nature of products the insurer underwrites. Opportunity costs arise from holding regulatory reserves; naturally, providers of capital require returns for their investment and investing funds in insurance capital bears additional risk greater than other types of investments given exposure to potential claims; therefore, providers of capital require higher rates of return than from other less volatile investments. While the deposited capital does earn interest, typically from money market and bond markets, surplus returns expected by investors must be generated from other possible sources, of which insurance operation is the main activity. Therefore, insurance pricing has to factor in expense loadings to fund the insurer's cost of capital (Wrede & Phily, 2015:91). The supply-side conditions for commercial viability of insurance can be stated as follows (Binswanger-Mkhize, 2012:189):

Insurance premium >expected loss + risk margin + administrative costs + cost of capital.

A good pricing strategy for new products is to compute premium rates as accurately as possible and then incorporate a moderate risk margin of between 10 - 20 per cent. Risk margin addresses potential errors pertaining to the loss experience data in estimating the true underlying risk premium. If initially calculated premiums are close to correct, that is, they cover all costs and generate a 'fair' return, this method would allow faster accumulation of surplus capacity, allowing for future product refinement, innovation and better servicing of clientele without the price having to increase. The loading will also ensure that future premium rates are moderately adjusted to keep prices stable and acceptable, with limited price shocks being transferred to a fragile client base (Wrede & Phily, 2015:14).

Although the actuarially fair premium is determined by the insurance provider, the insured client has the option, within certain limits, to alter the final premium charge for the service at the level of insurance coverage and/or account of deductibles in the form of excess or franchise structures. In selecting a deductible level, insured clients integrate an element of self-insuring through absorbing a degree of risk and financing the first amount payable in a loss event (Ulbinaite, Kucinskiene & Le Moullec, 2014:10). Deductibles in traditional indemnity insurance have an additional role in reducing moral hazard; with the insured assuming a part of the risk, the incentive to exercise due care to avoid losses is increased because of the built-in co-payment structure of deductibles. An excess may additionally be used to eliminate minor losses that are uneconomical for the insurer to process, thus allowing efforts to be focused on material losses (Still & Stokes, 2016:18).

Index insurance policies are usually priced using historical data series to estimate the frequency and magnitude of prospective indemnity payments (Jensen & Barrett, 2016:206), requiring a minimum of 15 years and ideally 30 years or more of data (Hansen et al., 2017:25; Tadesse, Shiferaw & Erenstein, 2015:7), where missing or out-of-range values are minimal (Coleman et al., 2017:17). In establishing the premium rate, the initial steps entail determining which peril/(s) to insure and which index best models crop failure under those insured perils. The process requires the setting of parameters under which the insurance contract will respond by establishing the threshold and limit; these are the trigger and exit points. A contract prototype is then developed based on the risk tolerance and preference of the insurance provider, as well as the insurance return period. The concept of a return period implies the modelled expected frequency of an event of a given severity or magnitude. For example, if the return period of drought is five years, then a region can expect to experience drought every five years and insurance may then be designed to compensate on a five-year basis to cover the expected loss over that period.

Lack of historical data can have severe implications on pricing and efforts to provide commercially orientated index insurance. Inadequate data is a serious concern and was the main motive for withdrawal of a weather--index insurance scheme in Thailand (Sinha & Tripathi, 2016:9). Rainfall and temperature data in developing countries for designing weather-based indices is often characterized by short time series, high frequencies of missing data and overall low quality (Castillo, Boucher & Carter, 2016:95). Making provision of comprehensive, adequately priced index-based insurance solutions is often a process fraught with too many pricing assumptions bringing into question the integrity of the pricing models. Raju et al. (2016:10) emphasize that daily observed weather for the last ten years is critical, given climate change. Without such observations, uncertainty exists which may need to be compensated for by a high-risk margin loading, the effects of which increase the premium rate.

Contingent on sufficient data, an index insurance contract may have significantly lower transaction and administrative costs that can directly benefit the farmer in the form of a lower premium, compared to traditional indemnity-based insurance. In determining the price of weather--index insurance, components of administrative cost loadings can be excluded to a certain extent such as cost for controlling adverse selection and moral hazard, as well as the primary cost for conducting on-field loss assessments. Further administrative and transactional savings arise because weather index insurance contracts are standardized across a geographical region, requiring no individual tailoring (Kusuma, Noy & Jackson, 2017:18).

2.5.4 Distribution channels

By and large, the adequacy of premium rate determination depends on the processes involved in administering, marketing, and servicing the identified client base. When insurance providers market new products, they usually utilize already existing processes, tried and tested for other product lines; this includes existing sales personnel, and marketing channels, the same administrative protocols, information technology infrastructure, and similar claims-handling and settlement procedures and processes. With index insurance, standard operating procedures and models of delivery are considerably varied and are often experimental and untested (Wrede & Phily, 2015:31). Given the relatively low sum insured per farmer, selling index-based insurance directly to individual farmers is usually uneconomic through the traditional intermediaries (agents and brokers) distribution model which may result in additional costs passed on to the client, thus contributing to making the product more expensive (Mapfumo, Groenendaal & Dugger, 2017:24). However, the advantage that comes with the process of using intermediaries is potential access to established retail networks, making it possible to reach a greater number of farmers (Mookerjee & Nyoni, 2016:2). With about 80 per cent of the overall gross written premium coming from the intermediated delivery system, intermediaries are highly prevalent in the South African insurance environment (Still & Stokes, 2016:99). This is exactly why consideration of the distribution approach for index insurance to low-income farmers is a critical component of programme design as it has implications for the final product pricing and potential product outreach (Stoppa & Dick, 2018:15).

Across Africa, financial institutions, input aggregators, farming cooperatives, associations and organized groups such as unions have been used in various forms to reach a large scale of farmers because of the public trust and credibility accorded to these institutions through frequent transactions, provision of services, or information sharing. Index-based insurance can be integrated at one of the customer touch-point stages through one or more of the various distribution partners. Leveraging synergies to provide various target markets with index insurance on an economically effective basis (Herbold, 2014:211). For example, banks are well placed to act as intermediaries for the sale of insurance by virtue of their distribution networks (branches, call centres, online platforms) and client relationships. This is a significant avenue in developing economies like South Africa where levels of financial literacy are low and clients may need the products and services to be well explained (Ketley, Mela, Thomas, Nixon & Van Rensburg, 2015:1).

Financial institutions

As a viable distribution channel, insurers should look to directly market index insurance products to financial institutions to reduce their business exposure and client default risk (Hill et al., 2019:16). By layering hedging protection into debt servicing obligations, which, when the underlying index is triggered, offsets loan payments, financial institutions can improve risk-bearing ability, enhancing the supply of credit (Shee, Turvey & You, 2018:5). Meso-and macro-level programmes have greater leniency towards basis risk. This is because the organizations using them can diversify their risk on a larger scale (Insurance Regulatory Authority, 2015:18). Therefore, basis risk is reduced as policies cover a more substantial portfolio through a single index written at an aggregate level (Sandmark, Debar & Tatin-Jaleran, 2013:22).

Another channel is through marketing the product to clients of a financial institution. The distribution approach can take the forms of a bancassurance model; where a bank and an insurance company collaborate to market insurance products to the customers of the bank to provide comprehensive financial solutions. The integration of financial services as it exists in a bancassurance model offers a number of synergies to both the bank and the customer. In terms of the number of active insurance policies in South Africa, bank channels accounted for 32 per cent of all life insurance policies and around 8 per cent of non-life policies (Ketley et al., 2015:9). This gives an indication of the strength of a bancassurance model in insurance market penetration. This is the trend worldwide, from 2011 to 2017, the growth of the bancassurance channel has consistently outperformed other channel platforms in both life and non-life insurance products (Bueno, Dinis, Neves, Kotanko & Maggiora, 2019:1).

Group schemes

Offering index insurance to a collective, such as a farming association, union or grouping could improve scalability, as it is likely to translate to wholesale savings and adoptation (King & Singh, 2018:24; Nyaaba, Nkrumah-Ennin & Anang, 2019:372; Pacheco, Santos & Levin, 2015:1007; Würtenberger, 2019:19), considering that group insurance is formed on the basis of minimal individual underwriting, lower administrative as well as distribution costs (Wrede & Phily, 2015:36). Even if low-income farmers have single buying power, groups have collective bargaining strength translating into more affordable insurance for its members (Chigada & Hirschfelder, 2017:3). Findings show that farmers, when offered it, prefer group index insurance over individual index insurance contracts (Vasilaky, Sáenz, Stanimirova & Osgood, 2020:17). Interestingly, Castellani, Vigano and Tamre (2014:1684) report that farmers are willing to pay a higher premium if index insurance is supplied through a farming cooperative or group. Lastly, findings indicate that interventions focusing on groups are more successful at encouraging a particular behaviour and outcome than those focusing on individuals (Steinmetz, Knappstein, Ajzen, Schmidt & Kabst, 2016:225).

From a group scheme perspective, index products are recommended to mostly be implemented on a mandatory basis providing a relatively basic level of cover, with a clear transition plan to a voluntary basis in the medium term. This is because typically take-up rate is very low if the products are sold on a voluntary basis from the outset. An example is a weather index insurance product in Ethiopia sold on a voluntary basis via cooperatives where the take-up rate was 7 per cent (Belissa, Bulte, Cecchi, Gangopadhyay & Lensink, 2020:11), after customers are acquainted with the product over a few years, demand for the product can be generated based upon customers' experience (Mookerjee & Nyoni, 2016:3).

Input aggregators

There are opportunities for bundling agricultural insurance products with input seed provision without eroding the value of the agriculture product (Mookerjee & Nyoni, 2016:2). Bundling insurance with agricultural inputs is a question of aligning value, the bundling should make sense for each stakeholder, and it should offer real value to the farmer while being accessible and affordable. Input providers traditionally have a wide network, including in the most remote areas. Such a bundling strategy would ensure that insurance is distributed via a large network to achieve scale and a greater reach at reduced distribution costs; while the input provider will benefit from an additional stream of revenue arising from commission or service fees (Mukherjee, Pandey, & Prashad, 2017:5). Many small-scale farmers rely on input providers for information on the latest farming practices, techniques and seed varieties; this interaction subsequently influences the transfer of knowledge. Research indicates that contact with input providers is positively related to farmers' awareness of crop insurance. Such awareness of crop insurance enables farmers to assess the benefits of insuring their farms carefully, which in turn is expected to increase their propensity to pay (Nyaaba, Nkrumah-Ennin & Anang, 2019:370).

According to Lybbert and Carter (2014:15) products that are packaged to integrate drought-tolerant seeds and weather index insurance offer a better solution to managing drought risk. Farmers that use a combination of these products are better insulated from shocks and recover much quicker from drought events, even reporting higher yields (Boucher et al., 2020:2). Ward and Makhija (2018:165) found evidence that supported the complementary relationship; the perceived value of drought-tolerant seeds increases when there is an insurance component, this is because weather index insurance has a beneficial impact that extents over the point where benefits of drought-tolerant seeds start to diminish. Designing parametric solutions to cover drought risk above this critical point where drought-tolerant seeds lose their yield advantage offers another value proposition dimension to farmers and is also expected to reduce premiums since the insurance only responds after another layer of risk mitigation has failed. This cushion or buffer is factored into insurance pricing. This has the potential to stimulate index insurance demand, improve the pool and mix of policyholders and reduce underinsurance, the effects of which improve prospects of sustainability and scalability (Awondo et al., 2019:3).

2.6 Limitations of Weather Index Insurance

The scientific, financial and development community, including politicians, have divergent views if weather index insurance indeed works – more specifically in relation to performance so far, and the innate teething troubles associated with calibrating accurate indices (Tadesse, Shiferaw & Erenstein, 2015:9). Upheld as a panacea by some and condemned as fundamentally ineffective by others (Ceballos & Robles, 2020:3), some insurance schemes have reported excessive loss ratios, exemplified by a weather index insurance scheme in Bangladesh with a loss ratio above 500 per cent (Microinsurance Network, 2017:51) and a combined average producer loss ratio of 405 per cent in Iran (Mahul & Stutley, 2010:128). Exorbitant loss ratios are typically a combination of inadequate rates and incorrectly calibrated indices or in some clear cases, catastrophic risk events. Predicated on this evidence, it stands to reason that insurance companies perceive weather index insurance as risky and unattractive (Afriyie, Zabel & Damnyag, 2017:3), this view undermines the overall scalability and sustainability of weather index insurance (Coleman et al., 2017:9). In light of these challenges, Carlos (2016:3) argues that there is no clear sign of commercial sustainability for index insurance products, as no product in sub-Saharan Africa has proved to be sustainable despite donor support in the form of scientific applied research, operational expertise, and insurance systems. Herbold (2014:204) believes that the repeated failures of index insurance schemes emanate from a lack of sustainable risk management systems, where a system approach instead of a standalone product approach in effect. Such a system approach creates functioning institutional, organizational and legal governing standards for implementation and regulation under which insurance policies can operate successfully.

Without this system approach, weather index insurance adoption has remained comparatively modest, barely reaching 30 per cent of the expected target population putting into question the legitimacy and economic feasibility of index-based insurance as a serious risk mitigating solution (Timu, Gustafson, Ikegami, Jensen & Takahashi, 2018:3). Following this, Ahmed, McIntosh and Sarris (2017:31) believe that mass-scale adoption of weather index insurance cannot be based on private demand alone. Basis risk appears to be the biggest limitation to scalability and sustainability of these insurance schemes. Sceptics paint these limitations as unsolvable, while practitioners are determined to overcome these issues with promising evidence that weather index insurance can be a valuable instrument (Carter, Janzen & Stoeffler, 2018:223).

2.6.1 Basis risk

Many scholars agree that basis risk is the main drawback of weather index insurance (Carter, de Janvry, Sadoulet & Sarris, 2014:3; Ceballos, Manuel, Robles & Butler, 2015:4; Mookerjee, 2014:255; Jensen, Barrett & Mude, 2016:25, Roznik et al., 2019:447; Stoppa & Dick, 2018:19; Ward, Makhija & Spielman, 2019:7). Basis risk is the imperfect correlation between the indemnity payments under an index insurance policy and the actual insured losses experienced by the policyholder (Jensen & Barrett, 2016:203). This results in contract failure, that is premiums are paid, losses incurred, but no indemnity payments are made, or losses are not incurred at farm level yet the index is triggered, and payments are made (Carlos, 2016:4; Morsink, Clarke & Mapfumo, 2016:3). If there are no indemnity payments in legitimate cases, then index insurance falls-short of its primary 'protection' mandate. This has to be balanced with the considerations that, indemnity payments that are high relative to actual loss experience undermine the sustainability of affordable insurance rates as increases are inevitable to accommodate high payouts and further dent the credibility of index insurance to investors as a viable business case. Both these extremes are likely to weaken incentives to develop insurance markets for the low-income sector and can result in a loss of trust and confidence in weather index insurance contracts where markets exist (WFP, 2017:24).

In reliance on the findings of Ward and Makhija (2018:174), farmers are sensitive to index insurance contracts because of the inherent basis risk element; when basis risk increases by 1 per cent, the insurance premium would have to be discounted by 3 – 4 per cent to maintain market demand. Mobarak and Rosenzweig (2012:29) report that where index insurance is based on observations from a reference weather station, demand for insurance contracts declines by more than 6 per cent for every kilometre distance from farm to the weather station. Basis risk significantly affects willingness-to-pay for weather index insurance contracts because of the possibility of failure of risk transfer to occur (Elabed & Carter 2015:151). In Kenya, 23 per cent of previously insured farmers cited basis risk as the main reason for their discontinued purchase of index-based weather insurance in the following year (Njue, Kirimi & Mathenge, 2018:8). On that account, even risk averse farmers with previous experience in hedging production risk through market-based contracts may have reservations due to basis risk surrounding the validity of the contract (Belissa et al., 2019:2).

Basis risk is unavoidable and endemic to index insurance contract design regardless of the index used to correlate crop losses. Even if better agronomic models can be developed, natural limits exist to the degree to which basis risk can be reduced (Miranda & Mulanga, 2016:8). Although index insurance is predicated on big data and sophisticated modelling tools, the problem remains that one is trying to use mathematical equations and statistics to represent a series of natural processes, which can be extremely complex (Carlos, 2016:4). From the supply-side, discerning the extent and distribution of basic risk should be of the utmost importance (Jensen, Barrett & Mude, 2016:3). It is suggested that the correlation between the index and the losses should be at least 70 per cent for a sustainable index insurance programme (Gulseven, 2014:18). A comprehensively calibrated index should consider multiple sources of climate information and acknowledge associated potential biases in the process, if not, insurers are likely to misrepresent and underestimate climate hazard risks (Daron & Stainforth, 2014:88).

Under conditions of high basis risk, that is, low correlation, farmers do not perceive index insurance as a form of risk transfer, but rather a lottery, which they lose if the insured event does not occur (Ehrlinspiel, 2017:10). It is the assessment of Elabed and Carter (2015:151) that basis risk creates a compound lottery effect: the first lottery outcome determines the individual farmer’s yield, and the second outcome determines if the index triggers an indemnity payment. Under these conditions, index insurance becomes a risk increasing gamble rather than the risk-reducing solution it should be (Jensen, Barrett & Mude, 2016:2). A strong focus to address basis risk may minimize perceived lottery ticket outcomes to an acceptable level of insurance protection (Jensen & Barrett, 2016:204). To maintain the risk transfer integrity of index insurance researchers are exploring the potential of including gap cover to respond to the uninsured portion of basis risk (Clement et al., 2018:850).

Bokusheva (2018:2329) proposes weather index insurance contracts to be designed as an instrument for catastrophe cover as opposed to coping with moderate and expected climate hazards. These catastrophic events can have severe effects on the long-term future of agriculture; an example is cyclone Idai which swept through Mozambique reducing the total maize harvest by over 80 per cent (Boucher et al., 2020:5). Concentrating insurance policy payouts on catastrophic events such as severe droughts where the trigger is an official declaration by government increases the likelihood that the index will be correctly correlated to ground experience (Insurance Regulatory Authority, 2015:18) since the entire area is likely to be affected evenly and in a proportional manner (Tadesse, Shiferaw & Erenstein, 2015:7).

However, such declarations are often long after the fact, when the planting season has concluded, and farmers are out of the production cycle. The challenge is finding a balance where insurance responds in a timely manner where early warning systems are implemented and payment is triggered prior to an official declaration.

2.6.2 Demand for weather index insurance

Questions in practice and academic literature remain unanswered about demand for weather index insurance, especially in developing countries (Norton, Osgood, Madajewicz, Holthaus, Peterson, Diro & Gebremichael, 2014:631). Despite the many theoretical benefits of weather index insurance, many schemes function as pilots and scaling up has proven to be difficult because of low demand and low insurance penetration among low-income farmers, even when premiums have been subsidized and extension services included (Ahmed, McIntosh & Sarris, 2017:31; Castellani & Vigano, 2017:517; Hansen et al., 2017:14; Jensen, Barrett & Mude, 2016:2; Matsuda & Kurosaki, 2019:20). For instance, in Santa Lucia, only 59 farmers purchased index insurance products between 2013 and 2015. This was considerably short of the envisaged 3 000 users (Ehrlinspiel, 2017:3). In Burkina Faso, 17 987 farmers used weather index insurance contracts from a targeted 60 000 to 80 000, at best this reflects a take-up rate of around 30 per cent (Koloma, 2015:118).

In Kenya, weather index insurance uptake showed a rapid decline from about 36 per cent in 2012 to a low of around 5 per cent in 2014 (Njue, Kirimi & Mathenge, 2018:8). The Kenyan economy is mainly driven by agriculture with approximately 70 per cent of the labour market highly dependent directly or indirectly on the sector for their livelihoods (Gulati, Terway & Hussain, 2018:25). Agriculture contributes 22 per cent to the country's overall GDP (Shee, Turvey & You, 2018:2). The topography of Kenya suggests that agricultural insurance is a necessity; the contradictory decline therefore in weather index insurance uptake is likely to be attributable to deeply rooted structural product issues, mainly, disparity between farmer expectations and the realisation, if any, of indemnity payments (Timu et al., 2018:14). Further afield, Indonesia recorded a modest 20 per cent penetration rate, and a 4 per cent demand level was evidenced in a pilot index insurance project in India (Ceballos et al., 2015:24). The low demand for insurance is despite Indonesia being highly exposed to drought risk brought about by the El Niño phenomenon and serious climate change impacts on its food production systems (Reyes et al, 2017:19). The case in India is no different, where agriculture plays a significant role with about two-thirds of the population employed in the sector (Singh & Agrawal, 2020:462).

Hill, Robles and Ceballos (2016:1268) suggest that affordable pricing specific to the target market and improving quality by reducing basis risk would be likely to increase demand. However, with such a product it is not always as simple as the solution suggests, Budhathoki, Lassa, Pun and Zander (2019:2) find that even with premium subsidies of up to 75 per cent as is the case in Nepal, demand for index insurance has been poor. This is surprising considering that farmers in Nepal have been suffering from the risks of climate change for the past three decades (Guo & Bohara, 2015:1).

Different theories exist in attempting to diagnose low demand. Binswanger-Mkhize (2012:190) underscores the fact that demand conditions for index insurance have two components, the first is that farmers obtain good working knowledge of the insurance offering and a clear understanding of events under which payments materialise. The second, expected utility derived under formal insurance must be higher than the utility experienced by utilizing informal risk-diffusion mechanisms. Mubhoff et al. (2018:117) further breaks it down and reduces low demand to two explanatory factors. The first is that risk-reducing effects of weather index insurance contracts are perhaps so minimal from a risk perception point of view, to the extent that farmers perceive little value in purchasing insurance. This builds on the concept of expected utility of a rational farmer put forward by the previous author. The second is that farmers fail to grasp the relative competitiveness of index-based insurance comprehensively. Financial constraints are also a prominent reason for low uptake of insurance by low-income farmers (Romero & Molina, 2015:22), added to that a lack of understanding when the product is purchased further adversely affects future demand. For example, poor product understanding resulted in farmers demanding repayment of their premiums following the purchase of drought insurance policies, where drought conditions did not materialise in that particular year of cover (Tadesse, Shiferaw & Erenstein, 2015:9). Notwithstanding, existing theories on demand, Fonta et al. (2018:3) believe that the major reason for low uptake is a generally poor understanding of farmers' willingness-to-pay and the related factors that influence the purchase consideration. This evidence will be valuable to key stakeholders in the agricultural sector, namely, state and developmental institutions, policymakers, and insurance providers, in addressing market failure through the right product to meet farmer's needs taking into account their existing financial constraints (Abugri, Amikuzuno & Daadi, 2017:2). In addition to the lack of understanding of willingness-to-pay components. Several studies provide supplementary explanations for low demand for weather index insurance contracts, these include:

- Index insurance products are not well-structured to respond to farmers specific preferences and needs (Sibiko, Veettil & Qain, 2018:12);
- Failure to engage stakeholders in the initial conceptualisation and design of the insurance scheme (Fonta et al., 2018:17);
- Low levels of awareness of index products among farmers (Aditya, Khan & Kishore, 2018: 167; Ehrlinspiel, 2017:3; Mookerjee & Nyoni, 2016:2);
- Inexperience with formal financial services by low-income farmers. This poses a challenge at multiple interaction points with a new product such as index insurance (Smit, Denoon-Stevens & Esser, 2017:8);
- Lack of trust that the contractual obligation will be fulfilled once the index is triggered (Belissa et al., 2019:277; Karlan, Osei, Osei-Akoto, Udry, 2014:601; Lence, 2015:28; Würtenberger, 2019:18);
- Poor insurance culture (Jensen & Barrett, 2016:209; Lence, 2015:28);
- High levels of basis risk which leads to reputational damage (Belissa et al., 2019:2; He and Zheng, 2017:3; Hill, Robles & Ceballos, 2016:1267; Lin et al., 2015:103);
- Lack of premium subsidies (Farrin, Miranda and O'Donoghue, 2016:19);
- High dependence on government disaster relief (Liu et al. 2018:41); and
- Unavailability of weather index products (Njue, Kirimi & Mathenge, 2018:9).
- Failure to recognize the impact of climate change and drought probabilities (Dougherty et al., 2019:40).

2.6.3 Strategies in response to low demand

Crop-based weather index insurance can only reduce risk and contribute to social and economic development if there is sustained and informed demand (Fonseca, 2016:7).Without this, inadequately developed pricing structure will exist and continue to hamper scalability and sustainability objectives. According to Vasilaky et al. (2019:3), it is important to avoid developing solutions that increase demand for insurance without resolving the concerns that manifest in weak participation. To negate low demand, scholars have recommended different initiatives to stimulate interest, namely deferring premium payments by farmers, low premium pricing strategy, frequent claim payouts, as well as education and training initiatives.

2.6.3.1 Deferral of premium payments

Low-income farmers are generally unable to mobilise the resources needed to pay insurance premiums upfront (Belissa et al., 2019:270). Therefore, Casaburi and Willis (2017:40) propose deferring insurance premium payments until crop harvest to stimulate uptake. In their experiment the authors find that insurance take-up reduces by 67 percentage points if payment is required upfront. This approach addresses liquidity constraints since insurance purchase decisions are often concurrent with decisions regarding agricultural production at the inception of the cropping season (Hill et al., 2019:3). Farmers are also receptive to the idea of post-harvest premium settlement (Budhathoki et al., 2019:6; Nyaaba, Nkrumah-Ennin & Anang, 2019:372). Although feasible, the approach requires the providers of insurance to be highly solvent and with enough liquidity to fund upfront costs and on-going expenses, while accommodating farmer’s cash flow requirements. The benefits of deferred premiums are evident for the low-income population group. In rural Ethiopia deferred payment terms were found to have a significant effect on insurance uptake, increasing the penetration rate from 8 per cent to 24 per cent, this supports the notion that liquidity constraints are among factors affecting uptake of insurance (Belissa et al., 2019:270). In easing liquidity constraints, Fonta et al. (2018:17) propose an alternative strategy which is to apportion insurance premiums into smaller, frequent and manageable amounts such as monthly payments to ease initial capital strain associated with lump sum crop insurance payments. In so doing this presents a mutually beneficial outcome for the insurer and the insured.

2.6.3.2 Low premium pricing

Farrin, Miranda and O’Donoghue (2016:5) believe that demand for insurance is low at both low-income and high-income farming enterprises. High income farmers may use their income to self-insure, and low-income farmers simply may not afford insurance. For low-income farmers, demand depends on whether or not basic physiological needs have been achieved (Zhang, Brown & Waldron, 2017:5). With low purchasing power and limited disposable income, insurance is most often not a priority expenditure line item in the budget of low-income households; hence a low pricing strategy would be an attractive value proposition for the market to consider formal risk mitigation tools (Wrede & Phily, 2015:16). Incentive-based pricing today could have dynamic future effects for insurance uptake through accelerated product diffusion and motivation for learning more about the product features, benefits and limitations (Cole, Giné, Tobacman, Topalova, Townsend & Vickery, 2013:106).

South Africa has an estimated 20 per cent penetration rate of funeral and life cover insurance within the low-income farming community. This demonstrates the capacity for financial product subscription if priced low enough (Accenture, 2018:14), especially in the context that considerable evidence suggests that demand for index insurance is price sensitive (Ward, Makhija & Spielman, 2019:13). Detailed analysis on price sensitivity finds that in developed markets, a 1 per cent decrease in premium accounts for a corresponding 0.5 per cent increase in demand, noting an inverse relationship (Sihem, 2019:186).

Offering less coverage may also be a technique applied to reduce pricing based on farmers' price sensitivity. Scholars such as Gulseven (2014:18) argue though that farmers' propensity to pay declines sharply for insurance schemes that offer less than 80 per cent coverage. In view of this, a balance should be reached between nuances of pricing, level of coverage and uninsured risk component, which is basis risk, and bearing in mind that essentially, the purpose of index-based insurance is to increase coverage of unprotected weather shocks in developing countries (Vasilaky et al., 2020:1).

2.6.3.3 Frequent claim payouts

Founding principles dictate that insurance provides its most considerable benefit for high value loss events with a moderate to low probability of occurrence. However, evidence from an index insurance scheme in Ethiopia demonstrates that low-income farmers require coverage for less severe but more frequent loss events (Vasilaky et al., 2019:5). Deductively, low-income farmers have less resilience to cope with climate shocks. Even less severe effects have a cascading effect on their livelihoods. Hence, these farmers have a strong disposition towards indemnity payments that occur at least once in three years (Norton et al., 2014:631). The results of Shirsath et al. (2019:8) affirm that farmer's greatest satisfaction from insurance is rooted in payouts. On that account, it is no surprise that infrequent payouts lessen the demand for weather index insurance (Karlan et al., 2014:601; Timu, et al., 2018:11). While an insurance payout immediately increases future re-purchase prospects by anywhere between 25 and 50 per cent (Cole, Stein & Tobacman, 2014:284). Low-income farmers need to feel that premium investments deliver value in the present (Zollmann, 2015:25). But increasing the frequency of claims payouts exponentially increases the likelihood of a higher premium charge to maintain regulatory capital requirements, sufficient reserves for future claims and sustainable profitability. All these considerations have subsequently led to the current discourse on premium subsidization in order to maintain the cost-effectiveness of insurance for farmers, the benefits of which have multiplier effects on the rest of the economy (Atsiaya et al., 2018:58; Barnett, 2014:211). Farmer satisfaction is also profoundly rooted in timely claim settlement (Singh & Agrawal, 2020:471). Hence, a compromising balance is required where efficiency should be prioritised as a countermeasure to frequent claim payouts.

2.6.3.4 Education and training initiatives

Pre-purchase research, especially when a product is not easily available, exertion of time, money and effort to collect information as well as no clear guide on the premium charge will invariably lead an individual to forego an insurance purchase transaction before it commences, more so if the risk perception on the occurrence of the event is low (Buzatu, 2013:38). The majority of non-adopters of weather index insurance attribute their non-participation in insurance schemes to a lack of understanding on how crop insurance works (Ceballos et al., 2015:5; Njue, Kirimi & Mathenge, 2018:9; Singh & Agrawal, 2020:472). In this light, Balmalssaka et al. (2016:1264) suggest extensive education and awareness creation campaigns as an effective way of stimulating demand. Various scholars share similar views expressing the view that training farmers on benefits of weather index insurance schemes can enhance adoption rates (Kumari et al., 2017:365; Sinha & Tripathi, 2016:17; Wairimu, Obare & Odendo, 2016:119; Würtenberger, 2019:19). More precisely, Zollman (2015:1) goes further to suggest that campaigns should be aligned to how low-income farmers perceive risk and risk management. At the same time, Vasilaky et al. (2019:3) assert that mechanisms that educate the farmer on how the products relate to risk optimisation can enhance demand.

2.7 Developmental impact of Weather Index Insurance

Index-based solutions have greater design flexibility and can be distinctively customized to specific scenarios to address covariate risk (Jarzabkowski et al., 2019:12). In their study of the three largest insurers in South Africa, von Loeper, Drimie and Blignaut (2018:170) find that all three insurers agree that there is a lack of sufficient historical financial data at a smallholder farmer level to structure crop insurance solutions for this segment. In addition, the costs of performing crop emergence inspections, which is a critical component of verifying insurable interest, post-emergence analysis and loss-adjusting further increase the price of the product to the exclusion of these farmers. On these grounds, weather index insurance is progressively championed for its capacity to build financial resilience by assisting farmers to access credit more easily, allowing them to innovate, invest in technologies that boost productivity and better manage the effects of climate change (Ceballos et al., 2017:71; Lin, et al. 2015:105; Rahman, Ghosh & Chowdhury, 2014:44; Zwane & Montmasson-Clair, 2016:4). Index insurance impact studies demonstrate that among other advantages farmers increase investment in production by 20 - 30 per cent while enjoying protection from downside weather-related risk (Carter & Chiu, 2018:4).

2.7.1 Improved access to credit

Low-income farmers lack access to financial services such as credit which is fundamentally linked to the availability of insurance (von Loeper et al., 2016:748). Credit access is a significant, if not, the primary restriction for low-income farmer's productive capacity constraints due to a lack of working capital (Meyer, Hazell & Varangis, 2017:1). In fact, Abdallah, Ayamga and Awuni (2018:19) find that credit access leads to significant gains in farm income of between 14 – 22 per cent. Access to credit is severely restricted for a large part of the resource-constrained rural farmers, mainly due to credit rationing and involuntary quantity rationing.

Financial institutions are in perpetual doubt about the economic and financial feasibility of low income-farmers and usually render the market unviable, even in the presence of high interest rates. The main constraints include small average loans, and high transaction costs in the absence of digitization fuelled by low technology adoption among the rural community, resulting in credit rationing. In markets where index insurance is available, credit rationing reduces by an estimated 12 per cent mainly because of the security element that is associated with index insurance enhancing the applicant's ability to repay the loan in the event of weather shocks (Belissa, Lensink & Winkel, 2020:8). Voluntary risk rationing is another aspect of consideration; financial institutions may in-turn impose high collateral and interest rates for expanding credit, exposing the farmer to unacceptable levels of risk, removing credit as a viable solution for a risk-rationed farmer (Ndegwa, Shee, Turvey & You, 2020:748).

Agricultural economics literature positions index insurance as the 'missing link' to low-income farmers' integration into the agricultural value chain. Index insurance is one of the tools for financial inclusion because of its extended functionality that works as collateral against loan defaults due to weather risk, thus improving the creditworthiness of farmers who were historically considered 'unbankable' (Johnson, 2013:2665). Insecure land tenure rights is a big stumbling block for low-income farmers to use land as collateral for financing purposes (DAFF, 2018a:3). Insurance offers an immediate solution, von Loeper, Drimie and Blignaut

(2018:167) in their study report that three of the four large commercial banks in South Africa are open to accepting crop insurance as first collateral to enable lending to low-income farmers, subject to attachment to an offtake agreement for the agricultural produce in order to ensure that there is a market to sustain the producer's cash flow. It is well documented that South African banks have a very low appetite for funding smallholder agriculture (Aliber, 2020:9). In this regard, insurance could be a key consideration in unlocking value, mostly in the rural economy.

Raju et al. (2016:1) state that insurance is invariably more appealing when it is linked to credit. This appeal is witnessed in the India market, where approximately 1 in 4 farmers are covered by index-linked to agricultural credit (Greatrex et al., 2017:10). More insight from Kenya shows that 97 per cent of insured farmers are able to obtain access to credit (World Bank, 2017:2). While production loans increased by 34 per cent in Mali attributable to the sale of index insurance (Mude & Carter, 2016:2). Without this linkage, farmers have no liquidity to fund premiums (Stoppa & Manuamorn, 2017:5). Therefore, it is no surprise that mounting evidence points to bundling index insurance with credit provision as a means to achieve better distribution and to enhance value for farmers (Hellin et al., 2017:3; Castellani & Vigano, 2017:516). In his study, Gulseven (2014:14) further complements the existing body of evidence when he discloses that bundling of insurance with credit is the primary reason for agricultural insurance purchase in Australia.

Since credit and insurance are complementary products, extending and strengthening credit can play an important role in improving insurance uptake (Tadesse, Shiferaw & Erenstein, 2015:3). Market demand for interlaced credit and insurance products is high and less price sensitive than for stand-alone insurance (McIntosh, Sarris & Papadopoulos, 2013:407). This credit and insurance mix by default addresses the problem of adverse selection for the insurance market, as both high and low-risk farmers' demand production credit (Romero & Molina, 2015:27). Hence, credit–insurance linkage is an essential ingredient to overcoming financial market imperfections, unlocking credit potential and the true underlying value of the agricultural economy.

2.7.2 Improved demand for chemical fertilizer

South African farmers pay significantly more for chemical fertilizer, which is 78 per cent higher than comparable countries, such as Argentina, Brazil and Ukraine. This is because

South Africa is a net importer of input fertilizer with exposure to weakening local currency risk, high margins on supply chain related costs such as deep sea freight, and inland transportation costs to retail channels (BFAP, 2020:25). High fertilizer costs result in lowered usage among low-income farmers, even though fertilizer has the ability to significantly improve crop yield and farm productivity. To contextualise this point, the recommended fertilizer usage rate in the SADC region is 50 kilograms per hectare (Finmark Trust, 2016:90), farmers in Sub-Saharan Africa generally apply around half the requires proportion per hectare, inadequate and ineffective to sustain crop and soil fertility (Sheahan & Barrett, 2017:15).

Studies show that weather index insurance adoption leads to significant increases of fertilizer and higher quality seed usage among small-scale farmers resulting in improved crop yield (Delavallade et al., 2015:3; Gebrehiwot, 2015:109; Haruna, Sohngen, Yakaya & Wiredu, 2017:84; Koloma, 2015:125; Sibiko & Qaim, 2017:17). Fertilizer is expensive, and there is potential for significant crop losses under adverse conditions, for this reason, farmers are often reluctant to apply chemical fertilizers in an environment of unmanaged risk (Hill et al., 2019:5). As such, fertilizer demand is price-elastic, a 1 per cent increase in fertilizer prices decreases fertilizer demand by more than 1 per cent (Sibiko & Qaim, 2017:18).

2.7.3 Adoptation of new technologies

Adoptation of new technologies is considered the primary way for low-income farmers to escape poverty traps (Wossen et al., 2017:223). Low-income farmers have benefitted greatly from insurance innovation, in terms of confidence to increase farm investment, and opportunities to experiment with yield improving methods (Moore et al., 2019:4), including the propensity to adopt new technologies (Tang et al., 2019:629). The effect of insurance adoption of new technologies is best described in research findings by Carter, Cheng and Sarris (2018:69) where 35 per cent of small-scale farmers would adopt technology without formal insurance, the figure increases to 45 per cent with index insurance and climbs to 55 per cent in an environment where insurance and credit are interlinked.

Adoptation of weather index insurance provides a transformed perspective of the operating environment, reducing risk aversion, which traditionally is a barrier to adoption of new technologies (Haile, Nillesen & Tirivayi, 2019:3). Technological innovation not only leads to improved yield, reported to be as much as 10 per cent yield increase in Emerick, de Janvry, Sadoulet and Dar (2016:153), but also significantly contributes to the adoption of improved crop husbandry on an ongoing basis. However, the rate of agricultural technology diffusion in emerging markets is sluggish, mainly due to persistence of poverty traps which limit the availability of financial resources directed towards innovation (Jumare, Visser & Brick, 2018:1), lack of credit markets and lack of knowledge and information on latest available tools. Therefore, technology adoptation as a tool to unlock value remain to be fully explored, and this is likely to continue in the absence of insurance solutions to instil confidence in the market to experiment with new technologies.

2.7.4 Improved livelihood of low-income farmers

Weather index insurance can play a long-term transformative role in poverty alleviation and food security (Isaboke, Qiao & Nyarindo, 2016:5). In addition, it provides time-efficient risk management strategies for low-income farmers. All-round, positive impact has been noted where weather index insurance has been adopted (Ntukamazina et al., 2017:172). These benefits are in respect of improved risk management and improved revenue generation (Hill et al., 2019:16), along with improved productivity which translates into long-term food security at household level (Munyoro & Moyo, 2019:28; Tang et al., 2019:637). In a large, randomized field experiment spanning 480 villages, Cai et al. (2015:299) found that insurance significantly increases agricultural production. The benefits thereof have a material impact on livelihood (Munyoro & Moyo, 2019:29). Following an index insurance payout in Kenya, Dubreuil and Tabegna (2019:7) report that most of the farmers utilized the payment to purchase food for the household, followed by reinvesting in agriculture through input and livestock purchases. This supports the narrative that payouts primarily secure livelihoods by satisfying food security needs, while maintaining and in some cases increasing investment in agricultural productive assets.

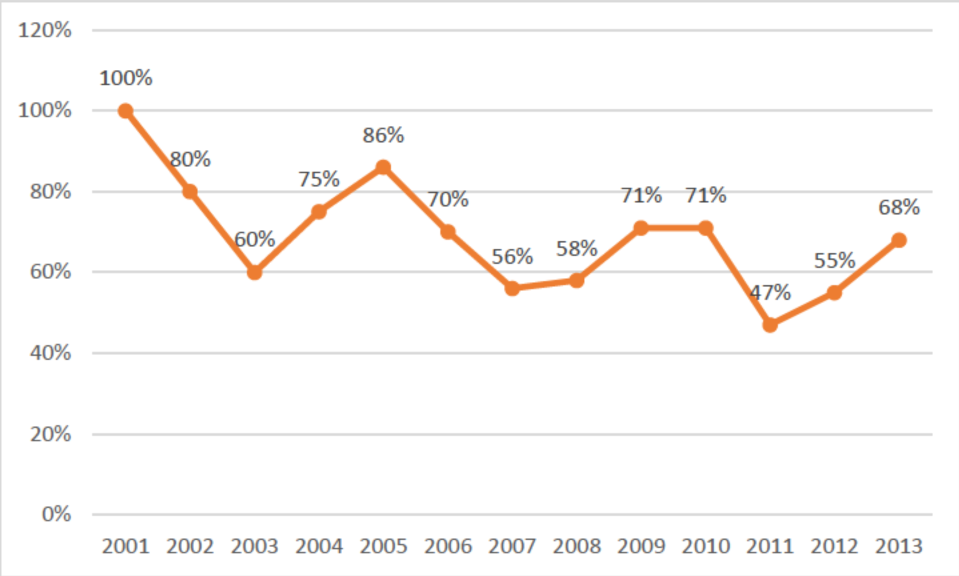
Post-drought, index insurance leads to 70 per cent decline in forced sale of assets by low-income farmers (Mude & Carter, 2016:2). Findings in Janzen and Carter (2019:668) confirm the curbing of unplanned sale of productive assets and further report that insurance helps maintain household food consumptions following weather related losses. Similar evidence is noted in Burkina Faso, West Africa, where index insurance payouts had significant spillover effects when it comes to purchases of livestock, food and agricultural inputs. Moreover, in their study, the authors reveal a 75 per cent increase in land under cultivation as well as a 35 per cent increase in livestock units (Stoeffler et al., 2020:23).

2.8 Government Participation in Index Insurance Markets

The government can play several roles as facilitator, user and provider of weather index insurance (Zhang, Brown & Waldron, 2017:23). This entails promoting the development of dedicated data collection and management systems; supporting the design and development of appropriate insurance solutions; appropriate regulatory supervision, farmers and stakeholders outreach programmes to increase awareness; engaging in targeted risk financing; and supporting the establishment of appropriate public and private structures (Stoppa & Dick, 2018:52). A growing body of evidence suggests that pilot schemes, especially in Africa have been challenging to scale up because insurance does not form part of the broader agricultural transformation agenda or a national agricultural risk management framework supported by the government (Syroka & Reinecke, 2015:2).

In this regard, the China Insurance Regulatory Commission (CIRC) has taken the lead and put forward a national policy promoting the development of weather index insurance (Liu et al., 2018:33), and subsidizing agricultural premiums by up to 80 per cent (Luy & Barré, 2017:69). Since 1982, the country's legal and regulatory framework has been continuously developing to support farmers all over the country. Now China represents one of the largest agricultural economies in the world with a fast-developing agricultural insurance model encompassing indemnity and index-based insurance (Krychevska, Shynkarenko & Shynkarenko, 2017:18). Agricultural insurance has also proven to be profitable (Figure 2.5) in China with loss ratios ranging from 47 – 71 per cent over a span of 8 years from 2006 – 2013, proving that when well structured, agricultural insurance schemes can be beneficial as well as commercially viable.

Figure 2.5: Loss ratio of agricultural insurance in China



Source: Li (2014:6)

Another case is the Government of India, which has committed to policy objectives of increasing insurance coverage through various insurance schemes, including Pradhan Mantri Fasal Bima Yojana (PMFBY) where the state subsidizes a bulk of the premium and the farmers are responsible for 2 per cent of the cost (Ward, Makhija & Spielman, 2019:3). Governments as key participants are rarely constrained by narrow market failure and often choose to subsidize premiums heavily for broader social and political objectives (Hazell, Sberro-Kessler & Varangis, 2019:9). Through government supported initiatives, mainly premium subsidies, agricultural insurance coverage has increased to around 30 per cent of the planted crop area in India, 69 per cent coverage; in China and 89 per cent coverage; in the United States (Gulati, Terway & Hussain, 2018:31). Similar to China, the United States crop insurance market has also been relatively profitable, generating premiums close to US$1 trillion and an average loss ratio of 81 per cent over 13 years measured from 2004 – 2017 (Hohl, 2019:200). The programme started in 1938 and currently covers almost 130 different crop types, with the federal government subsidizing crop insurance premiums by around 60 per cent (Shields, 2015:1).

2.8.1 Premium subsidies

In developed countries, the government has largely subsidized index insurance markets (Ward, Makhija & Spielman, 2019:7). International experience, except that of India, implies that weather index insurance is not sustainable without state subsidy or international financial assistance (Rahman, Ghosh & Chowdhury, 2014:50; Sandmark, Debar & Tatin-Jaleran, 2013:7). Moreover, Hill et al. (2019:16) assess that without monetary motivations, there would be practically no interest in index insurance, even at actuarially-favourable rates. Tang et al. (2019:623) oppose this view and argue that subsidies create complex boundaries between government and the market, disorder market competition and result in improper management of schemes. In addition, they impose significant fiscal burdens (Ward & Makhija, 2018:164) and need to be sustained on a long-term basis.

A trade-off arises between providing premium support and re-channelling resources to other areas of national importance. From a theoretical perspective, premium subsidization should be short-term in nature, as subsidies are an instrument to help stimulate business sector advancement and are not really expected to last for more extended terms. Just as seed retailers provide free samples of new varieties for farmers to test and experiment with products for which they have no related experience, premium subsidies which lower the costs of insurance may provide an avenue for experimentation with new insurance innovations (Hazell, Sberro-Kessler & Varangis, 2019:8). Subsidies are ideal to scale insurance distribution; once sufficient numbers are generated to support a well-functioning programme, better risk diversification and administrative effectiveness are expected to flow, translating into premium savings for farmers (Weingartner, Simonet & Caravani, 2017:27). The effect on premium subsidization on insurance uptake is substantial, in their analysis, Cia, de Janvry and Sadoulet (2016:26) record a sharp spike in participation levels from 28 per cent to 60 per cent following an increase of subsidy rates from 40 per cent of the actuarially fair price of insurance to 90 per cent.

Ahmed, McIntosh and Sarris (2017:17) argue the effectiveness of short-term subsidies and provide evidence that temporary subsidization fails to support long-term demand for weather index insurance. Alarmingly, the authors report that none of the interviewed farmers purchased weather index insurance outside of subsidized structures. Where subsidies are available, insurance coverage was only purchased to the limit of the subsidy, meaning that none of the farmers utilized their own funds for insurance purposes. According to a study commissioned by the World Bank (2014:73) direct premium subsidies often result in policyholders underinvesting in their adaptive capacity and risk mitigating practices; such as irrigation, drought resilient seed varieties or crop diversification. The study also finds that farmers, motivated by high commodity prices, invest in unsuitable crops for the respective agro-ecological zone, basing their decision on the availability of insurance to protect against crop failure. The report concludes that direct government subsidies are seldom appropriately targeted to reach the poorest farmers, and once established, they become politically very problematic to pull from the market. An indirect subsidy, potentially through the exclusion of agricultural insurance premium from Value Added Tax (VAT) could pose as an alternative (Mookerjee & Nyoni, 2016:4). Tax exemptions on agricultural insurance, as currently implemented in Senegal, forms the basis for indirect premium subsidy, which is simple to introduce and has a strong fiscal rationale. The loss of direct tax collections is expected to be offset by increases in agricultural productivity, with a direct impact on input purchases, fuel, machinery acquisition, employment which reduces the state social burden, increased number of insurance transaction stimulating the financial services sector (Stoppa & Dick, 2018:52).

South Africa is one of the relatively few markets in the world where agricultural insurance is not subsidized by the government (von Loeper, Drimie & Blignaut, 2018:171). The South African government's previously attempted to provide and broaden access to comprehensive crop insurance was by subsidizing 25 per cent of premiums from 1979 to 1986. Low participation rates by farmers resulted in poorly developed pricing structures leading to inadequate subsidies and subsequent closure of the scheme (Ministry for Agriculture and Land Affairs, 1998:43). Premium subsidization models differ from country to country and vary between different types of agricultural insurance programmes. A common theme appears to be higher subsidization for weather index insurance schemes (Clement et al., 2018:851). Among the different models, In Uganda the government subsidizes premiums according to the segmentation of farmers as either commercial or small-scale, where the rate of subsidization is 30 and 50 per cent respectively. High risk that are susceptible to significant weather risk receive up to 80 per cent in subsidies (van Asseldonk, van der Woerd & Vakaki, 2018:25). The Turkish government provides subsidies of about 50 per cent, and this increases to 66 per cent for crops with high export potential (Gulseven, 2014:13). The idea is that foreign exchange earnings from trade partners with stronger currencies will offset the subsidy portion and stimulate local economic growth. Spain provides premium subsidies of 50 per cent (Reyes et al., 2017:12) and Indonesia subsidizes 80 per cent of premiums (Mutaqin, 2019:2). In developed economies such as the United States, Canada, Japan and the rest of Europe average subsidy rates are 47 per cent (Hasan, 2019:37). Table 2.3 aggregates various index insurance schemes with the respective weighted average of subsidies.

Table 2.3: Scale of index-based insurance

	Approximate no. of policyholders	No. of schemes	Weighted average of subsidies
Africa	443 075	17	37%
China	140 000 000	1	95%
India	33 222 000	4	64%
Latin America	963 460	11	91%
Rest of Asia	3 315 626	8	64%

Source: Hess, Hazell and Kuhn (2016:15)

Insurance schemes that are unsubsidized could result in costly premiums in risk-prone areas, which is likely to be a barrier to insurance uptake (BFAP, 2016:41). Different approaches are proposed in literature for determining optimum subsidy levels. Cia, de Janvry and Sadoulet (2016:4) in assessing a weather index insurance programme in rural China recommend that subsidy rates be adjusted year on year dependent on the scheme performance. After a year of large losses, subsidies can be lowered to maintain the financial integrity and soundness of the programme and where loss ratios are favourable, meaning fewer claims paid, subsequent subsidies can be increased. The fundamental underpinnings of this recommendation are that after receiving subsidies in the first year, farmers are more incline to participate in the second year, and following claim payouts farmers continued participation is assessed as high, the interchange of the forces between take-up rate and payout rate contributes to a sustained level of insurance demand. Gulseven (2014:13) proposes that an idealized method to determine optimal subsidy rates is to determine the value of insurance, thereafter, assess the amount farmers' are willing to pay for the insurance, the difference if any, warrants the portion to be covered by the subsidy.

2.8.2 Regulatory framework

The protection of policyholder rights, standards for appropriate advice, treating policyholders fairly, the availability of suitable products are within the domain of regulatory authorities to maintain the integrity of financial markets. Index insurance, much like conventional insurance products requires oversight and an appropriate regulatory framework to govern its operation. The scope of governance under the regulatory framework extends to monitoring of financial performance through solvency and levels of capital adequacy, business conduct, complaints handling, claims management and, specific to index insurance, clear certification processes (Jensen & Barrett, 2016:202). In underdeveloped markets, regulators view index insurance as a derivative rather than as insurance. The problem with this view is that derivatives attract different regulatory supervision with much less protection when compared to insurance consumers. Insurers, therefore, can operate with impunity without their market conduct being subjected to specific consumer-centric standards (Insurance Regulatory Authority, 2015:6). As a technical instrument, derivative contracts track the performance of an underlying asset through a derived index and can be traded for speculative purposes, while insurance requires the policyholder to have an insurable interest (Hohl, 2019:26). The complexity of insurance and derivatives, given their different nature, warrants different regulatory regimes.

Very few countries have developed regulatory frameworks to enable the sale of index insurance products (Microinsurance Network, 2017:44) where poor regulatory environments have impeded the development of index insurance in sub-Saharan Africa (Ntukamazina, 2017:175). In South Africa, index insurance products are not even mentioned in law (Microinsurance Network, 2017:27). But, the South African legislation makes provision for the establishment of microinsurance products through the promulgation of the *Insurance Act of 2017* which aims to promote financial inclusion by introducing standards and a regulatory framework (Montmasson-Clair, Mudombi & Patel, 2019:36). Through the Insurance Act, less stringent regulations and capital requirements are imposed on microinsurance businesses in South Africa, serving as an incentive for insurers to access the uninsured at a reduced cost (PWC, 2018:40). The previous and current insurance legislation provides for Policyholder Protection Rules (PPR) to help a policyholder make informed decisions with respect to insurance products and to ensure that intermediaries and insurers conduct business honestly, fairly and with due care and diligence (Gibson, 2011:8). In terms of the amended PPR framework, the standard structure policy benefits of a microinsurance policy must be as follows (FSCA, 2018:26):

- Policy may not have a contract term of more than 12 months.
- The value of the policy benefits under a microinsurance policy may not exceed the maximum amounts as prescribed by the Prudential Authority, which is R120 000.
- A microinsurance policy must, upon expiry of its contract term, either be – automatically renewed; or terminated in accordance with the requirements set out in these rules.

This defined structure as enlisted in the insurance act could be a basis for defining index insurance policy rules. With the quality of index insurance products unregulated in most developing economies, low-income farmers are exposed to unnecessary risk form the product itself. Carter and Chin (2018:4) are of the view that Minimum Quality Standards should be imposed on index insurance products; this would ensure basic levels of transparency for complicated insurance offered to mostly rural farm households. In his hypothetical assessment of select index insurance programmes in Senegal, Kenya and Tanzania, Carter (2019:2) applies a metric to critically evaluate the structure of these programmes. He finds that the index insurance programme in Tanzania is the only one which meets minimum standards because of adequate index and contract design that correlate accurately to losses, in addition to being affordable. Structured certification consistent with international standards could prevent substandard products from entering the market. This will also improve risk transfer capacity of insurance providers to global reinsurance markets because of the uniform, standardized nature of the products (Hess, Hazell & Kuhn, 2016:24).

Regulatory approval has its challenges and it's not uncommon to experience prolonged delays in obtaining the final authorization. The Caribbean index insurance programme was delayed by close to a year (Johnson, 2013:2673), with similar delays noted in the Dominican Republic (Vasilaky, Sáenz, Stanimirova and Osgood, 2020:5) due to a regulatory impasse. Notably, international experience suggests an increasing trend where insurance regulatory authorities generally have been supportive of initiatives for index insurance, provided consumer interests are properly protected (Coleman et al., 2017:127).

2.8.3 Government structured schemes

Governments of high and middle income nations play a direct active role in structuring crop insurance markets. Aside from premium subsidies and establishment of regulatory and supervisory environments, these governments are key in creating models that centralize insurance provision while encouraging private sector participation to bring an edge of development and innovation in the supply of insurance. One such model is a coinsurance pool consisting of insurance providers where standard insurance terms and conditions are established by the government. In such a pool, all participating insurers are shareholders in a joint management entity, sharing the risk and premium in proportion to their shareholding. Crop insurance business is then written in this pool, aggregating different crop risks spread across a larger geographical and reaching a wider audience. This is a critical element in ensuring that the scheme is sustainable. (Herbold, 2014:206). The advantage of such a scheme is that the risk pool can absorb a large portion of risk accommodating a large number of farmers, insurance becomes more affordable, shared services result in reduced administrative costs, traditional barriers to crop insurance participation by private entities are reduced, claim settlement and assessment are on the same terms for the entire market and such organized pools can better advocate for government subsidization because of their impact, scale and outreach. The agricultural insurance pool in Turkey and the Spanish agricultural insurance system are examples of coinsurance programmes. An example of another model is the United States market where the federal government establishes the annual premium crop insurance rates, which are legislatively required to be actuarially fair, meaning that, the premium should be sufficient only to cover losses with no additional loadings (Du, Feng, Hennessy, 2014:3). Insurance contracts are then marketed and administered by approved private companies at the federal premium rate who compete for business on the basis of quality of service. Since premium rates exclude any operational margins, the administrative and operating expenses to administer policies are then reimbursed by the federal government to a maximum amount as defined in the Standard Reinsurance Agreement (SRA) for all approved private insurance companies. The SRA further sets out guidelines under which private companies can transfer risk to the state through reinsurance arrangements where the United States Department of Agriculture (USDA) is the reinsurer. The private companies setting their own risk bearing capacity according to their risk appetite and financial position, determine their optimum risk retention level to a maximum of 35 per cent of risk retention as legislation permits, the rest is transferred to the state (Shields, 2015:24). The idea is that the government has greater risk bearing capacity and will be able to absorb large losses when compared to private companies. The coinsurance framework and its fundamental structural aspects contribute to sustainable agricultural insurance systems in the United States, where crop insurance coverage extends to over 90 million hectares per annum from 2004 to 2013 (Shields, 2015:27). Providing insurance solutions that cover both production and price risk (Reyes et al., 2017:15).

2.9 Reinsurance Markets

The insurance industry is faced with increasing internationalization and globalization (Ulbinaite, Kucinskiene & Le Moullec, 2014:1). This global environment presents an increased opportunity to manage the systemic risk element associated with a smallholder agricultural insurance portfolio; thus most insurers use reinsurance arrangements to transfer at least part of their total risk exposure to well-diversified international markets (Meyer, Hazell & Varangis, 2017:7). Reinsurance is effectively the purchase of insurance by an insurance company with the aim to transfers a portion of its risk exposure to reinsurance providers for the purpose of spreading risk (Mapfumo, Groenendaal & Dugger, 2017:283). The principle of reinsurance is that correlated risks at local level become independent at a global level (Balaban, Simeunovic & Markovic, 2018:426). It is precisely for its risk-bearing and risk-spreading capacity that the insurance industry worldwide has long used the global reinsurance market in the provision of index insurance (Johnson, 2013:2673).

The usage of reinsurance contracts as risk transfer mechanisms provides access with respect to expertise to optimize underwriting and to provide clear standards and guidelines; moreover, reinsurance stabilizes loss experience to within the risk appetite of the insurer, and limits the financial impact of catastrophic loss on the balance sheet of the insurer (Alhassan & Biekpe, 2019:1378). Essentially, reinsurance can also reduce capital requirements for insurers that are regulated under the risk-based solvency assessments management approach because reinsurers share in the underlying risks (Wrede & Phily, 2015:51). Reinsurers share risk with the insurer through a wide variety of different forms of traditional reinsurance cover; these include arrangements to share premiums, claims and expenses on a proportional basis as well as non-proportional coverage that will only apply to losses above a certain threshold. Reinsurance coverage can also be arranged on a per-policy basis, particularly for large individual policies, that represent an outlier to a homogenous portfolio or for a portfolio of policies (OECD, 2018:14). In most markets, agricultural insurers prefer proportional reinsurance and typically add another layer of non-proportional reinsurance to protect their net retention (Hohl, 2019:370).

Support from reinsurers does come with its own limitations, since the market is made up of a few insurers and reinsurers, information asymmetry is high, and there is a lack of price transparency, often resulting in reinsurers demanding a high premium for risk transfer, leaving the insurer with lower margins (Balaban, Simeunovic & Markovic, 2018:426). This is a precarious position for insurers given that index insurance margins are already low (Wrede & Phily, 2015:18) and require high premium volume paradigm to be successful. When pricing, reinsurers will consider nature of risk, premium volume, market size, growth potential, the product design and data quality, insurer expertise and market reputation before granting capacity (Coleman et al., 2017:128). The ideal reinsurance protection for an insurer is, therefore, a compromise between the price of reinsurance and reducing exposure to considerable losses (Hohl, 2019:370). Reinsurers are not immune to cover and may also acquire insurance coverage from other reinsurers or capital market investors to further diversify and reduce their exposures, typically covers includes catastrophe risk, which is low frequency, high severity risk events. This type of insurance is referred to as retrocession (OECD, 2018:11).

2.10 Conclusion

Chapter Two provides a frame of reference for weather index insurance in the South African operational environment in order to gain an appreciation of elements that influence farmers' behavioural intentions towards weather-based crop insurance as part of developing a comprehensive conceptual framework. The literature in the chapter demonstrates that weather index insurance can be a gateway to promote insurance access to thousands of uninsured low-income farmers at reduced costs. The resultant reduction of micro-level farmer risk has, in some cases, been shown to stimulate various agro-economic activities in terms of increased adoption of technologies, improved fertilizer usage and better access to credit. The chapter demonstrates that in the long run, insurance can create certainty within investment, planning and development of agricultural activities if integrated as part of a systemic approach. The evidence thus far indicates that, albeit the developmental impact is visible, index insurance schemes suffer from low-participation rates affected by, among other factors, lack of involvement of farmers in the design and pricing process; failure to understand farmers traditional risk mitigating tools and integrating insurance within these traditional practices instead of a stand-alone solution; as well as the inherent limitations of basis risk associated with index insurance design. This chapter concluded by highlighting the role of government and reinsurers as key stakeholders and facilitators in removing barriers to successful risk mitigation. Government has an obligation to protect the welfare of its citizens by addressing market failures of agricultural insurance through creating an enabling policy, legislative and regulatory environment, while reinsurance markets offer an opportunity to manage and diversify risk globally, thus increasing the risk-bearing capacity of local insurers.

The following chapter details empirical findings of low-income farmers willingness-to-pay for weather index insurance and factors influencing willingness-to-pay taken from various studies, evidenced from diverse social settings in order to assist in identifying factors that will guide the formation of a conceptual framework for the South African environment.

CHAPTER THREE: WILLINGNESS-TO-PAY – EMPIRICAL FINDINGS

3.1 Introduction

Chapter Three examines recent research, empirical findings, evidence and approaches underpinning willingness-to-pay investigations for agricultural index insurance solutions. A synthesis of research from leading organizations in the development and implementation of weather index insurance, government publications, academic journal articles, and published and unpublished theses were used. In this chapter low-income farmer's willingness-to-pay is discussed and framed in the context of economic theory on agricultural insurance purchase decisions. According to Ulbinaite, Kucinskiene and Le Moullec (2014:16), deep insight into consumer purchase decisions is key in the broader understanding of market forces of supply and demand. As such, there are different approaches to determine willingness-to-pay, namely, revealed and stated preference which are both considered and each discussed according to its merits. Chapter Three further presents' findings from a considerable number of studies on farmer's preferred price range expressed as a percentage of the farmer's total income that is considered as fair compensation for weather index insurance. Lastly, factors that influence low-income farmer's willingness-to-pay for weather index insurance are drawn from the literature and grouped into socio-demographic, socio-economic and socio-psychological variables in order to obtain tangible and behavioural attributes that will guide the conceptual framework as set out in the main objective of the research. This framework may assist in outlining possible relevant policies to be adopted by the South African public and private sector in the future provision of index insurance solutions.

It is the view of Atsiaya et al. (2018:52) that the biggest hurdle associated with the provision of agricultural insurance is farmer's willingness-to-pay insurance premiums. This is a situation that is potentially exacerbated in South Africa because low-income farmers generally lack access to agricultural insurance (Elum, Modise & Marr, 2017:253). This lack of exposure and access is expected to influence positively or negatively their interaction with a hypothetical weather index insurance scheme. From a substantial body of work, hypothetical weather index insurance schemes have been studied in the literature (Abdullah, Auwal, Darham & Radam, 2014; Aditya, Khan & Kishore, 2018; Arshad, Amjath-Babu, Kächele, Müller, 2016; Lin et al., 2015; Gaurav & Chaudhary 2020; King & Singh; 2018; Liu et al., 2018; Stoeffler et al., 2020) and they generally show mixed results towards index-based insurance acceptance decisions.

3.2 The Concept of Willingness-to-pay

The concept of willingness-to-pay is common in agricultural risk management literature. When agricultural risk extends beyond the scope that can be mitigated and managed at farm level, there is *prima facie* evidence that increased interest in insurance will follow thereafter (World Bank, 2011:29). Marketers often want to investigate this *prima facie* evidence by assessing consumers' willingness-to-pay for a product, especially when developing new products and promotion strategies (Schmidt & Bijmol, 2020:499). Knowledge on market demand is crucial for strategy formulation, product design and most notably product pricing. Willingness-to-pay values are, therefore, essential in constructing financial models and insurance purchase decisions that underpin the development of insurance products (Braun, Schmeiser & Schreiber, 2016:761).

Willingness-to-pay is defined as the maximum amount of money that a person is willing to spend to procure a product or service. According to Carter et al. (2014:10), willingness-to-pay can be considered as the minimum level for weather index insurance demand. The advantage of measuring willingness-to-pay is that it is a direct and inexpensive way of interacting with the potential market. The disadvantage is that hypothetical questions are asked over unfamiliar financial products, where the respondents may behave differently in reality (Fahad & Wang, 2018:571; McIntosh, Sarris & Papadopoulos, 2013:401). More often than not, willingness-to-pay studies have produced inflated estimates of insurance demand (Platteau, De Bock & Gelade, 2017:140). According to Janzen and Carter (2017:16) in the absence of predictive market information willingness-to-pay analysis provide useful information of market intentions and future behaviour. Therefore, willingness-to-pay studies contribute to improved market knowledge, identification of suitable segments within the market, and an understanding of potential barriers to product success. All of which provide business intelligence that can be used to effect consumer behavioural change or product modification (Castellani, Vigano & Tamre, 2014:1673). Effectively, willingness-to-pay studies determine potential demand rather than effective demand. In weather index insurance studies, it is a common approach to test willingness-to-pay in order to analyze price elasticity of demand, establish appropriate subsidy levels, if required, and to determine the level of government involvement and intervention. Finally such studies can help to determine optimal coverage, as well as product terms and conditions (Vasilaky et al., 2019:3).

Willingness-to-pay approaches can be categorized as revealed or stated preference (Danso-Abbeam, Addai & Ehiakpor, 2014:168). Revealed preference refers to predicted choices based on observed market data, purchasing habits, psychosocial motives, non-economic factors, and current transactions associated with the commodity offered and use of this information to determine a value for non-publicly traded commodities. The premise of revealed preference is that past behaviour is the best indicator of future behaviour as predicted in the TPB, and this assertion is supported by much empirical evidence (Ajzen, 2020:315). In TPB, intentions to perform a behaviour are conceptualized as the closest precursor of actual behaviour (Judge, Warren-Myers & Paladino, 2019:260). Stated preference, on the other hand, is used where revealed preference data is not available. Such is the case in South Africa where there are no comprehensive historical financial data on low-income farmers. This is because low-income farmers engage less often with the formal sector than higher income farmers who have a portfolio of financial products (Smit, Denoon-Stevens & Esser, 2017:7). To compensate for the lack of consumer data, an exercise to collect primary data is required usually through acquiring information about consumer preferences. This is achieved by conducting surveys based on hypothetical market scenarios where participants state their preference. Stated preferences methods are commonly referred to as contingent valuation methods primarily because they are contingent on the observed choice constructed in the survey (Carson & Hanemann, 2005:824).

Contingent valuation is highly recommended in instances where there is no or little market information, as is the case in this study and has been widely used by many researchers in previous studies specifically to solicit willingness-to-pay for weather index insurance (Abebe & Bogale, 2015; Aditya, Khan & Kishore, 2018; Arshad et al., 2016; Ellis, 2017; Fonta et al., 2018; Fahad & Wang, 2018; Guo & Bohara, 2015; Hill, Hoddinott & Kumar, 2013; Obasoro, Obisenan & Onabajo, 2016). Contingent valuation is deeply rooted in welfare economics, within the neoclassical concept of economic value under the framework of utility maximisation (Hoyos & Mariel, 2010:329). The intention is, given the absence of market prices, to measure the perceived utility that consumers would derive from the product or service. (Gyrd-Hansen, Jensen & Kjaer, 2013:550). Existing literature in insurance favours a stated reference approach using the contingent valuation framework for estimating willingness-to-pay for new insurance products (Braun, Schmeiser & Schreiber, 2016:762). This method is further discussed in the research methodology chapter.

3.3 Empirical Findings on Willingness-to-pay

King and Singh (2018:12) find that 75 per cent of sampled farming households in Vietnam reported a willingness to pay zero when responding to a survey on a weather insurance product‘s hypothetical demand. High recorded incidents of crop production loss and related negative impacts on household food consumption, as well as repeat confirmatory findings of climate hazards across Vietnam bring to the fore the question of why insurance interest is so low when there is a clear need. According to Frey and Pirsche (2019:2), a substantial number of zero bids, as reported in Vietnam, may signal a strong political or moral protest or a string of other non-insurance related influences driving willingness-to-pay decisions. A similar case of very limited interest in weather index insurance among low-income farmers was observed in Ethiopia. Two different studies report a negligible interest of less than 5 per cent of the sampled population (Ahmed, McIntosh & Sarris, 2017:17; Hill, Hoddinott & Kumar, 2013:390). Again the results are puzzling considering that 50 per cent of GDP comes from agriculture, where the sector provides jobs for around 80 per cent of the population and accounts for 90 percent of income generated from exports (Ahmed, McIntosh & Sarris, 2017:6). With such a strong agricultural base, the general expectation was that insurance demand would be moderate to high as a protective mechanism to secure the livelihood of farmers.

Findings in Ghana reveal that 41 per cent of farmers were not willing to participate in weather index insurance markets. These farmers view insurance as an unnecessary and additional burden (Balmalssaka et al., 2016:1263), indicative of the insurance culture in the region. In contrast, another study in a different region of Ghana reveals that 93 per cent of farmers were willing to purchase index insurance contracts (Afriyie, Zabel & Damnyag, 2017:2). While examining both studies, key differences emerged, showing that the first study investigated willingness-to-pay of maize farmers, where maize is a major cash crop and staple food in the study area. Comparatively, Afriyie, Zabel and Damnyag focused on cocoa production, which serves as the main source of employment in Ghanaian agriculture. The contrast in results implies that the importance ascribed to crop types and economic motivations may have an influence on insurance purchase decisions. In addition, different crops have a different risk profile and respond differently to weather perils, this along with the different geographical setting of both studies may partly explain the great variance in results.

A strong majority of 88 per cent of low-income farmers in Burkina Faso were interested in participating in a proposed weather index insurance programme (Fonta et al., 2018:11). Burkina Faso has an agricultural-based economy contributing nearly one-third of the country's GDP and employing around 80 per cent of the population. Index insurance has been operational in the country since 2011 (Stoppa & Dick, 2018:5). In Bangladesh, 97 per cent of farmers are willing to pay for index insurance (Clarke & Kumar, 2016:235). Agriculture in Bangladesh is highly exposed to vagaries of weather such as droughts and floods which have historically made large impacts on agricultural production (Hazell, Sberro-Kessler & Varangis, 2019:16). The sector is also the largest source of employment in Bangladesh (Hasan, 2019:32). This may explain the positive reception of index insurance in the region.

In Pakistan, 87 per cent of small-scale farmers were willing to purchase weather index insurance (Fahad & Wang, 2018:574), although Arshad et al. (2016:241) report a 30 per cent willingness-to-pay level in rural Pakistan, which is unexpectedly low considering that rural Pakistan is one of the most disaster prone areas in the world, with extreme exposure to flash floods in the monsoon season and severe drought because of extreme deviations in monsoon rainfall. Participants in the related study indicated a desire to mitigate crop loss following extreme weather events, however, this was not supported by intentions to participate in weather index insurance schemes. The explanation of the material contrast in both studies in Pakistan may rest on the research approach, sample size and study population. Furthermore, the contrast highlights the impact of different microclimates and different socio-economic dynamics on the concept of willingness-to-pay. In the case of the first study, the research setting was Khyber Pakhtunkhwa province, where data were gathered from four districts which represent the most under-developed regions in Pakistan in terms of communication, road infrastructure, provision of microcredit and medical services. A sample of 600 farmers was tested, using systematic random sampling. Arshad et al. (2016:237), sampled 240 small-scale farmers with different exposure levels to floods and droughts on a stratified random sampling across eight districts.

In the Hainan province of China, 60 per cent of farmers were willing to pay for a hypothetical weather index insurance product (Lin et al., 2015:111). The author hypothesizes that interest is relatively high because other neighbouring provinces to Hainan already have market-based index insurance; therefore, interest might be stimulated from knowledge transfer from participants in other areas.

3.4 Empirical Findings on Premium Rate

Agricultural losses are increasingly occurring with high frequency, and many catastrophic events such as drought attract large indemnity payments that theoretically premium rates may need to be between 10 – 15 per cent to cover the pure risk cost of the insurance (Hess, Hazell & Kuhn, 2016:17). Some of the pilot insurance schemes in Africa have had to implement high rates as presented in Table 3.1 to remain economically feasible.

Table 3.1: Select weather index insurance schemes in Africa

Country	Insured peril	Index type	No. of farmers	Premium rate
Mali	Drought	Satellite	17 481	11.5%
Mozambique	Drought Excessive rain	Satellite	43 000	15%
Rwanda	Drought Excessive rain	Satellite and Weather station	35 134	9% -14%

Source: Impact Insurance (2018)

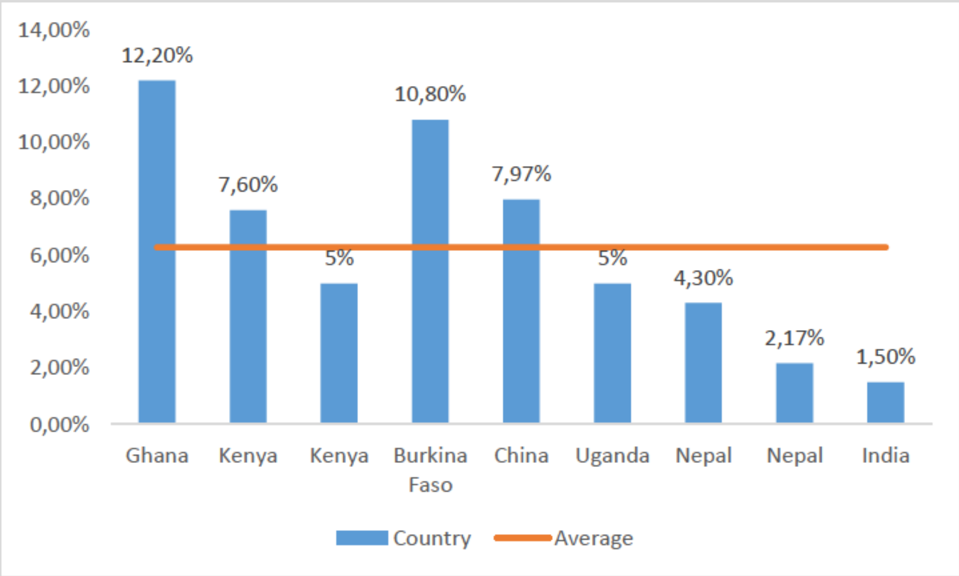
However, in most regions, market forces and demand undercurrents result in application of a commercially lower premium rate. Lybbert and Carter (2014:4) are of the view that low-income farmers are not willing to pay actuarially fair prices to access weather index insurance. The amount low-income farmers are willing to pay is driven by a careful assessment of the effectiveness of other available risk coping mechanisms (Ramasubramanian, 2012:19). Moreover, risk aversion plays a significant role in the maximum amount that an individual is willing to pay to cover an insured event (Buzatu, 2013:34).

Where crop insurance options are available, as is the case in Bangladesh, farmers show a strong preference for indemnity-based crop insurance rather than weather index insurance and are willing to pay more for the former, given that losses are physically verifiable translating to a greater degree of certainty and accuracy in loss quantification, with no presence of basis risk (Akter, Krupnik & Khanam, 2017:2462). As an indication of the premium rate for indemnity-based insurance, maize farmers in Zambia pay 4 per cent of the value of the harvest, which is the sum insured (van Asseldonk et al., 2015:2), this is approximately the same rate in the South African market (World Bank, 2016:45) and an estimated 5 per cent in the Turkish crop insurance market (Gulseven, 2014:16).

Willingness-to-pay for weather index insurance studies reveal a range of average prices influenced by different factors across different study areas. On average, Ghananian Cocoa low-income farmers are willing to pay 12.2 per cent of their yield towards index insurance premiums (Afriyie, Zabel & Damnyag, 2017:2). In other studies, Sibiko, Veettil and Qaim (2018:11) find willingness-to-pay to be 7.6 per cent of Kenyan farmer's maize harvest. On the same basis, a separate study reports that a majority of farmers in Kenya are willing to pay 5 per cent on average for weather index insurance (Ellis, 2017:713), and 10.8 per cent for maize insurance premiums in Burkina Faso (Koloma, 2015:118). In China, mean willingness-to-pay for a hypothetical index insurance is around 7.97 per cent of the harvest (Liu et al. 2018:42). In Uganda, index insurance premiums on all subsidized products are limited to 5 per cent and increase to 10 per cent in disaster-prone areas to ensure affordable pricing and adequate coverage (van Asseldonk, van der Woerd & Vakaki, 2018:25).

With reference to demand for index insurance in Nepal, Budhathoki et al. (2019:8) estimate a mean willingness-to-pay for wheat crops of 4.3 per cent of gross income from harvest. In another setting in Bahunepati, Nepal, Guo and Bohara, (2015:3) find an average premium of 2.17 per cent of harvest. Meanwhile, in India, the premium is subsidized and set at 1.5 per cent across all states, however, a willingness-to-pay analysis of farmer's preference show premium of 1 per cent in states like Punjab (Aditya, Khan & Kishore, 2018:11). The collective evidence from the enlisted studies as summarized in Figure 3.1 suggests that a premium range of between 5 – 10 per cent, with an average of 6.3 per cent of the annual harvest is more acceptable for low-income farmers in the developing economies.

Figure 3.1: Summary of mean willingness-to-pay



Source: Author's compilation

3.5 Factors that Influence Willingness-to-pay

From the literature evaluation, several factors have been identified as being associated with willingness-to-pay. Further analysis highlights that these wide-ranging factors are specific to different population groups, context, analytical approach and the studies vary in focus on measured attributes (Castellani, Vigano & Tamre, 2014:1673). Evidence from economic and behavioural literature suggests that factors can be grouped into tangible and behavioural attributes (Jumare, Visser & Brick, 2018:12). Over the past 30 years, behavioural economics has thrived, offering compelling evidence that individuals routinely deviate from predictions of economic models of rationality this may affect classical predictions of insurance purchase decisions (Elabed & Carter, 2015:150).

Using the literature review as a basis, the researcher identified 10 (ten) prevalent socio-demographic and socio-economic factors that were highlighted in previous empirical studies (Afriyie, Zabel & Damnyag, 2017; Arshad et al., 2016; Balmalssaka et al., 2016; Fonta et al., 2018; Haruna et al., 2017; Isaboke, Qiao & Nyarindo, 2016; Lin et al., 2015; Sibiko & Qaim, 2017), as possibly associated with index insurance purchase decisions. Furthermore, three socio-psychological (insurance culture, financial capability and risk perception) were deduced from literature using TPB as a base. Central factors of farmer behaviour are not well-understood, therefore identifying and understanding these factors in the proposed operational environment in South Africa is key to motivate or deter behaviour which will form the basis of product design, marketing and distribution (Danso-Abbeam, Addai & Ehiakpor, 2014:167).

3.5.1 Socio-demographic factors influencing willingness-to-pay

A wide variety of strong drivers scattered across the social spectrum of South Africa influence preferences of individual farmers. These drivers include socio-demographic antecedents of low-income farmers which are essential to understanding the factors influencing willingness-to-pay for insurance. As has been well documented, the agricultural sector is segmented into classes of commercial, smallholder and subsistence farmers, each with their own profile and various sub-segments within each category of farmers. Each segmentation has its own class challenges that ultimately has a bearing in perceptions and attitudes towards insurance. Socio-demographic characteristics are commonly used as explanatory variables within the willingness-to-pay function (Rankin & Robinson, 2018:6). The socio-demographic aspects identified through literature that have an influence on low-income farmers purchase decisions on weather based index insurance solutions are age, gender, marital status, education and the size of the agricultural household.

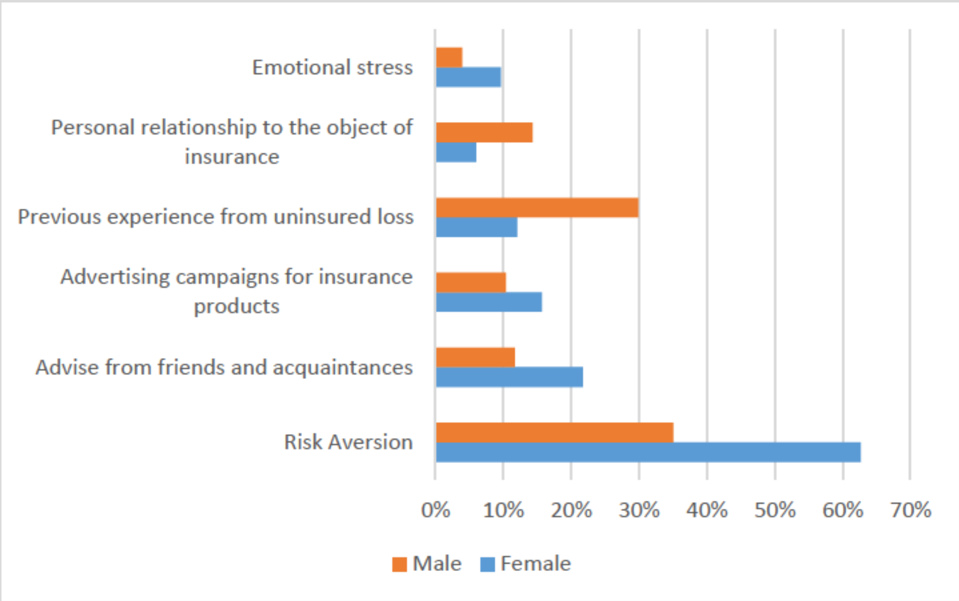
3.5.1.1 Demographic analysis: gender

Progressive societies provide equal access to opportunities for men and women across all sectors, occupations and roles. Others clearly distinguish between the roles of men and women. In that case, men are typically given more dominant and assertive roles in society, and women more service-oriented roles. Gender disparity is an issue in most developing countries which to a large extent undermines women's equitable and profitable participation in agricultural trade. It hinders women's capacity to adapt to climate change, access finance as well as arable land and infrastructure (Njobe, 2015:6). Economic inequalities among males and females remains a major challenge in South Africa. Female-led agricultural households earn roughly half the income of dual-headed households, with the income of male-headed households slipping between the two classes (Flatø, Muttarak & Pelser, 2017:48). Inequality also occurs in the context of decision making powers between male and female households; this has been seen to make a substantial contribution to the choice of risk adaptation approach (Muthelo, Owusu-Sekyere & Ogundeji, 2019:15). In view of the gender gap, gender-specific preferences have been found to influence participation rates in weather index insurance schemes (Clarke & Kumar, 2016:221). Born, Spillane and Murray (2018:12) find that gender has a positive influence on willingness-to-pay for index insurance.

From a choice experiment in Bangladesh, based on a weather index insurance covering maize, female farmers were identified as showing significantly lower interest towards insurance. The observed gendered preferences were driven by farmers' financial literacy and level of trust in insurance companies, with both elements found to be low among female farmers (Akter et al., 2016:217). Moreover, evidence collected from 10 villages in Southwestern Burkina Faso reports that female farmers consider paying much less for weather-based crop index insurance than their male counterparts (Fonta et al., 2018:15). That may be because women face greater financial pressures or are not the main decision makers in matters of agricultural production (Clarke & Kumar, 2016:238). On the contrary, in the Hainan province of China, female respondents have a greater propensity to purchase weather index insurance because of increased levels of risk aversion (Lin et al., 2015:110). While supporting evidence in Kenya, Isaboke, Qiao and Nyarindo (2016:10) and similar evidence in Nepal, Budhathoki et al. (2019:8) reveals that female small-scale farmers take up insurance at a much higher rate than males, but Guo and Bohara (2015:23), in the same study area in Nepal, reports that it is females that are less likely to participate in such schemes. Whereas, Danso-Abbeam, Addai and Ehiakpor (2014:176), observe no statistically significant relationship between gender and insurance uptake in Ghana.

Evidence from Burkina Faso and Senegal suggests that the need for emergency savings is greater for women, and the need for insurance is far higher for men. The perceived threat of death or illness to livelihood may drive female preferences for access to emergency funds (Delavallade et al., 2015:3). Experimental evidence implies that women perceive risk as a certain degree of uncertainty, as opposed to men who view risk as an opportunity to gain (Jurkovicova, 2016:186). These different perspectives are influenced by various factors highlighted in Figure 3.2, which show that aside from risk aversion, females are encouraged to purchase insurance on the advice of friends and acquaintances, while previous loss experience is a significant driver for males. Diverse index insurance findings from a gender perspective are consistent with the conjecture that men and women face different risks and respond to them differently (Delavallade et al., 2015:2). A systematic literature review exploring risk aversion and the influence of gender shows that most studies report women to be more risk averse than men. The findings remain consistent even when controlling for socio-economic variables such as education, age and income status (Outreville, 2013:7).

Figure 3.2: Factors that encourage gender purchase of insurance coverage



Source: Jurkovicova (2016:189)

3.5.1.2 Demographic analysis: age

Africa has the fastest-growing population in the world, along with the youngest individuals, the median age in 2010 was 19.7 years due to low life expectancy and high child mortality rates, by 2050, the median age will have risen to 26.4 years (PWC, 2018:22). In 2017, 47 per cent of South Africa's population was younger than 25 years. This reflects a rising working-age demographic that, if job opportunities are increased and unemployment reduced, could provide an incentive for economic development (BFAP, 2018:24). Evidence points to the fact that population increases above the working age result in declines in economic growth. A 10 per cent increase in the proportion of the population aged over 60 cuts the per capita GDP growth rate by 5.5 per cent (Maestas, Mullen & Powell, 2016:3).

However, an ageing agricultural workforce can have favourable effects on agricultural productivity — as age increases, agricultural expertise, management practices, knowledge and skills in production also improve. The amassed experience enables farmers to capitalize on the efficient use of agricultural resources, labour and machinery inputs as well as optimum usage of fertilizers and pesticides. In their study, Loki, Mudhara and Pakela-Jezile (2020:89) report that as age increases, farmers expand their search for information including engaging multiple sources of extension services in the public and private sector to obtain a broad range of views and technical advise on farming practices before committing resources to planting. Moreover, highly experienced farmers are more food secure than their less experienced counterparts (Maziya, Mudhara & Chitja, 2017:47). The challenge for an ageing agriculturalist is technology adoptation to compensate for physical deficiency because of the intensive physical aspect of farming (Guo, Wen & Zhu, 2015:2). For this reason, the youth are viewed as an important force for transforming the agricultural sector and stimulating economic growth due to their affinity to innovation and modern technologies (Njue, Kirimi & Mathenge, 2018:12).

Age has a bearing on insurance interaction and uptake. In their interacting with insurance, younger farmers are found to be more interested in weather index insurance and more willing to pay for it than older farmers (Abebe & Bogale, 2015: 2744; Abugri, Amikuzuno, Daadi, 2017:7; Fonta et al., 2018:13; Ntukamazina et al., 2017:175; Wairimu Obare & Odendo, 2016:118). The rationale behind this is that younger farmers have an increased probability of adopting new technologies due to less lifelong experience, therefore rely on insurance as a buffer to reduce uncertainties. On this premise, prospects of innovation, technological development and adoptation in Africa are broadly encouraging.

Findings differ substantially in another context, adopters of crop-based index insurance in Eastern Kenya are elderly with a mean age of 51 years (Isaboke, Qiao & Nyarindo, 2016:12). Further research brings to light that older Kenyan farmers are more likely to invest in risk management by purchasing more insurance coverage (Njue, Kirimi & Mathenge 2018:11) and Hountondji, Tovignan, Kokoye and Chabi (2019:322) find that as farmers age and gain more experience in crop production and a better appreciation of the inevitable nature of weather related-losses, their participation in weather index insurance markets increases. Eitzinger, Binder and Meyer (2018:511) also report that as farmers' age, they are more concerned than younger farmers about climate change and related effects.

From a more neutral perspective, data collected evenly from a sample of farmers operating on irrigated and dryland in rural India shows that the age of a farmer has no significant influence on willingness to take-up an insurance policy (Senapati, 2019:8). This may be because agriculture is the most important occupation in India (Singh & Agrawal, 2020:462), where participants of all ages are well represented in the sector, and the existence of other prevalent dynamics takes precedence.

3.5.1.3 Demographic analysis: marital status

Single farmers have been found to be interested in purchasing crop-based index insurance than married ones. This implies that farmers with fewer responsibilities are better able to afford insurance (Mbonane & Makhura, 2018:6). To the contrary, married farmers in Nigeria and Ghana are more likely to adopt index insurance (Aina, Ayinde, Thiam & Miranda, 2018:14; Danso-Abbeam, Addai & Ehiakpor, 2014:175; Ellis, 2017:713). The authors' put forward that married farmers have a responsibility to protect their household from vulnerability; thus, there are more risk averse in their approach. A similar finding in two districts of rural India shows marital status to positively influence willingness-to-pay for weather index insurance products. Furthermore married farmer's purchase intentions for index insurance products against covariate risks are always higher than those of single farmers (Senapati, 2019:10).

Owing to their reproductive and traditional communal roles, married women are more vulnerable to climate change and income variability than married men. Having said that, women are typically left to head the household when men migrate to urban areas because of effects of weather-related risk on production, further exposing them to more unmitigated vulnerability (Omolo & Mafongoya, 2019:750). In their study of identifying factors that determine household food security among smallholder farmers in Kwazulu-Natal, Maziya, Mudhara and Chitja (2017:47) find that overall, households that are food secure are those headed by individuals that are married. This may be linked to the role marriage plays in access to resources such as land and water. Obi and Ayodeji (2020:13) report that married farmers in South Africa are more technically proficient in term of maize production, demonstrating skilful use of labour, seed, fertilizer and land resources.

Interestingly in Kenya, households of married women suffer more in terms of food security than single women-headed households. The author philosophizes that for patriarchal reasons, if husbands are present, then wives have less decision making power on land allocation regarding crops and also the power to decide on how income derived from crops is utilized, this affects family food availability as male-headed households tend to have different priorities (Kiriti & Tisdell, 2014:147). According to investigations by (Jusufovic, 2016:11) single individuals have a more risk taking in nature, while married individuals have higher risk aversion. The association between risk aversion, insurance demand and marital status is not as evident in many other studies (Outreville, 2013:9). For this reason, further insight regarding the effect of marital status on agricultural insurance purchase decisions is required in order to understand the South African context.

3.5.1.4 Demographic analysis: education

Sibiko, Veettil and Qaim (2018:2) find that farmers with access to weather index insurance training and those organized in farming associations are more likely to purchase weather index insurance. This is because organized farmers are likely to have better access to information about existing or emerging technologies (Atsiaya et al., 2018:57; Isaboke, Qiao & Nyarindo, 2016:10; Wairimu, Obare & Odendo, 2016:117). This is supported by evidence from an experimental study, where weather index insurance was explained and presented to a group of farmers in Ethiopia, uptake increased from 2 per cent to 36 per cent (Microinsurance Network, 2017:39). A similar experimental study conducted in India shows comparable results; farmers that received intensive index insurance training and education are 75 per cent more likely to adopt the insurance than an experimental group that received basic training (Ceballos et al., 2015:27). At the same time, Castellani and Vigano (2017:516) find that basic knowledge and training of insurance can increase willingness-to-pay by up to 60 per cent. Risk mitigation with weather index insurance is a new concept for low-income farmers, that is why, training to an extent guides their attitude and perception towards agricultural insurance as well as their degree of risk aversion (Njue, Kirimi & Mathenge, 2018:9).

A study by Matlou and Bahta (2019:41) indicates that education contributes significantly to household resilience. Educated households are 30 per cent more likely to not live in poverty (Omoregbe, Ighoro & Ejembi, 2013:15). In addition, insurance provision has been found to have significant effects on production decisions for educated farmers, where education is measured in terms of literacy levels and years in formal education. Among literate farmers, insurance provision raises the probability of investing in crop production by 15 per cent; whereas no observable effects are noted for less educated farmers (Cole, Giné & Vickery, 2013:4). Overall, a high level of education has been found to contribute positively to purchase decisions of weather index insurance (Danso-Abbeam, Addai & Ehiakpor, 2014:175; Ellis, 2017:713; Gebrehiwot, 2015:103; Gulseven, 2014:13; Hountondji et al., 2019:322; Koloma, 2015:126; Lin et al., 2015:110; Hill, Hoddinott & Kumar, 2013:396; Senapati, 2019:8; Wairimu Obare & Odendo, 2016:119; Zhang, Brown & Waldron, 2017:21), with Balmalssaka et al. (2016:1263) finding that farmers with formal education are 12 times more likely to participate in these schemes. He and Zheng (2017:18) support these finding by indicating that farmers with higher cognitive ability can better understand the benefits of index insurance and hence are more likely to purchase it. Information on the trigger and exit levels, interpretation of indices and computation of payments can be conceptually complex, as such better educated farmers are more likely to understand and use index insurance contracts (Jin, Wang & Wang, 2016:371).

To the contrary, Fonta et al. (2018:15) find that farmers with tertiary education were less willing to pay for weather-based index insurance. This is explained by that highly educated farmers typically have irrigation systems and access to credit, these ex-ante and ex-post adaptation strategies respectively, allow high income farmers to navigate volatile climatic conditions. Irrigation and participation in weather index schemes is significant and has a negative association with willingness-to-pay intentions. Irrigation addresses seasonal drought risk; thus small-scale farmers who operate on irrigated land are less concerned with purchasing insurance to avoid financial loss (Arshad et al., 2016:240). Similarly, Timu et al. (2018:16) find that education is negatively correlated with the probability of purchasing index insurance, probably because of the availability of other risk transfer mechanisms at these farmers disposal. Arshad et al. (2016:239) report that educated farmers demonstrated less willingness-to-pay for index insurance, probably due to the low possibility of risk events occurring of in the surveyed agro-ecological zones - providing further insight that more educated farmers appear to have greater risk assessment propensity both in terms of alternative procedures for managing risk and also purchasing farm lands in areas of low risk. For this reason, further insight into education and agricultural insurance purchase decisions is required in order to understand the South African context.

3.5.1.5 Demographic analysis: household size

Chronically poor individuals in South Africa, live in households with an average number of seven people, which is more than double the size of non-poor households (World Bank, 2018:40). Size of households has a significant influence on the perception of low-income farmers towards weather index insurance (Njue, Kirimi & Mathenge, 2018:11). Research reveals that an increase in the size of the household encourages the household to view innovative measures such as index insurance as appropriate in cushioning against crop loss (Atsiaya et al., 2018:56; Isaboke et al., 2016:72; Matsuda & Kurosaki, 2019:20). This is because low-income farmers are already vulnerable; therefore, the consequences of poor decision making can be catastrophic (Mookerjee & Nyoni, 2016:1). With regards to family human capital, a 10 per cent rise in the number of family workers raises the probability of having access to by one percentage point, which means that the greater the number of family employees, the higher the likelihood of use of index insurance (Koloma, 2015:126).

The findings are contradictory to that of Wairimu Obare and Odendo (2016:119) who observe that the size of a household did not have an effect on adoption and extent of adoption as anticipated. On the opposite end, Nyaaba, Nkrumah-Ennin and Anang (2019:371) find that larger households are not willing to pay as much for crop insurance when compared to smaller households, this is consistent with a *priori* expectation because an increase in household size raises the household's financial burden which is expected to have a negative effect on low-income farmer's ability to purchase insurance. Evidence points to the direction that large households will have food security challenges as the number of family members increase. An increased number of household members, where income remains constant, means that not only are there more members to feed, indirectly income per head reduces, and per capita food consumption increases, supporting the findings by the previous authors that household size increases household financial burdens (Maziya, Mudhara & Chitja, 2017:47). Further, Wan et al. (2016:6) explain the effect of a large household size on insurance purchase decisions founded on marginal economic theory, in a farm of a particular size, the marginal product of additional family labour in crop production falls as the household expands in number, which makes alternative sources of revenue appealing to household members, this diversification of labour has reducing effects on the demand for index-based crop insurance. Similarly, Obi and Ayodeji (2020:13) report that a large household size reduces farm technical efficiency in the production of maize.

3.5.2 Socio-economic factors influencing willingness-to-pay

Socio-economic variables play an important role in the development of a person's attitude. These variables influence the behaviour of a person, their choice or risk mitigating tool, and ultimately their purchase decisions (Kumari et al., 2017:362). Farmers' socio-economics characteristics, in –turn play a major role in their participation in insurance schemes (Hountondji et al., 2019:324). There exists considerable literature and experience to draw upon socio-economic drivers that influence willingness-to-pay decision making. This study has considered the most common and prevalent, namely, access to credit, farm turnover, farming experience, farm size, and group membership among the main drivers that influence willingness-to-pay for weather index insurance.

The farm itself represents a source of livelihood with income generating capacity form which farmers undertake their operations. Being the focal point of production, determinants of willingness-to-pay for index insurance solutions based on farm specific characteristics and the farmer's characteristics in relation to the farm are assessed. The farm size, level of farming experience and previous loss experience on that particular farm has been identified in the literature as influencing willingness-to-pay for index-based insurance. As the primary source of livelihood, farmers will utilize the best possible resources and tools at their disposal to maximize returns on the production land.

3.5.2.1 Access to credit

Availability of formal credit facilities has been found to have a significant influence on the farmers' overall awareness of weather index insurance schemes (Senapati, 2019:7). This is because, in the process of engaging financial services' offerings, financial services providers discuss an array of options and provide advice to farmers. Findings by Atsiaya et al. (2018:57) indicate that farmers with access to credit have a strong willingness-to-pay for weather-based crop insurance. In fact, these farmers are 46.9 times more likely to participate in crop index insurance than those who do not have access to credit (Balmalssaka et al., 2016:1262). This is corroborated with related studies in a different context in Burkina Faso (Fonta et al., 2018:12) and Kenya (Isaboke et al., 2016:70). By its nature, credit relaxes cash constraints on farmers, with more disposal income, weather index insurance purchase become more accessible and changes of purchase increase (Haile, Nillesen & Tirivayi 2019:13; Kumari et al., 2017:364; McIntosh, Sarris & Papadopoulos 2013:397).

Research demonstrates that farming households with access to credit have proved to be more resilient to agricultural drought (Matlou & Bahta, 2019:41) and that purchase of this parametric insurance has been found to result in farmers subsequently taking more credit, indicating a complementary relationship (Ceballos et al., 2015:68). Low-income farmers who buy index insurance in isolation from credit are likely to have different reasons or socio-economic standing relative to those who buy credit-bundled insurance. Greatrex et al., 2015:11). However, access to informal credit has been found to have negative effects on farming households and their insurance purchase decisions. Households who use informal credit have a higher risk of food insecurity when compared to households that are debt-free. This result is not in conformity with the *priori* expectation. The authors expected that credit use would improve food security and livelihood. To the contrary, informal credit by rural farming households is acquired from unregulated lenders at overpriced interest rates and is typically used by impoverished households desperate to make a living. Paying expensive credit, further reduces these household's capacity to purchase insurance (Maziya, Mudhara & Chitja, 2017:48).

3.5.2.2 Income level

Low-income farmers frequently cite lack of funds as the reason for not buying insurance (Cole et al., 2013:106; Jin, Wang & Wang, 2016:370; Senapati, 2019:10). As income increases the likelihood of incorporating climate change response initiatives into farming operations increases (Thinda et al., 2020:6). This has been proved in several studies, where favourable associations between income and weather index insurance have been observed (Abugri, Amikuzuno & Daadi, 2017:7; Balmalssaka et al., 2016:1261; Fonta et al., 2018:14). In a study sampling smallholder farmers in the Free State province, a moderately high monthly income had a positive influence on farmers desire to improve their participation in agricultural insurance schemes to protect against drought risk (Muthelo, Owusu-Sekyere & Ogundeji, 2019:14). Consequently, the use of agricultural insurance in South Africa is associated with increases in farm income (Elum, Nhamo & Antwi, 2018:509). In another setting, Njue, Kirimi and Mathenge (2018:8) analysing socio-economic and demographic attributes of insured and non-insured households; report that insured farmers recorded on average higher incomes than non-insured counterparts; and that as the level of income increases, so does interest in crop insurance.

The effects of income on insurance purchase decisions may, in fact, be ambiguous (Castellani, Vigano & Tamre, 2014:1673). In their study of assessing complexities of insurance purchase decisions, Ulbinaite, Kucinskiene and Le Moullec (2014:12) find a non-linear relationship between income and insurance purchase intentions; other factors, notwithstanding behavioural considerations, may play a role in informing these purchase considerations. The authors report that at a certain level of risk perception, some consumers would purchase insurance regardless of their level of income. However, Farrin, Miranda and O'Donoghue (2016:6) report that demand for agricultural insurance, when assessed over several years, is primarily driven by income rather than the farmer's attitude towards risk.

High-income farmers typically have the capacity to self-insure, especially against minor risk events (Norton et al., 2014:644). In general, wealthy farmers tend to purchase more advanced crops both in the form of drought-resistant crops and improved seeds (Jumare, Visser & Brick, 2018:12). Therefore, the finding by Liu et al. (2018:38) that high-income farmers are less interested in index insurance contracts is not surprising. These farmers would only be interested in an index insurance contract if it is offered at a low cost, and consistently reduces their exposure to risk compared to existing self-insurance mechanisms (Binswanger-Mkhize, 2012:187). According to Hountondji et al. (2019:324), high income farmers often experiment with weather index insurance products to mitigate losses and increase income in the short term. With the availability of income, these farmers have better capacity and scope to test the functionality and benefits of the products. However, future use of index products declines sharply among this group in the following season; this is likely because non-substantial gains were observed during the period of insurance. Therefore, farmers resort to their tried and tested mitigation methods. As a substitute for insurance, high-income farmers mitigate risk through other means such as income diversification, off-farm activities, savings and investments (Jin, Wang & Wang, 2016:372). Off-farm income has been proven to reduce demand for index-based insurance (Tsikirayi, Makoni & Matiza, 2016:5). When non-farming activities increase so too do the opportunity costs of farmer’s time in managing their farming activities and risk associated with it, as a consequence contributing to lower demand for insurance (Zhang, Brown & Waldron, 2017:22). Income diversification brings a stabilizing effect to farming income and creates opportunities for greater competitive advantage when compared to specialized farmers, as farmers with multiple income streams are better able to mitigate weather-related loss (Wan, Wang, Liu & Chen, 2016:2). It is recommended that an effective income diversification strategy could in related activities such as agri-processing and agri-tourisim (GreenAgri, 2020:9).

Farrin, Miranda and O’Donoghue, (2016:5) find that for high-income farmers, there is an inverse relationship between insurance purchase and farm enterprise savings, that is, insurance and savings are found to be substitutes. While Stein and Tobacman (2015:17) find exceptionally low demand for weather index insurance bundled with savings; farmers prefer either pure savings or pure insurance products. In a study by Isaboke et al. (2016:67) on low-income farmers, savings are indicated as the most preferred coping strategy and this poses a conundrum because these limited resourced farmers are not always able to amass sufficient wealth to cover their losses in the event of crop damages. Tadesse, Shiferaw and Erenstein (2015:3) are of the view that in the short-run, current consumption needs of low-income farmers compete with future savings ambitions. To this point, Ramasubramanian (2014:199) reports that where savings are a means of risk management for farmers, willingness-to-pay amounts are below market value, marked by 20 percentage points lower than the average premium price. This indicates that farmers have established risk coping mechanisms, and they see microinsurance as an additional strategy for risk management; thus they are willing to pay a small amount to secure their residual risk.

3.5.3.3 Farming experience

Danso-Abbeam, Addai and Ehiakpor (2014:175) find that farming experience is positively correlated with the probability of farmers being interested in insurance especially from farmers with a greater number of years understand the economic impact of adverse weather on livelihood and the difficulty associated with the recovery process. Therefore, it is no surprise that more experienced farmers have a better chance of purchasing weather index insurance (Fahad et al., 2018:463; Hountondji et al., 2019:322; Jin, Wang & Wang, 2016:371; Nyaaba, Nkrumah-Ennin & Anang, 2019:371). Other scholars found similar patterns in their research that the adoption of weather-based insurance is significantly influenced by the length of farming experience (Atsiaya et al., 2018:52; Elum, Nhamo & Antwi, 2018:509). On the other end of the spectrum, Ellis (2017:207) reports that it is less experienced farmers, who have been in agriculture for less than five years that have a higher demand for insurance. For this group, insurance is seen as a tool to support their learning curve, build resilience and longevity in farming. Mbonane and Makhura (2018:7) confirm similar findings that less experience maize farmers in Swaziland have a high preference for crop insurance.

On the other hand, Senapati, (2019:9) finds that farming experience has no significant association with willingness-to-pay for weather index insurance. This is because as farmers' specialize in a particular crop, their learning, adaptive and responsive capacity to climate change variations increases greatly, so too do the risk management techniques applied; consequently, these farmers show very little interest in taking up the insurance. As experienced farmers have higher levels of technical efficiency (Obi & Ayodeji, 2020:13). Experienced farmers have been demonstrated to recover between 50 and 90 per cent of their crop yield through applying in-season risk response strategies such as withholding or adding inputs, labour, strategic use of irrigation and delaying harvesting, at a cost of between 4 and 34 per cent of the recovered crop yield. However, there are certain weather events for which farmers had no coping response; these include low rainfall and hailstorms (Shah, Siderius & Hellegers, 2020:11).

Agronomic considerations over time have an effect on the farmer's risk perception, and risk management strategies, and will ultimately influence the decision to consider or not consider insurance. For example, a farmer with more soil and water management expertise is less likely to be adversely impacted by flooding than those with little or no experience. The experienced farmer will only consider insurance that caters for catastrophic events, and would only be willing to pay a premium that is discounted and which takes into account farm practices, control measures and methods applied to reduce risk and the likelihood of loss (Tadesse, Shiferaw & Erenstein, 2015:8).

3.5.3.4 Farm size

Farm size is a consideration that is frequently proposed as essential in decision making on agricultural focused activities (Tsikirayi, Makoni & Matiza, 2016:5). Farm size has been found to have a positive effect on insurance uptake of weather index insurance (Sibiko & Qaim, 2017:14; Haruna et al., 2017:81; Danso-Abbeam, Addai & Ehiakpor, 2014:176). As farmer's plant more hectares of maize, they tend to subscribe more to weather index insurance (Hountondji et al., 2019:322). For every one unit increase in farm size, there is a 5 per cent increase in the amount of willingness-to-pay (Ramasubramanian, 2012:12). Low-income farmers with small farmlands perceive that since their crop yields are too low, insurance coverage may not be worth purchasing because income from crop production is inadequate to support their day-to-day family needs (Senapati, 2019:10).

Consistent with agricultural insurance literature, low-income farmers who own large parcels of farmlands were willing to purchase index-based insurance (Fahad & Wang, 2018:576, Clarke & Kumar, 2016:235). This indicates that there is a clear relationship between commercial intent and insurance, intuitively, with more resources invested in the farm, farmers are willing to purchase insurance to secure their livelihood (Budhathoki et al., 2019:8). In addition, farmers with greater commercialization intent and larger farms, generally search for more information about crop management, pest and disease management programmes, post-harvest processing, and marketing initiatives, such farmers will subsequently have exposure to insurance, increasing the likelihood of uptake in future (Baiyegunhi, Majokweni & Ferrer, 2019:5).

Contrary to the mentioned findings, Wairimu, Obare and Odendo, (2016:119), detect that farmers with large farmlands are negatively disposed towards using index-based insurance. A possible explanation for this finding could be that farmers who cultivate larger areas are wealthy and can use other risk management strategies influencing adoptation of weather index insurance negatively. Nyaaba, Nkrumah-Ennin and Anang (2019:371) provide an additional perspective that as farm size increases, the premium payment also increases which places a higher financial burden on the household which negatively affects the ability to pay for insurance, hence leading to lower demand. Lastly, in their study, Lyu and Barré (2017:74) find that farm size has no effect on willingness-to-pay decisions for highly risk averse farmers.

3.5.3.5 Group membership

Tolno et al. (2015:131) find that age and access to credit are among the main factors that influence farmers' decisions to join a group with objectives to derive higher income from skills transfer on risk reduction, improve their livelihoods and access to relevant opportunities. The authors report access to credit of 75 per cent for farmers that belong to an organized group, whereas this percentage declines sharply to a little under 15 per cent for non-group members. While almost all group members have access to support and extension services. Wossen et al. (2017:231) find that group membership, therefore, has positive and significant influence on technology adoptation. This impact is significantly higher on household welfare and poverty reduction for farmers who also have access to credit. Manda et al. (2020:10) report eight years as the average time for a farmer to adopt improved technologies. Group membership accelerates this process rapidly. Technology adoptation rates reduce to four years and below for a cooperative member.

Evidence discussed in King and Singh (2018:24) shows that smallholder farmers are more likely to participate in weather index insurance schemes if they are part of farming cooperatives or other organized groups. The relationship between insurance purchase and cooperative membership has a strong positive correlation. It is on this basis that (Zhang, Ju & Zhan, 2019:2910) argue that group membership is in itself a mitigating strategy against weather risk. In their research, the authors find that farmers join cooperatives to manage both productions and price risk. Membership in a local agricultural cooperative increases productivity and results in more fertilizer purchase (Ramasubramanian, 2014:156), as well as significant increases in uptake of improved seed varieties (Wossen et al., 2017:231), both fertilizer and improved seed varieties are associated with better income earning capability. Literature on low-income farmers in South Africa has come to the conclusion that farmers have formed various forms of associations to solve their socio-economic, institutional and technical challenges. Agricultural associations or cooperatives are seen as an institutional solution to support the livelihood and commercialization of low-income farmers (Sikwela, Fuyane & Mushunje, 2016:548).

Farmer groups are a hub of social capital which serves as a social network and learning channel where farmers can exchange ideas, expertise and insights that can shape attitudes positively towards improving agricultural productivity. Within existing literature, group member participation in some cases shows no tangible benefits on income or welfare of low-income farmers (Ofori, Sampson & Vipham, 2019:218). On this basis, Gulseven (2014:15) finds that group membership is not a statistically significant factor associated with willingness-to-pay, while Addey, Jatoe, Kwadzo (2020:13) determine that group membership is statistically significant and negatively affects willingness-to-pay. The contradictory results indicate that further insight on group membership and the relationship with agricultural insurance purchase decisions is required in order to understand the South African context.

3.5.3 Socio-psychological factors influencing willingness-to-pay

Decision making patterns are often influenced by a series of social and psychological factors such as culture, the financial capability and risk perception (Buzatu, 2013:32). In the same light, preference for certain risk management options is also influenced by sociological and psychological elements (Ward, Makhija & Spielman, 2019:14). It is on this basis that, Domingo, Parton, Mullen and Randall (2015:5) call for proper profiling of specific farmer groups needs to be made if research and development initiatives are to be better grounded for insurance provision. It is essential for insurance companies and stakeholders interested in the provision of weather index insurance to have a comprehensive approach to understanding the perceived threats and risks facing the market, how the market evaluates options for responding to risk, to the market's valuation of insurance, and to the economic realities on the ground (Ulbinaite, Kucinskiene & Le Moullec, 2014:2).

Theory of Planned Behaviour

Socio-psychological variable in this study originate from the Theory of Planned Behaviour (TPB), a behavioural framework for predicting intentions and subsequent behaviour. TPB has been one of the most widely cited and influential models for the prediction of human social behaviour since its inception in 1985. The number of citations of the theory have increased many fold from 22 in the year or its formulation to 4550 in 2010 (Ajzen, 2011:1113). Its success has drawn much discussion and even controversy. An often expressed critique of the

TPB is that it may be highly rational in its approach, failing to take cognitive processes that account for human bias in decision making. Most commentators accept the underlying reasoned action principles of the theory that intention and behaviour are closely correlated but challenge its adequacy in fully explaining behaviour without considering socio-economic statuses and other demographic considerations (Ajzen, 2020:321). The TPB makes no claims about the manner in which beliefs are formulated, nor any assumptions about the validity of these beliefs. Instead, it postulates that intention and behaviour are consistent with an individual's beliefs (Ajzen & Dasgupta, 2015:120).

According to Jurkovicova (2016:182) intention and related behaviour is neither unplanned nor irrational, rather it is methodical and can be predicted. This is because, given limited time and processing capacity of the human brain, people develop pathways that inform habits and patters for speedy decision making (Buzatu, 2013:36). Intention in TPB is predicated by attitude, subjective norm and perceived behavioural control. The theory is based on the foundation that intentions are formed on behavioural beliefs, where subjective values are formulates that shape a person's attitude; normative beliefs, where internal motivations are created based on aspirational associations with individuals or groups to form subjective norms; control beliefs, where the existence of variables combine that can affect the capacity of an individual to perform the behaviour to form perceived behavioural control (Ajzen, 2015:125). When the three dimensions of TPB are applied to crop insurance purchase considerations, they are shown to be strong predictor of outcomes (Abd Aziz, Abd Azi, Aris & Abd Azi, 2015:241). Attitude refers to the perception towards a behaviour, subjective norms are informal guidelines followed by a particular society while perceived behavioural control represents the availability of financial resources, information and time to perform a behaviour.

From a conceptual perspective, these three concepts of attitude, subjective norm and perceived behavioural control have been adapted in this study where willingness-to-pay is influenced by farmers' risk preferences indicative of their attitude (Atsiaya et al., 2018:52), financial capability based on availability of financial resources indicative of perceived behavioural control (Domingo et al., 2015:3) and insurance culture indicative of subjective norms (Zhong, Sun, Lai & Yu, 2015:41). A good understanding these dimensions in relation to willingness-to pay for insurance could be particularly useful in designing interventions to increase insurance uptake. The TPB is a valuable tool for planning strategies for behavioural modification and designing intervention processes that have an impact on behaviour. A number of studies have been undertaken to determine the role of TPB in effecting behavioural change. These studies have used particular techniques such as motivation, persuasion and target setting to successfully modify behaviour by changing perceptions of individuals and groups, influencing culture, and improving knowledge thus reducing barriers to enacting a specific behaviour (Steinmetz et al., 2016:216). According to Olum et al. (2020:27) only a few studies have been conducted on farmers' willingness-to-pay that consider intrinsic behavioural factors that could inform their preference for agricultural insurance. This study is among the few to consider behavioural traits, demographic and economic drivers in an integrated approach.

3.5.4.1 Insurance culture

Insurance culture forms an integral part of insurance purchase considerations (Ulbinaite, Kucinskiene & Le Moullec, 2014:6). Worldwide socio-cultural dynamics are a leading factor in explaining the dissimilarities in insurance participations (Zhong et al., 2015:41). According to Jarzabkowski et al. (2019:30), insurance is not entrenched in the socio-economic fabric of developing economies, either from a financial or cultural mindset. This directly affects insurance density, intensity and penetration. Mai, Nguyen, Vu, Bui, Nguyen and Do (2020:1699) in their study of life insurance purchase intentions based on TPB find that insurance culture has a positive but non-significant effect on purchase intentions. The authors assume that since life insurance products are personal in nature based on individualized financial security needs, the viewpoints of others in consideration of buying bear no weight in the final decision. As the level of take-up and experience sharing improves, the element of culture is likely to have a higher impact on purchase intentions. Limited knowledge and poor insurance culture often result in low uptake of insurance initiatives (Roznik et al., 2019:447). An example is Africa's agricultural premium volume which accounts for roughly US$ 200 million, which is less than 1 per cent of the global agricultural premiums of US$ 25 billion (Karekezi, 2017:36). In South Africa, one of the aspects contributing to low participation in agricultural insurance is that small-scale farmers do not adequately identify and weigh probabilities of losses, which affects the uptake of adaptive mechanisms (Jumare, Visser & Brick, 2018:12). Farmers tend to underestimate losses and are overly optimistic about future prospects, with this perspective insurance continues to be seen as a privilege rather than as a component necessary for economic growth (Jarzabkowski et al., 2019:29). This is evidenced by the highly skew non-life insurance usage for low-income population in South Africa of less than 4 per cent (Endres, Ncube, Hougaard & van As, 2014:19). This systematic undervaluing of agricultural insurance is witnessed in other developing countries as well, such as Vietnam (King & Singh, 2018:3) and Kenya (Zollmann, 2015:13).

In all societies, there are accepted social norms and values, and these established ways are directly related to the culture of that society. Culture plays an important role in shaping financial habits and response strategies such as insurance purchase decisions (Fonseca, 2016:9). Insurance culture notably influences willingness-to-pay since insurance is intangible and is often perceived in most low-income societies as an impractical solution because there is an immediate outflow of capital towards an unguaranteed future event, where this outflow competes with tangible and often more pressing immediate livelihood needs (Mahul & Stutley, 2010:38). Furthermore, theoretically, aside from socio-economic variables low-income farmers will value agricultural insurance if the marginal net benefit of weather-based crop insurance exceeds the marginal net benefit of other insurance products such as medical aid assuming that there is an embedded culture of insurance usage (Zhang, Brown & Waldron, 2017:5).

Sihem (2019:178) believes that economic rationality aside, farmer's interest in insurance is driven by their cultural beliefs. Hence, aspects of culture have a strong impact on insurance demand and subsequent purchase. For instance, in Poland, where farmers are highly risk averse (Sulewski et al., 2020:15), the most important risk coping strategy for farmers is insurance (Sulewski & Kłoczko-Gajewska, 2014:144). Other authors also reveal similar findings, from their study in Nepal, Guo and Bohara (2015:23) report that 87 per cent of farmers commended weather index insurance as the best protection mechanism against adverse weather. By way of comparison, evidence from Zimbabwe indicates that farmers consider insurance to be an unnecessary expense, instead of being an investment to minimize potential risk (Tsikirayi, Makoni & Matiza, 2016:2), even though Zimbabwe is predominantly an agro-based economy which is highly vulnerable to risks and constraints such as drought, floods and hailstorms (Munyoro & Moyo, 2019:17). In acknowledging the role of insurance culture, insurance companies and policy makers may find better ways to stimulate interest in weather index insurance (Zhong et al., 2015:26).

3.5.4.2 Financial capability

Financial capability is an abstract principle that cannot be evaluated explicitly; it is defined as the capacity to handle financial resources and use financial services in a manner that better fits individual interests. Financial capability relies on manifestations in the form of behaviour, motivations and decision making in areas of financial management and future planning such as budgeting, investments and savings (Kempson, Perotti & Scott, 2013:44). Financial decisions often involve complexities that individuals have difficulty understanding in relation to their own education, information, and experience (Cia, de Janvry & Sadoulet, 2015:81). In this regard, according to Kempson, Collard and Moore (2005:13):

> "Financially capable people are able to make informed financial decisions. They are numerate and can budget and manage money effectively. They understand how to manage credit and debt. They are able to assess the need for insurance and protection. They can assess the different risks and returns involved in different saving and investment options. They have an understanding of the wider ethical, social, political and environmental dimensions of finances".

Insurance being a financial instrument for risk management, financial capability significantly affects demand for crop insurance (Awel & Azomahou, 2015:21; Aditya, Khan & Kishore, 2018:13). Tsikirayi, Makoni and Matiza (2016:9) claim that the lack of financial capability is a key constraint to agricultural insurance uptake. On the authority of Refera, Dhaliwal and Kaur (2016:9), this lack of financial capability leads to suboptimal financial choices and decisions, which could translate into undesirable financial and economic repercussions for individuals and entire financial systems. Poor financial choices have long-term consequences for low-income households because the margin for error is already low (Sherraden, 2013:7). The thought of purchasing insurance and not receiving a payout creates fear and raises legitimate questions on whether limited resources have been optimized in relation to immediate household needs. The low degree of financial inclusion seen in developing countries is motivated in part by limited financial capability. Historically, low-income consumers in South Africa have been informally serviced by micro-lenders and loan sharks. On the other hand, middle and high-income individuals have been serviced by established financial institutions. Therefore, the financial capability between the two classes is vastly different (Pearson, Stoop & Louw, 2017:2). Financial capability which is often used interchangeably with financial literacy is a broader term which has a positive effect on financial inclusion, which in turn is generally accepted as a poverty reduction strategy which seeks to improve access to and usage of formal financial products such as saving, credit, money transfer, investment and insurance (Refera, Dhaliwal & Kaur, 2016:9).

Financial literacy encompasses a wider range of skills, including behavioural disposition towards money. This differs from general literacy as the result of a basic level of education (Pearson, Stoop & Louw, 2017:2). In their study on providing a benchmark profile of financial literacy, Nanziri and Leibbrandt (2018:10) find that there are below average financial literacy levels among Black South Africans, the most affected groups being women, the youth, those in rural areas as well as individuals with less than high school education. With limited financial literacy and inclusion, individuals and households are restricted and cannot use financial resources effectively to reduce and mitigate risks as well as to smooth consumption in the long-term (Kempson, Perotti & Scott, 2014:44).

As specified by Fonseca (2016:20), financial inclusion requires broader financial capability and financial literacy if insurance is to achieve its full development potential. Results from a study by Carpena, Cole, Shapiro and Zia (2015:2) shows that for every one unit increase in financial literacy, there is an associated 2 per cent increase in the likelihood of purchasing index insurance, highlighting that financial literacy has a positive correlation with better financial decision making. Based on similar positive results, Timu et al. (2018:15) report that low-income farmer who have high levels of financial literacy, a good working knowledge of insurance, and actively acquire market information, have a better likelihood of purchasing insurance because of an appreciation of its inherent value. These farmers demonstrate financial capability to assess, plan and deliberately search for the best risk mitigating solution to address their needs. But, Dercon, Gunning and Zeitlin (2018:14) uncover that financial literacy training has no effect on demand for insurance. This might be because recent effects of training might not yet fully translate into long-term habits in decision making. Over time and with experience, the training is expected to translate into positive results for better decision making, which may translate into insurance demand.

The South African legislation such as the *National Credit Act of 2005,* and the *Financial Sector Regulation Act of 2017* sets out obligations for financial literacy and education as a tool to promote financial inclusion, improve decision making and to induce changes in consumer behaviour (Pearson Stoop & Kelly-Louw, 2017:13). Research shows that the overall impact of financial education on financial capability is not clear (Sherraden, 2013:9). According to Estelami (2009:282), empirical evidence continues to point to repeat trends of substandard decisions, especially financially and economically, that cut across the education levels of individuals. The research shows that the fundamental cognitive bias that contributes to weak financial decision making cannot readily be overcome by enhancing consumer education alone. The solution may require a broader shift of internal mental processes that guide an individual's thought patterns. Effective programmes are those that seek to modify human behaviour and to re-programme instinctive responses to gain a deeper understanding of risk perception. Among these effective programmes are the implementation of budget management tool, encouraging saving and use of insurance initiatives in addition to financial education. A combination of these interventions is found to have positive outcomes on financial decision making (Carpena et al., 2015:6). According to Sherraden (2013:4) financial capability not only resides within people but exists within an institution and ecosystem framework that surrounds the person's reality. When financially vulnerable people hear that certain products are not for them, financial capability is then influenced by their social position, not their ability to manage finances.

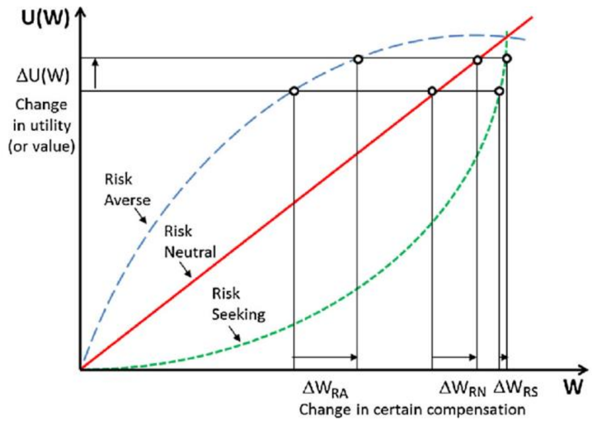
3.5.4.3 Risk perception

Insurance purchases are linked to events with a low probability of occurrence, which, by their very nature, carry low resonance with human experience. This is where misrepresentation and inaccurate assessment of risk occurs, which causes low coverage or complete avoidance of insurance (Buzatu, 2013:35). Risk perception is defined as a set of beliefs about potential harm or the possibility of a loss. Perceptions emanate from a subjective judgment that individuals make about the characteristics, frequency and severity of risk (Darker, 2013:110). A farmer's risk perception, that is, their attitude towards risk will determine the level and extent of risk mitigating tools. The choice of risk reducing methods is often difficult due to the need for quick response action during the planting season to address weather risk as it happens and usually incorporates uncertain interchanges between expected crop yield recovery and additional costs (Shah, Siderius & Hellegers, 2020:2). In the field of agricultural economics, farmer's perception towards risk has been found to depend on the frequent adverse weather conditions and how this affects crop production (Aditya, Khan & Kishore, 2018:12; Danso-Abbeam, Addai & Ehiakpor, 2014:166), the extent of previous losses (Liu et al., 2018:38; Haruna et al., 2017:81) and prevalence of drought risk (Lin et al., 2015:109; Hill, Hoddinott & Kumar, 2013:397; Mutaqin, 2019:17). All these considerations have been found to have a positive effect on weather index insurance participation and purchase decisions (Jin, Wang & Wang, 2016:371). However, farmer' views on weather risk are not only influenced by their perception of the climate. Influence also comes in the form of societal norms and principles, as well as other sources of agricultural production risk. When assessing priorities pertaining to their livelihood strategies, farmers form a mental risk model and make appropriate decisions about investments in agricultural production (Eitzinger, Binder & Meyer, 2018:511).

Traditional economic theory dictates that experiences of the past have little to no effect on the current and future decision making processes (Buzatu, 2013:38). Instead, the classical theory maintains that an individual is most concerned with utility maximization. Hence, insurance demand is often modelled in an expected utility maximization theoretical framework (Jurkovicova, 2016:183; Liu et al., 2018:34). Expected utility explains economic behaviour, decision making process, economic preferences and economic choices under conditions of uncertainty (Koçaslan, 2019:535). Since the goal of a farmer is to maximize returns under all circumstances over time subject to input, weather and commodity prices (Thinda et al., 2020:2), the rational farmer will opt for the best strategy that maximizes utility, that is, the perfect smoothing of consumption in line with their individual risk preference. Rational decision making processes involves a detailed analysis of all available information and impartial consideration of all relevant data to arrive at the best possible outcome (Ajzen & Dasgupta, 2015:118). Risk aversion measures in expected utility maximization presume that farmers consider the effects of losses and gains objectively in reaching this stated best possible outcome (Jumare, Visser & Brick, 2018:3). It is idealized in the framework that farmers have explicitly articulated priorities from the outset and understands all the appropriate alternatives and their implications (Robert, Thomas & Bergez, 2016:4). However, a rational decision is often not possible in reality, individuals often trust their intuition and feelings as opposed to carefully considered options especially in relation to insurance coverage judgment (Kunreuther & Pauly, 2014:1). According to Koçaslan (2019:544), even though expected utility maximization may not fully address daily economic problems in a practical manner, it remains the foremost fundamental concept explaining behaviour under risk and uncertainty.

Elabed and Carter (2015:151) argue that under expected utility maximization theory the desirability of index insurance appears to be overstate. Therefore, it is not surprising that under the expected utility theory, a risk neutral individual will not purchase insurance based on their risk preference classification (Platteau, De Bock & Gelade, 2017:145). Risk preference may be classified into three categories, each specifying the level of risk, which is acceptable for the individual, in this case, the farmer. These are risk averse, risk neutral and risk taking categories. Risk averse farmers are generally those who avoid risk taking; risk neutral farmers are indifferent to risk; and risk taking farmers have a strong preference for the manner in which they conduct their farming operations (Kahan, 2013:4). Farmers risk preference can be demonstrated in the shape of individual utility functions. Figure 3.3 reflects risk averse farmer's decreasing marginal utility shown by a concave utility function, a linear utility function represents risk neutral farmers, and the convex utility curve represented risk taking farmers (Domingo et al., 2015:4).

Figure 3.3: Utility curve of different risk preferences in relation to wealth



Source: Harris and Wu (2014:285)

Low-income producers, particularly in rural areas of emerging markets, are believed to be risk averse (Haile, Nillesen & Tirivayi, 2019:1; Meyer, Hazell & Varangis, 2017:5; Tang et al., 2019:624). Finding in Brick and Visser (2015:395) based on their laboratory experiment study of South African farmers confirms these finding. Risk aversion influences how farmers respond to different risk mitigating options as farmer's risk aversion habits determine the choice of risk management strategy (Helamo, 2018:26). It is thus common for farmers with high risk aversion to adopt ex-ante coping strategies such as insurance to mitigate the undesirable impacts of potential risk (Mutaqin, 2019:16), as insurance has been found to increase utility of risk averse farmers (Belissa, Lensink & van Asseldonk, 2019:2; Hill et al., 2019:3; Jin, Wang & Wang, 2016:371). This is mainly because even though the insurance premium payment represents an immediate cash outflow, the probability of a significant loss that has potential to erode wealth can result in diminishing utility; therefore risk averse farmers seek protection against a possible decline in income. Where index insurance is available, Ramasubramanian (2012:16), reports that for every unit increase in risk aversion there is an increase of 26 per cent in the amount of willingness-to-pay. Although risk aversion appears to encourage insurance purchase, Sulewski et al. (2020:10) observe that farmers with a high degree of risk aversion generally reduce their reliance of credit for crop production purposes to maintain financial security. Most of these farmers engage in mixed farming as a source of risk diversification and also avoid technological innovations as new technologies are associated with uncertainly. Therefore, the effects of using weather index insurance might not have an exponential impact of farm productivity for risk averse farmers. Instead of increasing farmer's risk bearing capacity, the primary goal of insurance is to reduce the level of uncertainty that exists in agricultural production.

Intrinsically, index insurance coverage is low partly due to underlying basis risk, but even under conditions of basis risk, there will be demand for index insurance contracts at actuarially fair prices given that for risk averse individuals, some insurance is better than no insurance (Farrin, Miranda & O'Donoghue, 2016:4; Weber, 2019:5). In accordance with Bulut (2016:5), if the insurance is actuarially fair, that is, the premium rate equals expected loss, then a firmly risk- averse and rational farmer will choose to insure at a full level of coverage. In fact, Platteau, de Bock and Gelade (2017:140) report that risk averse farmers, in order to avoid risk, could consider paying even more than what is presented as an actuarially fair premium. Jurkovicova (2016:183) cautions that risk aversion is not homogenous in the rural population; individual farmers respond to uncertainty differently depending on their financial capacity, cultural orientation as well as on demographic considerations. In the absence of insurance, risk averse farmers will more commonly opt for low-risk, low-return farming methods and will in all probability not use any modern inputs and implements that need external funding (Brick & Visser, 2015:384).

Goodrich, Yu and Vandeveer (2018:11) find that risk neutral farmers typically view index insurance as in investment rather than purely a risk mitigating tool. In their assessment of risk preference patterns from 2013 - 2017 of participants in a weather index insurance programme in Nebraska and Kansas. The authors report that over the years, the number of risk neural farmers has increased due to better understanding of how the scheme operates, therefore, these farmers are careful and strategic in selecting periods within which to invest, that is, purchase insurance because of their objective approach to risk management. On the contrary, in a different setting Orduño Torres, Kallas and Herrera (2019:13) find that risk neutral farmer's perceptions of climate change and its related impact on crop production are not defined clearly, therefore their response and subsequent take-up of mitigating solutions might be slow and reactive. While risk taking farmers are found to be proactive in their approach including the use of technologies, available subsidies and risk mitigating tools to increase production.

3.6 Conclusion

Findings from the literature indicate significant drivers identified from various studies that have a positive influence on willingness-to-pay for weather index insurance. These drivers have been categorized as socio-demographic (age, gender, marital status, education, and size of the agricultural household), socio-economic (access to credit, farm turnover, farming experience, farm size and group membership) and socio-psychological elements (insurance culture, financial capability and risk perception). Similar studies conducted in a different context have persistently reported mixed results on variables associated with willingness-to-pay. These contrasting findings speak to the objectives of the study, which were to identify factors unique to the South African environment, as there are seemingly inconsistent findings in the literature depending on the study area. A common theme that emerges from Chapter Three is that amounts low-income farmers are willing to pay for insurance also vary across crops and microclimates, a range of between 5 to 10 per cent appears to be more acceptable to farmers. In light of the increasing frequency of weather-related hazards, scholars suggest that insurance providers may demand a premium rate of between 10 and 15 per cent to offset the sheer risk cost of insurance. This indicates a premium shortfall from a supply point of view, which may require subsidization as the maximum willingness-to-pay is lower than the costs of providing insurance. All indications are that the equilibrium position between supply and demand has not been reached because not enough pilot studies have reached scale and demand without a level of subsidization is low.

The following chapter discusses how the research subject was conducted by providing a detailed discussion of the research design and methodology.

CHAPTER FOUR: RESEARCH METHODOLOGY

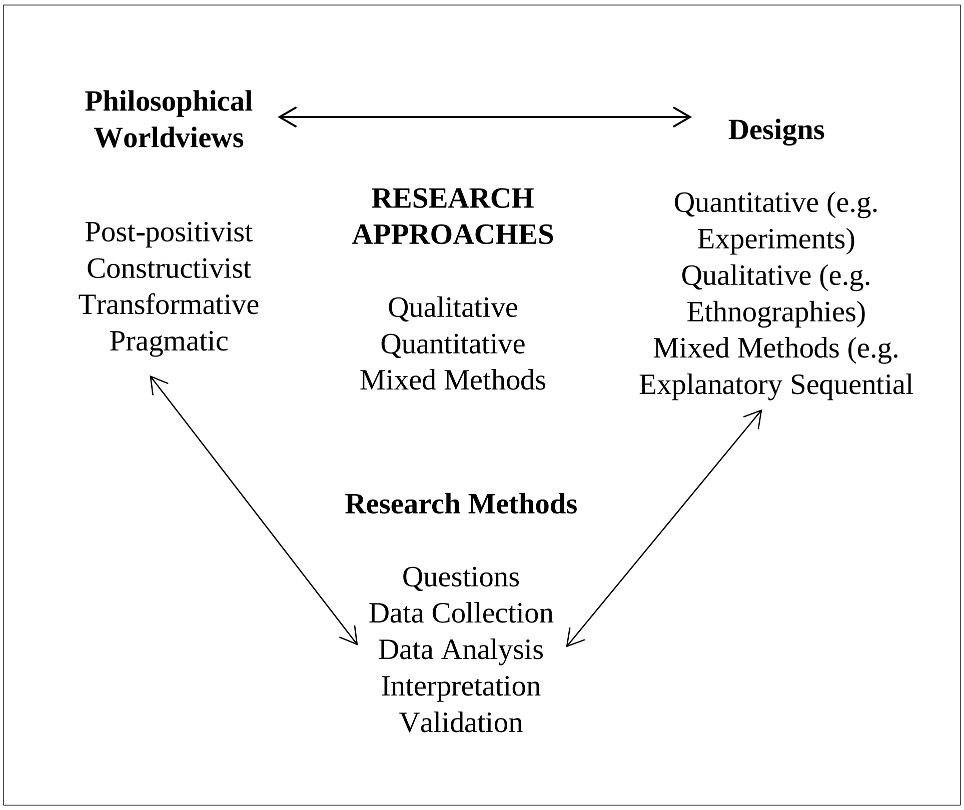
4.1 Introduction

This chapter introduces the research methodology entailing the design approach and strategy followed to address the research problem. As Neuman (2014:165) states, depending on whether it is mostly quantitative or qualitative, the approach for planning and performing a study can differ. Chapter Four commences by discussing the philosophical worldview underpinning this study as well as the guiding research approach. The chapter sets-out the various stages of research, which include defining the population of the study, the sampling methodology, and sample size determination, followed by a discussion of the data collection tools which assisted in addressing the research objectives. It was though the literature review that a better understanding was obtained of the concept of weather index insurance and willingness-to-pay for index insurance schemes, as well as which gaps in knowledge, exist. On this basis, a questionnaire was formulated from the literature review to ask probing questions that addressed the research problem. As guided by Mohajan (2018:23), a clear, disciplined, systemic approach was taken to obtain the most appropriate research results. Following the questionnaire formulation, the approach to data analysis is explained as well as steps taken to ensure that the research results were reliable and valid. Chapter Four concludes by discussing the ethical considerations undertaken in conducting the research.

4.2 Research Philosophy

Research philosophy relates to a system of values and expectations regarding knowledge creation. They include but are not limited to, conclusions about the truth of science, human knowledge, and the nature and manner in which a researchers' own beliefs can affect the research process (Saunders, Lewis & Thornhill, 2019:130). It is the view of Creswell and Creswell (2018:53) that research should be conducted following a clear and defined research approach, that is, a study strategy or roadmap involving the convergence of the reseach philosophy, the study design, and research methods. A structure is shown in Figure 4.1 which demonstrates the inter-relationship between the three key concepts. There are various philosophical worldviews that form the basis of research, the prominent modern schools of thought are the post-positivist and constructivist philosophical paradigms. The post-positivist and constructivist paradigms are very distinct philosophically, but the two can be used together in one research study. If the two paradigms are merged such that one paradigm sets the way for the other paradigm or contributes to the other, the approach is called a mixed approach (Gliner, Morgan & Leech, 2017:10).

Figure 4.1: A Framework for Research—the Interconnection of Worldviews, Design, and Research Methods



Source: Creswell and Creswell (2018:53)

The need to recognize and determine the factors that have an impact on findings is reflected by post-positivists. This approach is reductionist in nature as the goal is to simplify concepts into distinct variables that can form study hypotheses to be tested in addressing specific research questions.

The interpretation that emerges from a post-positivist perspective involves observation and analysis of the empirical realities that exist in the world. The development of numerical measurements of observations and the study of human behaviour is therefore important for a post-positivist perspective (Creswell & Creswell, 2018:54). This leads to the paradigm being more quantitative in nature (Creswell, 2014:36). The dominant research paradigm for much of the twentieth century was positivism; this has been largely replaced by a post-positivist philosophical view (Gray, 2017:61).

On the other hand, constructivism is usually regarded as an approach to qualitative analysis (often paired with interpretivism). The aim of the research is to put as much faith as possible in the viewpoints of the participants on the topic being examined. The questions are broad and generic such that the participants can create a situational context and provide their own analysis and interpretation typically based on discussions. The more open-ended the questioning, the better, as the researcher is able to gather in-depth and rich information on the subject under research (Creswell & Creswell, 2018:56). The goal of the researcher is to explain the interpretations that others have about the universe. Researchers establish a hypothesis or sequence of meaning inductively, rather than beginning with a theory as in post-positivism. Constructivist researchers engage with study participants in the co-construction process of knowledge. It is in this process that the researcher accepts, explores and discusses the implicit biases that exist within this interaction (Edmonds & Kennedy, 2017:146).

After careful consideration of the research philosophies, the post-positivists approach was the philosophical worldview adopted to answer the research questions for this study. Post-positivist research lays emphasis on inferential statistics with its focus on assigning probabilities that observed findings are correct (Gray, 2017:43). The study aims to test existing theories, and hypotheses identified in the literature in order to establish a conceptual framework of factors that influence low-income farmers' willingness-to-pay for weather index insurance in South Africa. The objective testing of these theories is to assess the possibility of their generalization and application in the South African farming context. Creswell (2014:36) suggests that there are rules or ideas that govern the universe, and in order to explain the world, they need to be checked or confirmed and perfected, in this case, these are the low-income farmer's common views, attitudes and beliefs.

4.2.1 Research approach

The approach is the first step to creating a structure for the research design, and it details a theoretical model of how the data will be collected (Edmonds & Kennedy, 2017:23). There are three main research approaches, qualitative, quantitative, and mixed methods. The key difference between qualitative and quantitative research is with respect to the objectives of each. Qualitative research is concerned with understanding human behaviour in its natural setting from the viewpoint of the participant, while quantitative research is a more structured scientific approach incorporating analysis of numerical data (Nardi, 2016:17). For this reason, qualitative research operates on the basis of probing open-ended questions with no specified list of responses, whereas quantitative research is generally based on closed-ended answers from surveys (Creswell, 2014:43). In a qualitative study, the focus is often on generating new hypotheses, interpreting study objects systematically and describing details of the causal mechanism or processes for a narrow set of cases, while in a quantitative study, the focus is on verifying or falsifying a relationship or hypothesis that is testing theory (Neuman, 2014:168). By analyzing the relationship between factors, quantitative analysis is an approach to evaluating objective theories. In turn, these factors are measured, normally based on survey data from which numerical results are interpreted using statistical analysis. Quantitative research tests theories deductively, factoring and guarding against bias, and being able to generalize and replicate the findings (Creswell & Creswell, 2018:51). In qualitative research, generalization cannot be claimed as results are subject to interpretation (Longbottom & Lawson, 2019:132), but qualitative analysis enables individualistic data to be collected and evaluated at deeper depths (Mohajan, 2018:19).

Mixed methods research resides in the middle of the qualitative and quantitative continuum by incorporating elements of both approaches. The central premise of this type of investigation is that qualitative and quantitative data integration offers further information beyond the data generated by either of these approaches alone (Shkoler, 2019:28). A researcher, for instance, would wish to both generalize the results to a population and establish a comprehensive understanding of the importance of a phenomenon or definition for a group of people. This may involve distinct designs which consider philosophical assumptions and theoretical frameworks (Creswell, 2014:5). This study lends itself to quantitative research approaches because of the underlying principles of post-positivism and deductive logic. As a scientific method that stresses structure, quantification, generalizability and testable theories, the post-positivist philosophy, is underpinned by the deductive approach (Saunders, Lewis & Thornhill, 2019:154). According to Creswell and Creswell (2018:69), certain research problems call for specific approaches such as the identification of factors that influence outcomes; a quantitative approach is the best suited method in this regard. In addition, advantages of quantitative research include efficiency in obtaining great coverage in terms of participation, rigorous testing which is key to achieving a clear understanding of behaviour and it is also relatively economical (Jansson-Boyd, 2019:7).

4.2.2 Research design

Research design is key in translating research objectives into measurable and valid information (Nardi, 2016:7). Research designs are detailed procedures for processes followed quantitative, qualitative or mixed methods research (Creswell & Creswell, 2018:60). The research design involves several stages (Nardi, 2016:45):

- generating ideas originating from hypotheses, or previous studies
- adapting those ideas and converting them into measurable variables;
- selecting the most appropriate research method to gather data;
- choosing a sampling strategy for deciding on the population to study and over what period of time (longitudinal across time or a one-time cross-sectional study);
- planning the data collection process and the parties involved in data gathering; and
- choosing the necessary statistical and analytical tools to make sense of outcomes of the findings.

This study makes a descriptive analysis of the factors that influence low-income farmers' willingness-to-pay for index-based crop solutions; therefore, descriptive research design was adopted which entails investigating the characteristics or particular behaviour or pattern in a defined population. Descriptive research aims to determine findings in a predictive way to understand the different features and to describe the reasons and observations (Joshi, 2019:78). A descriptive design is used to analyze the state of some phenomenon and to describe what exists with respect to groups, individuals, or conditions (Edmonds & Kennedy, 2017:161). Descriptive research is designed to measure scientifically what occurred, rather than why (Gray, 2017:321). Also known as statistical research, descriptive research is used to study the current situation (Akhtar, 2016:75).

Time is a dimension of every study, and it is incorporated in two ways, cross-sectional and longitudinal (Neuman, 2014:44). A cross-sectional design was used because it allows for the collection of the same data from multiple units at the same time while capturing the variations between respondents (Bukve, 2019:111). This approach supports the descriptive research design; in that, descriptive research captures the current situation; that is, it provides a 'snapshot' of the phenomenon being studied. Furthermore, cross-sectional research is easier to administer and it takes less time than longitudinal trials, where surveys of respondents are tracked over long periods of time (Nardi, 2016:127).

4.3 Target Population

The target population refers to all participants who meet the particular criterion specified for a research investigation (Alvi, 2016:10). The target population for this study was low-income farmers within Free State, Mpumalanga and North West provinces of South Africa, who have received or applied for loans or for grant funding from the Land Bank, within the last four years, from 2015 - 2019. The three identified provinces, as highlighted in Figure 4.2 on the map of South Africa, collectively represent the major maize producing areas in the country. The Free State accounts for 40 per cent, Mpumalanga accounts for 25 per cent, and North West represents 15 per cent of total maize production (DAFF, 2020:9).

Figure 4.2: The map of South Africa

Source: Author's compilation

The selection criteria are low-income maize farmers that have access to 20 hectares of land up to a maximum of 500 hectares. These farmers were viewed as having commercial orientation and a significant interest in terms of invested financial resources, labour and management efforts in ensuring successful crop production. Hence, insights received from these respondents were likely to provide a true reflection of low-income farmers in the country. The exclusion criteria were a safeguard to ensure that subsistence farmers do not form part of the sample as their focus is more on a livelihood strategy than on deriving profits. Furthermore, semi-commercial smallholders, that is, those producing on 500 hectares of land were specifically excluded as these are more likely to be outliers falling outside the scope of low-income farming on the basis of the sheer size of land ownership.

4.3.1 Sampling

A sample is a fraction of the population that represents the entire population in its characteristics proportionately (Dubey, Kothari & Awari, 2017:21). The process through which a sample is extracted from a population is referred to as sampling (Alvi, 2016:11). Survey participants for this study were randomly selected from the population of low-income farmers. The main advantage of random sampling is that it yields samples most likely to truly represent the entire population. It also allows the relationship between the sample and the population to be statistically determined, that is, the size of the sampling error (Neuman, 2014:255). Moreover, random sampling procedures are necessary to achieve high external validity (Crano, Brewer & Lac, 2015:220).

In establishing a representative sample for quantitative research, most studies use probability sampling, which relies on the mathematics of probabilities (Neuman, 2014:246). In probability sampling, every unit in the population has an equal and known chance of selection. This allows for rigorous statistical analysis and is effective in reducing sampling bias (Dubey, Kothari & Awari, 2017:186). Sampling bias is said to occur when the selected sample does not truly reflect the characteristics of the population (Alvi, 2016:12). Probability sampling allows for a more representative sample, that is a replica of the population and all its key variables (Gliner, Morgan & Leech, 2017:142). In non-probability sampling, it is not possible to quantify the likelihood that each individual will be included in the survey, hence this method is also referred to as judgement sampling which by its nature is open to sampling bias. For its many advantages and the ability for objective statistical analysis, probability sampling was considered the most appropriate for this study.

4.3.2 Sample size

Sample size determination is the technique to decide on the number of observations to include in a sample (Singh & Masuku, 2014:6). Sample size depends on different factors, such as the time component, the expense component and the degree of precision needed for the topic under investigation (Dubey, Kothari & Awari, 2017:186). There are many statistical based methods available for sample size determination. To ensure that predictions for an outcome are obtained with the appropriate amount of accuracy or trust, a statistical sample size calculator is necessary. A statistical sample size calculation is important to ensure that estimates for an outcome are obtained with the required amount of precision or confidence (Vishwakarma, 2017:1). A sample size of 326 low-income farmers who produce for markets was determined from a total population of 1774. The Taro Yamane method for sample size calculation with a 95 per cent confidence level was used to determine the sample. According to Vishwakarma, (2017:7) size for descriptive research, the estimation of the sample size is essentially dependent on confidence intervals, meaning, the accuracy needed to approximate rates, proportions and means. In management research, the common confidence level applied is 95 per cent. If a 95 per cent confidence level is selected, as is the case in this study, then 95 out of 100 samples will have the true population value; meaning that, survey questions have been asked to the correct population (Taherdoost, 2017:237). The Taro Yamane formula for determining the sample size is as follows:

$$\mathbf{n = N / (1 + N (e)2)}$$

Where:

n = is the sample size,

N = is the population size,

1 = is a constant

e = is the level of precision.

$n = 1774 / (1+1774 (0.05)^{2})$

$= 1774 / 5.435$

$= 326$

The aforementioned statistical calculation was interrogated against the Bartlett, Kotrlik and Higgins (2001:48) table for sample size determination in order to assess the reasonableness and as a cross-check reference. Based on the table, a population of between 1501 - 2000, requires a sample of 323. The consistency of sample size across two different approaches points to the reasonableness and adequacy of the determination. Determination of sample size is key because a sample size smaller than needed may not be capable of detecting major variations or correlations that may be present in the population under investigation and a larger than required sample size may be uneconomical to administer (Omair, 2014:142). The degree of variability in the population affects the adequacy of the sample, meaning a homogenous population will require a smaller sample size compared to a heterogeneous population (Shkoler, 2019:38). With the inclusion and exclusion criteria applied for low-income farmers in terms of hectares and income, a more homogenous portfolio was established that represents the population. As per Suresh and Chandrashekara (2012:7), the criterion for inclusion and omission should take account of all potential factors that could have an impact on the measured units and observations. On this basis, the researcher is of the view that the sample size is adequate to make valid inferences about the population based on cross-references to other sample determination methods, along with the homogeneity of the population defined through the inclusion and exclusion criteria.

4.3.3 Sampling methodology: stratified random sampling

According to Dubey, Kothari and Awari, (2017:194) when a population can clearly be divided into groups based on the same identifiable and important characteristics, for example, age, gender, geographical area, then a stratified random sampling may be used. This is where randomly selected participants are chosen from each subgroup of the population (Edmonds & Kennedy, 2017:20). The advantages of stratified random sampling are that it is proportionally representative of the population; there is minimum sample bias, and the exact representativeness of the sample is known (Dubey, Kothari & Awari, 2017:194). Stratification of a sample also increases its reliability such that a small sample size is required relative to simple random sampling for degree of statistical accuracy (Carson & Hanemann, 2005:904).

Each province featured in the study was stratified as a sampling unit, and a random sample selection made from each stratum by assigning a random number to each individual on the list using the random number generator function on Microsoft Excel. The random numbers generated were then sorted by ascending order and the required sample was selected in sequential order starting from the top of the list. According to Gliner, Morgan and Leech (2017:145) when participants are geographically spread across the country, it is common to stratify based on geographical location so that appropriate proportions of the selected sample come from the different regions. Table 4.1 presents the stratified sample, which was used for each province.

Table 4.1: Stratified sample per province

Province	No. of low-income maize farmers	Proportion split	Sample Size
Free State	116	6.5%	21
Mpumalanga	137	7.7%	25
North West	1 521	85.7%	280
	1 774	**100%**	**326**

Source: Author's compilation based on population data

4.4 Data Collection Instruments

Data is a collection of related observations, facts or figures (Dubey, Kothari & Awari, 2017:16). The data collection process entails defining the research parameters for the investigation in the form of sampling and recruitment, then collecting data either using structured, semi-structured or unstructured interviews; finally, developing of procedures for data recording (Creswell & Creswell, 2018:301). Data and data collection procedures are usually gathered with some sort of instrument that can be scored numerically and reliably (Gliner, Morgan & Leech, 2017:8). Typically, this is through the use of a survey which is the most widely used data-gathering technique (Neuman, 2014:316).

Surveys are used to identify patterns, activities, or perceptions of the target population. In particular, to discern inter-relationships and distribution of social science, behavioural or psychological factors (Edmonds & Kennedy, 2017:133). They are a list of questions where each respondent answers the same set of questions (Shkoler, 2019:40). As stated by Gliner, Morgan and Leech (2017:9) studies done mainly from the post-positivist viewpoint are usually based on surveys either taking the form of structured interviews or questionnaires. Questionnaires are research instruments which require participants to respond to the same series of prescribed questions usually by selecting responses from a set of given options (Gray, 2017:471). They are the primary method of collecting quantitative data (Stoppa & Rani, 2012:273).

Questionnaires are more suitable for probability sampling and are ideally suited for this study as they are an effective tool for collecting a vast amount of data efficiently, within a short time period while utilizing minimal resources. Furthermore, questionnaires allow for generalizing results to a larger population (Nardi, 2016:72). Questionnaires can be structured or semi-structured. Structured questions limit the number of allowable responses by using a fixed schedule of questions and pre-set answers (Crano, Brewer & Lac, 2015:288). In comparison, semi-structured questionnaires do not have a set of predetermined responses, allowing the interviewer to probe the range and depth of responses by asking additional questions to the participant to uncover more information in knowledge creation to address the research problem. This type of questionnaire is often used in qualitative studies. Structured questionnaire is ideally suited for quantitative research (Gray, 2017:518). For these reasons, a structured questionnaire in the form of a survey was used to collect primary data from low-income farmers as it fits the research design of the study.

4.4.1 Structured questionnaire

Where the audience is relatively large, and where standardized questions are proposed, the questionnaire is a suitable instrument which allows for an empirical approach to analyze interactions between variables (Gray, 2017:471). Suitable questionnaire design is crucial to the effectiveness of a survey. Reasonable questions presented in an appealing format, and an appropriate order can encourage participants to take part in the survey (Roopa & Rani, 2012:273). The hypothetical market scenario investigated in this study requires questionnaires to be highly structured, meaning that, to be able to make an informed decision, the respondent needs to be given adequate details on the valuation scenario, but without being overwhelmed by the data (Carson & Hanemann, 2005:897). To achieve this, the questionnaire was structured in such a manner that it addressed the research objectives for this study. Questionnaire design can take four different forms; these are: contingent questions, matrix questions, close-ended and open-ended questions (Stoppa & Rani, 2012:273). Contingent questions are those which require responses only if the participant provides a specific answer to the previous question. Matrix questions are those that offer respondents are a series of statements where they are required to evaluate each on the basis of an identical response category. These commonly take the form of Likert scale questions. Likert scale questions are commonly used to measure perceptions, attitudes, behaviours, opinions and feelings (Sullivan & Artino, 2013:541), which makes them ideally suited for the objectives of this study. Closed-ended questions offer a fixed set of responses from which a respondent can choose (Neuman, 2014:331), making it easy to compare responses between participants (Gray, 2017:484). Most questionnaires operate on closed-ended questions as they are usually easier to understand and answer and facilitate data coding and processing (Shkoler, 2019:43). Open-ended questions are those where the participant responds to each question in accordance with their views and not a pre-populated list of responses. Although open-ended questions are generally simple to answer for a knowledgeable audience, they tend to be difficult to analyze and categorize responses (Gray, 2017:483). The questionnaire in this study was categorized into five parts summarized in Table 4.2, consisting of closed-ended questions and five-point Likert scale responses. These two forms of questionnaire design were selected based on the ease at which responses could be compared between participant's allowing for consistent data analysis and application of inferential statistics for generalization.

Table 4.2: Summary of different sections of the questionnaire

Section	**Description**	**Type of question**
Section A	Section A consists of question 1 – 7, which requires demographic information, such as gender, age, and education levels of low-income farmers.	Close-ended
Section B	The second part of the questionnaire consists of question 8 – 12, which features specific questions key to obtaining an understanding of farm-level characteristics.	Close-ended
Section C	Section C enlists question 13 – 16 with a focus on understanding farmer's weather risk exposure and applicable risk mitigating strategies.	Close-ended
Section D	Section D features question 17, which uses a five-point Likert scale to ask questions relating to understanding the insurance culture, financial capability and risk perception of low-income farmers.	Five-point Likert Scale

Section E	The questionnaire concludes with question 18 – 21. This section explains the concept of weather-index insurance and addresses related questions in order to determine willingness-to-pay and to gather data on the amount farmers are willing to pay if anything at all.	Close-ended

4.4.2 Administration of the questionnaire

It is only when questionnaires are adequately designed and administered in a responsible and consistent manner that vital conclusions can be drawn about specific groups and the population under investigation (Roopa & Rani, 2012:273). Even the best designed questionnaire will not create an impact if care is not taken with its administration, one of the fundamental objectives of which is to maximize the return rate (Gray, 2017:505). The questionnaire was administered through a mixed-mode combination of a telephonic or self-administered online questionnaire. For survey enquiries, the single mode model, which means that one data collection mode suits all participants, is no longer tenable (de Leeuw, Suzer-Gurtekin & Hox, 2016:2). By using various types of data collection methods, a researcher can enhance the validity and reliability of the collected data.

The surveys were administered between February 2021 and March 2021. SMS's were sent to all farmers notifying them of the study, requesting their participation and advising on the date and time to expect contact. On the mentioned date, telephone calls were made, making reference to the SMS and enquiring if it is a suitable time. For those who indicated that the time was not suitable, an appointment was rescheduled to conduct the survey, and an option was also presented to send the online survey link via email. This advance notification strategy was undertaken to improve response rates in the survey. In agreement with Edmonds and Kennedy (2017:134), owing to various factors outside the scope of the study, the time at which the survey is performed may have a significant effect on the findings. Following telephonic introductions, the informed consent form (Appendix A) was read to each participant. Participants were requested to confirm their understanding thereof and permission was requested to proceed with the survey. In instances where permission was declined, the farmer was thanked for their time and the conversation was concluded. Where permission was received, farmers were then briefed on weather index insurance, what it entails and how it operates, and those that elected to participate were given the option to respond telephonically or be sent a Uniform Resource Locator (URL) link to self-complete an online version of the questionnaire. The online questionnaire was to ensure that participants had sufficient time to undertake the survey in an unhurried manner and to improve the prospects of those who would ordinarily opt-out of telephonic surveys. Mixed-mode surveys have a distinct advantage of reducing non-responses to studies (de Leeuw, Suzer-Gurtekin & Hox, 2016:9).

Mixed-mode data collection creates an environment where the strength of one data collection method overcomes the weakness of another allowing for the collection of maximum data within resource and time constraints (Dillman, Smyth & Christian, 2014:12). Telephone surveys are the most widely used of all the survey methods (Gray, 2017:339). There is an estimated 80 per cent cell phone penetration rate among smallholders in South Africa (Accenture, 2018:9), making it easier and faster to reach respondents, even those in remote areas, where contact numbers are available. Telephonic interviews have an excellent response rate and reduce errors in response selection as the interviewer has control over the selection process of possible answers (Stoppa & Rani, 2012:275). Online questionnaires, on the other hand, have the advantage of convenience, where the respondent can reply in their own time, they are cost-effective in addition to having visual appeal (Gliner, Morgan & Leech, 2017:226). Like telephone interviews, response bias is reduced in online surveys; however, response rates of online surveys are between 15 – 20 per cent (Bhattacherjee, 2012:80). Response bias arises by virtue of the respondent enhancing his or her education details, occupation, income and so forth, or understating his or her age, thus resulting in wrong information to safeguard his or her personal interests (Dubey, Kothari & Awari, 2017:208).

The planning for a mixed-mode design was also influenced in part by the global health crisis originating from the Covid-19 pandemic. Strict intra-provincial travel restrictions were imposed in South Africa with citizens required to stay at home where possible to control and curb the spread of the virus. From the 15th of March 2020, the national government declared a National State of Disaster and started a process of adopting strict protocols to prevent further infections. Subsequently, a risk based approach was adopted to open economic activity and resume life as normal in a gradual and responsible manner guided by scientific evidence (South African Government, 2020:12). Therefore, in planning the data collection approach, face-to-face interviews were considered high risk in light of government restriction and in observing safety measures, mailing of questions were also not considered because of disruptions in postal services during the pandemic and the risk that the questionnaire may not reach the intended participant on a time. On this basis, the selected mixed-method approach of telephonic interviews and online surveys where possible was considered the most appropriate for data collection.

4.5 Pilot Study

A pilot study is a formal process of collecting data with a sample similar to the planned research study prior to actual data collection for the study; it is particularly important to provide evidence about the reliability and validity of the research outcomes (Gliner, Morgan & Leech, 2017:248). The pilot study is necessary to contribute to the overall improvement of the integrity and quality of the main research, minimising unnecessary efforts through pre-testing the questionnaire (In, 2017:601). Piloting a questionnaire usually streamlines the data collection process by eliminating or at least reducing questions that are likely to be misleading, intrusive or simply where respondents may not know how to answer, this helps in reducing prospects of missing data (Gray, 2017:474).

A pilot study featuring a sample of 15 randomly selected maize low-income farmers similar in profile to the target population was chosen from the Land Bank database. These farmers were based in Eastern Cape and Gauteng, and similar inclusion and exclusion criteria as the main study were applied in the selection. Permission to use the database and contact details was received from the organization's Chief Executive Officer (Appendix C). Through the process of conducting pilot surveys elements of the questionnaire were redesigned to improve respondent understanding and the overall flow of the questionnaire, that is, improvements were made to questions, format, and scales (Crewsell, 2014:207). As per Nardi (2016:105), design aspects such as ordering items on a questionnaire in different ways can also lead to alternative outcomes which can improve the quality of data collected. Once the questionnaire piloting was complete, modifications were made to the questionnaire, and the overall final review was done with the assistance of a statistician.

4.6 Data Analysis

Statistics can be descriptive, where the data summarises a given dataset so that patterns may emerge from the data or inferentially where statistically significant differences are identified between groups and conclusions are made about the dataset (Jansson-Boyd, 2019:7). A dataset is a collection of the data of individual cases (Mishra, Pandey, Singh, Gupta, Sahu & Keshr, 2019:67). Essentially, descriptive statistics describe numerical data, whereas inferential statistics are based on probability theory to formally test theories, they make inferences from a sample to a population (Neuman, 2014:396).

The simplest way to explain numerical data is with frequency tables, cross-tabulations, measures of central tendency represented by the mean, median and mode, along with measures of dispersion represented by the range and standard deviation. The most common value around which most values in the distribution appear to converge is measured by central tendency. However, extreme values are still present in each distribution. These are measured by dispersion or variance or spread measurements signifying the number of values which vary significantly from the mean, median or mode (Dubey, Kothari & Awari, 2017:9).

There are two main types of inferential tests: parametric and non-parametric. Parametric tests are more powerful tests that make certain assumptions about the underlying population from which the research data has been obtained while non-parametric are less powerful tests that make fewer assumptions of the collected data. If a data set is interval or ratio and normally distributed, parametric tests such as Analysis of Variance and Pearson's coefficient can be applied. If data is interval or ratio but are not normally distributed, one would most likely be using a non-parametric test. Bearing in mind that if data is nominal or ordinal, parametric tests may not be used, only a non-parametric statistical test is applicable (Bettany-Saltikov & Whittaker, 2013:6).

4.6.1 Correlation analysis

Correlation is a measure of association between two continuous variables. In correlated data, the degree of change in one variable is associated with a change in the magnitude of another variable (Schober, Boer & Schwarte, 2018:1763). The degree of association can be between dependent and independent variables, or between two independent variables (Senthilnathan, 2019:5). Correlation coefficients are used to assess the strength and direction of the linear relationships between these two identified quantitative variables. When data for both variables has a normal distribution, Pearson's product-moment correlation coefficient "r" is applied. If not, Spearman's rank-order correlation coefficient "ρ" is applied, which is a non–parametric test that is more resilient to extreme values than Pearson's correlation coefficient "r". The results of correlation analysis produce a correlation coefficient which ranges from -1 to +1. A correlation coefficient of +1 shows that the two variables are perfectly positively correlated, a correlation coefficient of -1 suggests that two variables are perfectly negatively correlated, while a zero correlation coefficient reveals that there is no linear relationship between the two variables under investigation (Gogtay & Thatte, 2017:78). Senthilnathan (2019:4) presents an ideal spectrum for interpreting correlation coefficient results within a range of acceptability.

Table 4.3: Ideal spectrum for interpreting correlation coefficient

Positive	Interpretation	Negative
0 to 0.2	Very weak or negligible correlation	0 to -0.2
0.2 to 0.35	Weak correlation but to be considered	-0.2 to -0.35
0.35 to 0.5	Fair or moderate correlation	-0.35 to -0.5
0.5 to 0.7	Strongly considered high correlation	-0.5 to -0.7
0.7 to 1	Very strongly considered correlation	-0.7 to -1

Source: Senthilnathan (2019:4)

Correlation analysis does not confirm that the association between two variables is a cause-and-effect relationship (Schober, Boer & Schwarte, 2018:1765). For the investigation of causal relationships in this study, SEM was used.

4.6.2 Structural equation modelling (SEM)

The data were analyzed using SEM specific programme AMOS in SPSS. This allowed latent variables in the study represented by the socio-psychosocial elements of insurance culture, financial capacity, and risk perception presented in Chapter 3 to be tested towards understanding their impact on willingness-to-pay. The empirical model is specified as follows:

$$\text{WTP} = \beta_1 \text{insurance culture} + \beta_2 \text{ financial capability} + \beta_3 \text{ risk perception} + \varepsilon$$

Where the β is the empirical estimated weights or path coefficients depicting the relative importance of each of the three constructs and ε is the error term.

SEM is a dynamic, multivariate approach that is well suited to evaluating different hypothesized or implied relationships between variables (In'nami & Koizumi, 2013:23). SEM uses various types of models to describe complex relationships between observed and latent variables. Observed variables are those that can be directly measured, while latent variables also denoted as unobserved variables which cannot be measured directly (Teo, Tsai & Yang, 2013:3). The aim of SEM research is to assess the degree to which sample evidence supports the theoretical model. If the theoretical model is supported by sample data results, then further complicated theoretical models can be inferred. If the sample data does not endorse the theoretical model, then it is appropriate to change and re-test either the original model or to create and test other theoretical models (Schumacker & Lomax, 2010:2). As SEM precisely locates which basic model feature conflicts with the research data (Rahman, Shah & Rasli, 2015:371). SEM offers a responsive and efficient way of measuring the quality of measurement instruments while concurrently and analysing causal relationships between constructs. The advantage of using SEM is that it models measurement error to produce unbiased estimates of the relationships between variables. Traditional statistical methods including, analysis of variance (ANOVA), multiple regression and path analysis of variance ignore measurement of error variables in a model (Wang & Wang, 2020:1). Furthermore, SEM overcomes the limitations of multiple regression analysis by allowing the ability to estimate relationships among multiple predictors and multiple criterion variables. Multiple regression was developed to extend the utility of the Pearson correlation by enabling the inclusion of many predictors. Still, this extension was restricted to a single criterion outcome (Crano, Brewer & Lac, 2015:172). As a result, SEM has become ubiquitous in all quantitative research (Rahman, Shah & Rasli, 2015:371).

SEM models often comprise two subsets of models: a measurement model and a structured model. A measurement model describes the extent to which the variables observed act as a measurement instrument for the underlying construct. A structured model hypothesizes and assesses potential relationships among latent variables (Wang & Wang, 2020:4). SEM can be applied both in confirmatory testing and in exploring the construction of new models. It is mostly used as a confirmatory tool to ascertain the validity of a specific model (Rahman, Shah & Rasli, 2015:371). Application of SEM as a statistical technique comprises five steps:

(a) model specification – this involves the formulation of a model based on a theory from prior research;

(b) model identification – considers if a unique value can be derived for each unknown parameter in the model using observed data (Wang & Wang, 2020:11);

(c) parameter estimation - The aim of parameter estimation is to approximate population parameters by reducing the difference between the observed variance and the predicted model-implied variance (Schumacker & Lomax, 2010:59);

(d) model fit – represents an overall index of how well all the computed estimates of the relationships in the model successfully reproduce the underlying correlation matrix. The better the fit (less discrepancy between observed and predicted values), the greater the support for the hypothesized structural model (Crano, Brewer & Lac, 2015:181); and

(e) model re-specification – involves enhancing model data fit. Any model re-specification should be justifiable from a theoretical basis by empirical findings (Wang & Wang, 2020:28).

While applying any statistical technique, there are certain assumptions and preconditions for implementation that required to be satisfied. These assumptions in SEM are multivariate data normality, data linearity, large sample size, no systematic incomplete data, and proper model specification (Rahman, Shah & Rasli, 2015:374). However, more often than not, data gathered for business research frequently does not comply with patterns of multivariate data normality. There are issues that routinely occur such as unusual data characteristics, for example, non-normal data (Hair, Sarstedt, Hopkins, Kuppelwieser, 2014:107). The findings on normality were assessed and reported in chapter five, where appropriate action was taken to ensure the validity of tests conducted in line with pre-requisite assumptions.

4.6.3 Contingent valuation method

A systematic literature review on willingness-to-pay studies for agricultural innovation in developing countries shows that over 50 per cent of studies prefer the contingent valuation method (Olum et al., 2020:9). Contingent valuation analysis is fairly easy to understand and apply, especially for low-income farmers in rural areas where financial literacy and education levels might be low (Arshad et al., 2016:236). The dichotomous choice contingent valuation elicitation technique was used for the study. This specific dichotomous choice method has been applied successfully in various willingness-to-pay studies (Aditya, Khan & Kishore, 2018:8). Under dichotomous choice – a hypothetical price is stated, and individuals make a choice to either accept or reject the price. The dichotomous choice methodology closely reflects real market scenario as most consumers are familiar with being confronted with a stated price for products or services and often need to make a decision to purchase at that price or not.

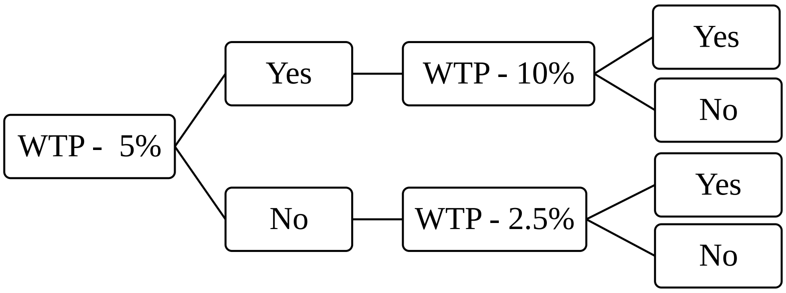
The advantage of the dichotomous choice method over other methods is that it simplifies the respondent's task, and it is easy to administer.

The dichotomous choice approach is further subdivided into variations: single-dichotomous choice using open-ended questions, single-dichotomous choice using close-ended. The second variant is closely related to what respondents are accustomed to as it simulates a standard negotiation phase in which the respondents first reject the offered bid and then state their own maximum willingness-to-pay (Fonta et al., 2018:5). The latter single-dichotomous choice using close-ended questions presents respondents with a value and requires a Yes or No answer as to whether or not they would pay this amount. Single-bounded dichotomous choice requires a large number of observations to identify the underlying distribution of resource values with any given degree of accuracy (Cameron & Quiggin, 1994:3). A refinement of this single-bounded version consists of introducing a follow-up question, known as the double-dichotomous choice.

Double-dichotomous choice entails a willingness-to-pay question asked at an initial starting price with respondents replying by indicating Yes or No. Based on the response, a follow-up question is asked with a new upper and lower threshold. The upper threshold is asked to respondents that answered Yes, the lower bound is asked to respondents that answer No to willingness-to-pay. The upper threshold is set to double the first bid, and the lower threshold is half the first bid (Cameron & Quiggin, 1994:3). The double-dichotomous choice is found to improve the efficacy of willingness-to-pay estimates by rectifying the poor choice of the initial price offers. For this reason, double dichotomous closed-ended formats are a more popular way of eliciting market information (Park & MacLachlan, 2008:693), and this was the basis of opting for the double dichotomous choice for this study.

On the basis of the literature review (section 3.4), the mean willingness-to-pay from various studies was established as 6.3 per cent. The initial bid for this study was set at 5 per cent after adjusting 1.3% for discounting factors that are unique to the South African context; namely, low-income farmers are previously uninsured, have no agricultural insurance products, they have limited interaction with financial services and by definition are resource constrained. To sum up, the commercial crop insurance premium rate in the country is around 4 to 5 per cent; therefore, this adjustment would be more or less within the bracket of an acceptable range. Similarly, Adjabui, Tozer and Gray (2019:496) applied an initial bid of 5% for a weather index insurance questionnaire. Using the double dichotomous choice, possible responses are modelled schematically in Figure 4.3 below.

Figure 4.3: Willingness-to-pay scenarios



Source: Author's compilation

4.6.4 Logistic regression

A systematic literature review from 2017 shows that most studies have used regression models to analyze the impact of various factors that influence farmers' willingness-to-pay for innovative agricultural technology (Olum et al., 2020:9). On this basis, logistic regression was used to address the secondary research objective of the study, which is:

- To identify factors that influence willingness-to-pay for weather index insurance;

Logistic regression is a type of multivariable analysis used with increasing frequency because of its ability to model linear and non-linear relationships between a dichotomous dependent variable and one or more independent variables (Park, 2013:162). In this case, farmers willingness-to-pay for index-based insurance was determined through a binomial outcome either Yes or No. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable which predicts the probabilities of the dependent outcome as a function of the independent variables. In addition, logistic regression makes no assumptions about the distributions, which is data normality of the predictor variables (Wuensch, 2020:1). The logistic model is derived from the Bernoulli probability function (Hilbe, 2009:63), which can be expressed as:

$$\pi_i = Pr(Y_i = 1|X_i = x_i) = \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)}$$

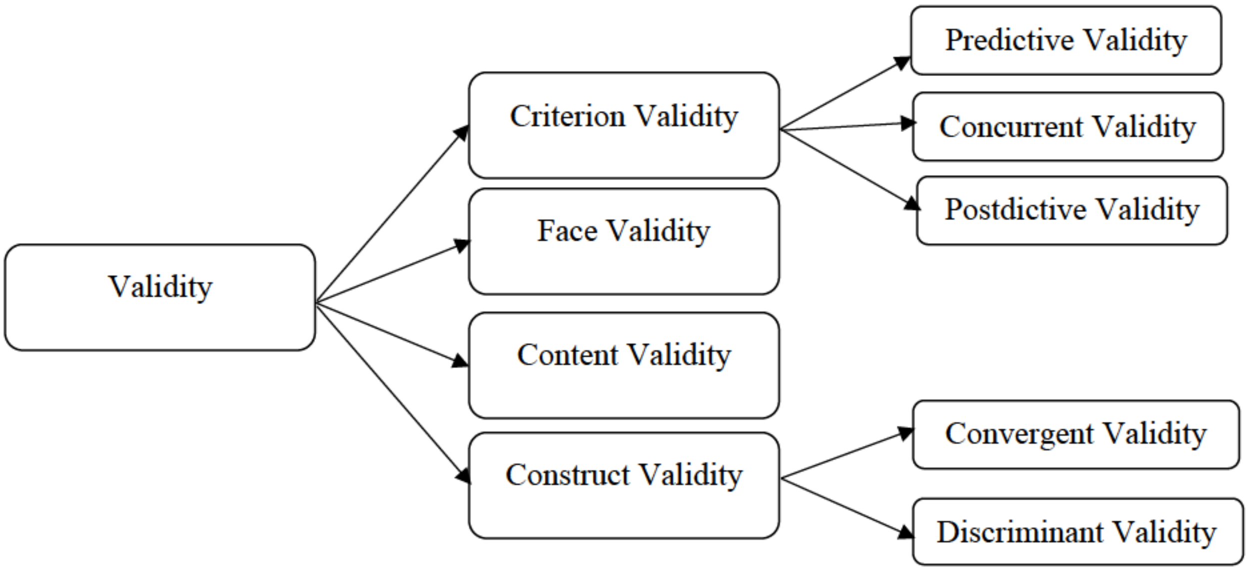
For the Bernoulli, π_i and *Pr* are defined as the probability of a success, where Y is the binary response variable, the variable Y_i represents the willingness-to-pay, with a value of 1 if the respondent indicates Yes or 0 if the respondent replies No. X represents (X_1, X_2, ...,) a set of explanatory or independent variables which can be categorical, continuous, or a combination. Lastly, x_i is the observed value of the explanatory variables for observation *i*. A similar logistic model was applied by Abdullah et al. (2014:24); Gulseven (2014:142) and Stojanović, Rakonjac-Antić and Koprivica (2019:1112) in their respective investigations of determining factors that influence willingness-to-pay for agricultural insurance.

4.7 Reliability and Validity

Reliability and validity are concepts that establish the truthfulness, credibility, or authenticity of findings (Neuman, 2014:212). They are two of the most important and fundamental features in the evaluation of any measurement instrument. The purpose of establishing reliability and validity in research is essentially to ensure that data collected is sound, replicable, and the results are accurate (Mohajan, 2017:1). Reliability refers to the consistency or accuracy with which the construct of interest is measured (Hinton & Platt, 2019:60). Reliability is a measure of consistency, of which the extent of this consistency is measured by a reliability coefficient using a scale from 0 to 1 where 0 is very unreliable, and 1 is perfectly reliable (Gray, 2017:505). This is usually ascertained by determining Cronbach’s alpha (Gliner, Morgan & Leech, 2017:188; Wang & Wang, 2020:44). Three techniques were adopted to ensure the reliability of the study, first, Cronbach alpha was calculated to determine reliability of the factors, second, calculating composite reliability which is a measure on internal consistency and lastly, by using questionnaires the procedures are usually standardized for all respondents to enhance the reliability of the data.

Validity is the general term most often used by researchers to judge quality or merit (Gliner, Morgan & Leech, 2017:121). Validity concerns what an instrument measures, and how well it does so. It is the degree to which results are truthful or not (Mohajan, 2017:14). For studies on hypothetical markets, services under provision should be clearly and accurately described, and the trade-off that the respondent is asked to make should be plausible in order to achieve validity (Carson and Hanemann, 2005:898). Validity can take various forms from face, content, construct and criterion validity which are all discussed further and graphically illustrated in Figure 4.4. Each of these approaches to measurement validity provides valuable and necessary information, and they should be employed concurrently whenever possible, with the aim of supplying data that enables the construction of more refined measures of some psychological or behavioural attribute (Crano, Brewer & Lac, 2015:74).

Figure 4.4: Various forms of validity



Source: Taherdoost (2016:29)

Face or content validity is a legitimate, but not quite mathematical and subjective approach to testing validity is to see whether the measure appears to be producing the desired outcomes. There is generally a consensus among researchers and analysts as to whether a metric does what it is intended to do (Nardi, 2016:62). A panel consisting of an agronomist (Herbert Mokoena), agricultural economist (Mmaphuti Mokwele) and underwriter (Muzi Dladla) employed by Land Bank Insurance and a statistician (Mlando Maseko) was consulted regarding the questionnaire to provide input on the adequacy and reasonableness of the survey in measuring what it intends to measure, which is the willingness of farmers to pay for weather index insurance. Based on the feedback, and further deliberations, the questionnaire was modified to the satisfaction of the panel of technical experts in agricultural insurance.

Construct validity: refers to how well a translated concept or behaviour establishes a construct into a functioning and operating reality, which is the operationalization. Construct validity has two components: convergent and discriminant validity (Taherdoost, 2016:31). Construct validity was assessed by performing a Confirmatory Factor Analysis (CFA). This is particularly helpful in identifying the factor structure that best describes the phenomena as observed on the basis of theory. Convergent validity was determined using the factor loadings from CFA to calculate Average Variance Extracted (AVE). Convergent validity is defined as the extent to which a set of indicators of a particular construct converge or share a higher proportion of variance than the norm (Hair, Gabriel, & Patel, 2014:50). From the AVE results, the discriminant validity index was computed. Discriminant validity relates to the degree that the construct indicators represent a single construct, and the indicators of the construct vary from other constructs in the model (Hair, Gabriel, & Patel, 2014:50). In brief, since convergent validity confirms that the measurements parameters completely capture the intended construct. Discriminant validity measures that constructs are not related to each other.

Criterion validity: this applies to the degree to which particular criteria variables can be estimated by test scores (Taherdoost, 2016:32). Typically, this validation method requires setting a correlation coefficient between the instrument and some sort of external criteria. The key to criterion validity is being able to establish a measurable externally observable criterion. There are two types of evidence for criterion validity, predictive evidence and concurrent evidence (Gliner, Morgan & Leech, 2017:203*)*. Predictive validity assesses the operationalization's ability to predict something that it should technically be able to predict, and concurrent validity assesses the capability of the operationalization to differentiate among classes that it should theoretically be able to separate (Taherdoost, 2017:32). All of which were evaluated by computing correlation coefficients between scale scores and outcome variables (Hinton & Platt, 2019:61). Correlation is commonly used for validation, although other techniques may be applied (Edmonds & Kennedy, 2017:241). Correlation analysis between dimensions was used in this study to establish criterion validity. Postdictive Validity was not assessed for this study as the validation requires an established test or criterion administered at a previous point in time (Taherdoost, 2016:33).

Threats to the validity and reliability of research exist at almost every turn in the research process. It can never be totally eliminated, so it is the goal of a researcher to try to minimize the threats as best as possible (Mohajan, 2017:20). External validity is one of the threats that relate to the generalization of results. If generalization is the goal, then the appropriate probability sampling technique should be used to ensure that external validity is not violated (Edmonds & Kennedy, 2017:134), as was the case in this study. Response bias as one of the threats exists to the extent that the researcher knowingly or unknowingly influences the obtained results. The degree to which data is affected by these factors that are independent of the construct under consideration partially determines the scale's validity. At the most extreme level, a situation of complete invalidity, in which the way that questions are worded totally determines participants' responses, independent of the content or meaning of the items themselves (Crano, Brewer & Lac, 2015:75). Another common threat is language difficulty, where there is either a lack of clear instructions or technical language not suited to fit the language of the respondent group. To reduce threats to validity and reliability, a pilot study was conducted to refine the questionnaire and data gathering approach while improving the understandability of the items on a scale.

4.8 Significant reduction of Bias

In every questionnaire, the possibility of bias through questionnaire design exists (Frey & Pirscher, 2019:7). Bias refers to the extent to which the researcher or respondents may seek to influence the process of data collection, analysis and findings either wittingly or unwittingly (Longbottom & Lawson, 2019:132). Bias distorts results and often leads to inaccurate conclusions. If the methods in their studies are repeated by researchers with different principles and views and produce comparable outcomes, it can be more confidently assumed that the methods and results are less influenced by any of the specific biases of the researchers (Nardi, 2017:9). Different types of biases exist in research in the areas selection bias and non-response bias. The use of contingent valuation methods requires guarding against starting point bias and hypothetical.

Selection bias applies to the selection process of participants and how the study inclusion criteria were formulated (Smith & Noble, 2014:3). This study applied probability sampling based on stratified random sampling techniques. The use of probability sampling ensured that each person in the target population had an equal chance of selection and application of random sampling is known to reduce selection bias since the researcher has no control of which participants in the target population will form part of the study. Non-response bias is also a problem since respondents who do not engage in the research are likely to hold different views from individuals who do take part in it (Zikmund et al., 2009:222). This effect was reduced though presenting alternative modes of data collection to increase the prospects of responses and guaranteeing anonymity which can reduce interviewer response bias. A mixed-mode approach was followed in the study making use of telephonic interviews and online surveys in order to reduce non-response bias.

Starting point bias arises when respondents take the initial bid value as indicative of market information. As such, their final offers appear to be impacted by the initial offer and might not reflect participant's true maximum willingness-to-pay. To overcome this challenge, initial bids for the study were based on literature reviews on existing index insurance programmes and other willingness to study finding in developing countries. Additional measures were also taken to evaluate the South African insurance landscape and current pricing structures for crop insurance premiums. Particular attention was given to the cash constraints of low-income farmers, current lack of premium subsidization and a reasonable entry price acceptable for insurance providers to consider bearing the risk. From the evidence presented in the literature, a starting point of 5 per cent of annual harvest income was determined to be a reasonable basis in determining the initial pricing point for the study. Subsequent bids were then established based on the initial starting point. The approach followed in this study is expected to reduce starting point bias and likely to lead to plausible willingness-to-pay results.

Hypothetic bias refers to the concern that the lack of a consequential economic commitment in contingent valuation surveys may result in overstated willingness-to-pay figures. To address the concern of potential bias, the scenario under investigation was explained to study participants in clear and easy language, the product under investigation, its features and intended use was explained along with the purpose of the research. In doing so, participants had a better understanding of the market scenario and the value of their contribution in the study. This approach was expected to encourage responses that would replicate actual market conduct. The study opted for the use of a questionnaire which was pre-tested through a pilot study. In agreement with Nardi (2017:106) good measures to avoid unintentional biases are through pre-testing items and pilot-testing questionnaires.

4.9 Ethical Considerations

Even where study subjects are unconcerned or unaware of ethical considerations, researchers have a legal and professional duty to be ethical (Neuman, 2014:145). All participants were informed about this study, its objectives, the process to be undertaken to collect the data and the value of their contribution. It was clearly communicated that participation was on a voluntary basis and that the respondent could choose to withdraw their participation at any time during the administration of the questionnaire. As per Crano, Brewer and Lac (2015:127) individuals considered to be voluntary participants are aware that they are under investigation, but they have made a conscious decision that the potential benefits outweigh the costs.

Participant's right to privacy and anonymity and confidentiality must be respected and maintained at all times (Nardi, 2016:37). Researchers preserve anonymity by not sharing the identity of the study participant's after the data is gathered (Neuman, 2014:154). When there is no way to connect any personal identifying details with the actual participant in the survey, anonymity is guaranteed (Nardi, 2016:38). In conducting this research, this was precisely adhered to, no personal information about the respondent was requested, and the database from which the sample was selected only featured contact details, with no other personal information to maintain confidentiality. Confidentiality also needs to be emphasized when data identifying respondents may be related to their individual responses and is only disclosed to researchers for the project's key objectives. Both confidentiality and anonymity were maintained throughout the research, with the researcher striving for honesty and integrity throughout the research process.

According to Neuman, (2014:148), researchers can inadvertently place study participants in conditions that are embarrassing, cause nervousness, or cause them to feel uncomfortable. By its nature, this study does not cover research involving vulnerable people, and the researcher was sensitive in engaging participants at all times to take cognizance of any matter that may arise harming a respondent's self-esteem. To this end, permission was sought from the Humanities and Social Sciences Research Ethics Committee at the University of KwaZulu-Natal prior to conducting the pilot study and primary data collection. An approved application for ethical clearance with a system identity number 00002388/2021 was issued to the researcher. See appendix D for its details.

4.10 Conclusion

In this chapter, a detailed description of the research methodology applied in addressing the research questions and objectives was presented. The target population under investigation was clearly set out and identified as well as the relevant sample, sampling methodology and the inclusion and exclusion criteria. A post-positivist philosophical worldview was applied because of its appreciation for identifying and assessing causes that influence behaviour and outcomes. This is particularly key for the study as it aims to address factors that influence farmers willingness-to-pay for weather-based crop insurance. A quantitative research approach was used based on its strength for generalizing results to a wide population, which in this case is the maize farming sector in South Africa. The research instrument used to collect the required data was a structured questionnaire in the form of a survey. The questionnaire was pre-tested and reconfigured based on a pilot study. Due consideration was given to addressing the consideration of reliability and validity of research data. Data was collected through telephonic interviews which literature has shown yields the highest response rate. To further improve the response rate, an element of online questionnaires was included to give respondents a further option to participate in the research at a time most convenient for them. The study was underpinned by principles of ethical conduct and consideration of ethics throughout the data collection process.

The following chapter presents analysis and interpretation of the collected data using graphs, charts and tables, as well as making reference to literature to provide context to discussions and findings. Various statistical tests and techniques were also used to draw inferences from the data to respond to the research questions posed in this study.

CHAPTER FIVE: DATA ANALYSIS

5.1 Introduction

Chapter Five details the presentation and interpretation of empirical findings, as well as analysis of collected data to address the research problem and objectives set forth in Chapter One. As described by Neuman (2014:18) data interpretation includes producing charts, tables incorporating frequencies and percentages, and descriptive statistics in addition to inferential statistics, where the data is analyzed to determine the underlying meaning, using knowledge of the research topic, and drawing on the existing body of theory to best respond to the research objectives. This process considers alternative interpretations of the data, comparing results with those of past studies, government reports, and relevant stakeholders market reports to drawing out wider implications of findings. This chapter begins with a discussion of the finding of the pilot study, which served as a basis for refining the questionnaire. Thereafter, the socio-demographic profile of the respondents, as well as findings on socio-economic characteristics, are presented to aid in providing a complete description of the sample composition. The purpose of a descriptive profile is to introduce the research participants and to provide the contextual frame within which the overall research results are understood. Following that, an analysis of the socio-psychological constructs is presented with the results assessed for reliability using Cronbach's alpha and Composite reliability. The last section of the chapter presents the proposed structural model with the specification of a measurement model through CFA to test the research hypotheses in order to assess the significance of behavioural factors as predictors of low-income farmers' willingness-to-pay for weather- index insurance. For the purposes of developing a comprehensive conceptual framework as outlined in the main study objective, an integrated approach was followed, and a binary logistic regression was carried out to separately consider significant socio-demographic and socio-economic drivers that influence willingness-to-pay designed to gain an overall picture of the determinants of low-income farmers tactical decision making to mitigate weather-related risks through insurance. Prior to the logistic regression, a Chi-square statistical test was applied to all categorical variables identified in the literature review to test the association between each variable with willingness-to-pay intentions. Factors that had no significant relationship were effectively removed from the final logistic regression model to improve the predictive accuracy and power of the model.

5.2 Pilot Study Findings

According to Dillman, Smyth and Christian (2014:229), it becomes important to realize that a questionnaire cannot be viewed as a compilation of completely independent questions that have no effect on each other. Following the pilot study, the questionnaire was expanded into five sections instead of the initial three to allow for better categorization and grouping of questions according to themes or pillars that related to the same concepts, this helped to achieve better overall cohesion and flow of the questionnaire and subsequently increased the response time of participants. Although the questionnaire included more sections, it became more concise in terms of the number of questions asked as a direct result of the grouping of similar items. This is in line with the suggestion by Shkoler (2019:40) that the length of the questionnaire should be kept brief; the longer the survey, then the more implausible it is likely to become and data received will be likely to become progressively less accurate.

Further improvements that were made to the questionnaire are shown in Table 5.1 where the annual turnover range was reduced from the initial questionnaire in attempts to obtain more granular details on the income level of farmers as the previous scales were too broad on the basis of the lower levels of income farmers disclosed in the pilot study. Moreover, options insofar as responses to the extent of crop loss following a specific event were changed from descriptive options to more clearly defined percentage terms. As from initial responses, participants had difficulty in quantifying loss based on descriptive terms.

Table 5.1: Summary of amended sections of the questionnaire

Item	Pre-testing	Post-testing
What is your annual turnover from crop harvest?	Less than R500 000 R500 001 – 1 000 000 R1 000 001 – R2 000 000 R2000 001 – R3 000 000 More than R3 000 001	Less than R250 000 R250 001 – R500 000 R500 001 – R1 000 000 R1 000 0001 – R2 000 000 More than R2 000 001
How much of your maize crop do you lose when the following weather events occur?	Less than a quarter Half More than three quarters	Less than 25% 26% - 50% 51% - 75% More than 76%

5.3 Response Rate

The research instrument was fully completed by 224 participants from a sample population of 326, resulting in a 68.7% response rate. A response rate lower than 50% will usually lower the quality of the data obtained, especially if the individuals who responded are different in a material matter in terms of attitudinal views, social standing, demographic representation and so forth from those who opted not to participate in the study (Gliner, Morgan & Leech, 2017:140). This consideration is particularly relevant for this study, and good representation is required to analyze statistical differences, and to avoid bias so as to capture wide ranging participation especially in terms of participants' age, education and cutting across farm size, turnover and farming experience. According to Edmonds and Kennedy (2017:134), the quality of the response rate can directly affect the validity of research outcomes. As guidance, a response rate of 60% and above is considered appropriate and credible (Fincham, 2008:5) and an obtained sample of at least 200 participants is adequate for SEM analysis (Westland, 2015:54).

Published research in a similar field of index insurance reports comparable usable surveys of 200 in Adjabui, Tozer and Gray (2019:496); 208 in Ellis (2017:704) and 235 in Fonta et al. (2018:11). The number of responses received for this study exceeds 200, and the response rate is above the 60% threshold. Also, the received responses are comparable with that of similar research. Consequently, the response of 224, leading to a rate of 68.7% was considered sufficient for purposes of this research and adequate for data analysis and for the application of the relevant statistical methods.

5.4 Preliminary Data Analysis

Each question in the questionnaire was regarded as an item, and a set of items was regarded as a measure or a research construct (Shkoler, 2019:41). For each of the items in the questionnaire, data were coded to synthesize and reproduce responses effectively in numeric format for easier analysis. Data coding is the process of exploring the data for themes, concepts, and categories and then marking related passages of text with a code label, for example, encoding males as (1) and females as (2), so that they can easily be retrieved at a later stage for further evaluation and examination (Edmonds & Kennedy, 2017:325). Subsequent to coding, data cleaning was done to detect and delete incomplete data in order to ensure integrity, consistency and compatibility with the rest of the dataset. Gray (2017:331) advises that data cleaning is a key process before data analysis can commence, that is, checking for glaring errors. If, for example, a question has only two possible responses: Yes (1), or No (2), but if the data file contains the number 3, then clearly an error has been made and must be corrected.

5.5 Presentation of Results

The findings of the study are presented, analyzed and discussed in various subsections according to the order in which they appear in the questionnaire. Pie charts, bar graphs and frequency tables are used to provide a clear and synthetic description of the relevant data, with a narrative following each presentation. Where percentages are reported, the figures have been simplified and rounded off to the nearest whole number for ease of interpretation.

5.5.1 Socio-demographic profile

This section explains in-depth the demographic composition of the 224 usable surveys completed by farmers who participated in the study. The profile covers characteristics of gender, age, race, and marital status, size of household, education and access to conventional insurance.

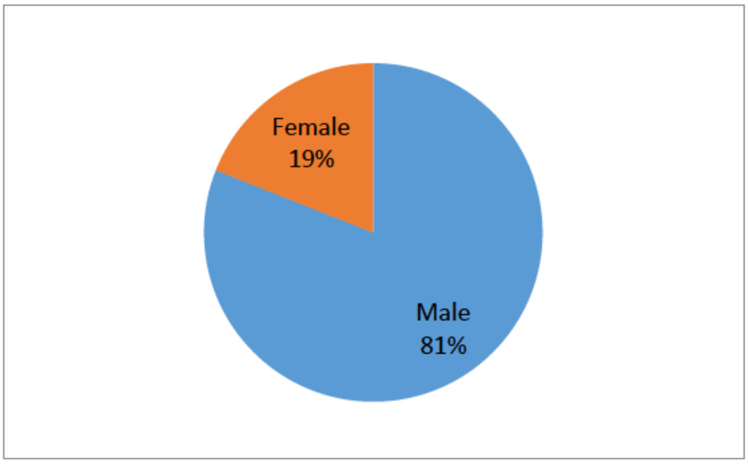


Figure 5.1: Gender of the study participants

Figure 5.1 illustrates the gender distribution of participants in the study, of the 224 respondents male participants feature prominently at 81% with female representation at 19%. The low participation of female respondents could be directly attributable to the historical marginalization of women in organized agriculture. Hart and Aliber (2012:2) feel that female farmers in South Africa differ in respect of household and cultural obligations and status from their male counterparts. This distinction tends to influence farming motivations where most women appear to engage in farming for household food provision with limited commercial orientation, therefore they would engage less with financial products. Female farmers interaction with agricultural financial services in this regard is also seemingly limited, as an illustration, in the 2018/19 financial year, the Land Bank loan disbursements for transformational and development purposes were R5,07 billion, of this, only R103 million which equates around 2% was disbursed to female farmers (Land Bank, 2019:56).

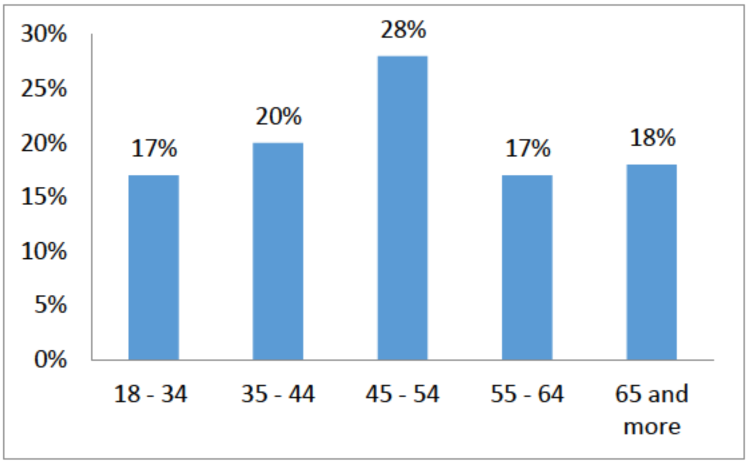


Figure 5.2: Age of the study participants

The participants were classified into five age groups, as illustrated in Figure 5.2. Most participants (28%) were between the ages of 45 and 54 years. This is consistent with the 2016 agricultural household survey undertaken by Statistics South Africa, which found that the majority of heads of agricultural household were between 45 and 54 years of age (Stats SA, 2016:3). The second highest class in this study was farmers between 35 to 44 years, comprising 20%, farmers over the age of 65 amounted to 18%, and lastly, youth participants between 18 to 34 years and 55 – 64 years were represented at 17% per age band.

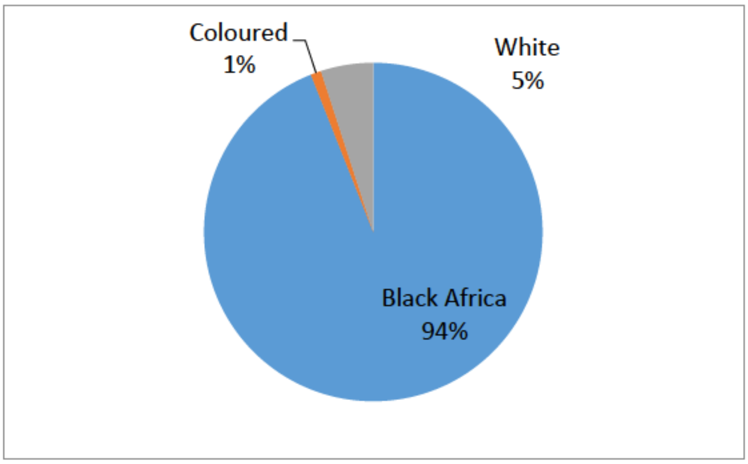


Figure 5.3: Racial population groups

Most small-scale farmers in South Africa are Black African. They farm on less arable land and produce marginal tons per hectare. Whilst the position of Black farmers compared to White farmers continues to be an open question in the new democratic dispensation, the government has remained relatively unsuccessful in improving the economic fortunes of Black farmers compared to White industrial farmers (Sebola, 2018:2). As such, adoption of new technologies and uptake of financial products is generally low among Black farmers. The analysis of the data in Figure 5.3 shows that 94% of participants in the study were Black African; 5% were White, and 1% of the respondents were Coloured.

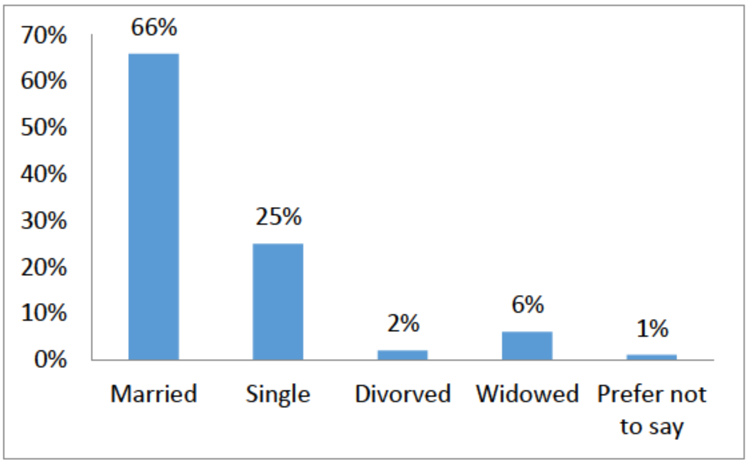


Figure 5.4: Marital status of the study participants

Figure 5.4 reports on the sample spread according to their marital status. In the main, around two thirds (66%) of the survey constituted members who were married, followed by 25% who were single, 6% were widowed, 2% were divorced, with the remaining few preferring not to disclose their marital status.

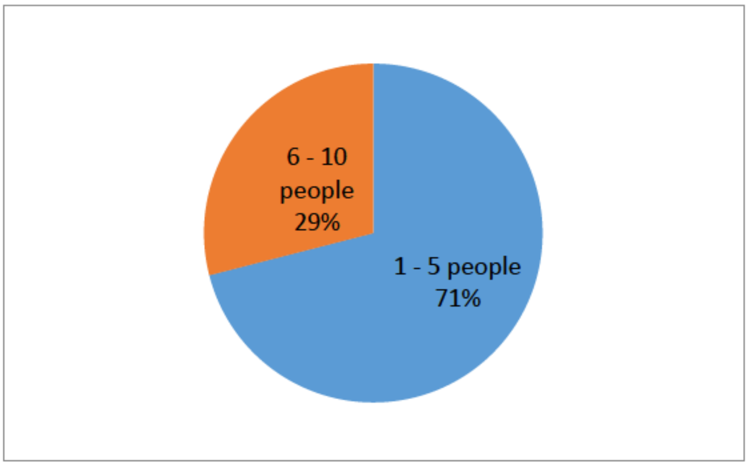


Figure 5.5: Household size

The national average household size in South Africa is 3 persons. The same statistics further reveal that a larger family exerts pressure on household level food security (Stats SA, 2019:18). This is likely to impact on future purchasing decisions as a larger household may be influenced by the individual needs of various household members as well as the overall well-being of the household as a unit. Consistent with national statistics, the results mentioned in Figure 5.5 demonstrate that a 71% majority of sampled farmers have 1 – 5 persons in their household, the remaining 29% represented households with between 6 – 10 members. No farmer reported their household as having more than 10 live-in members.

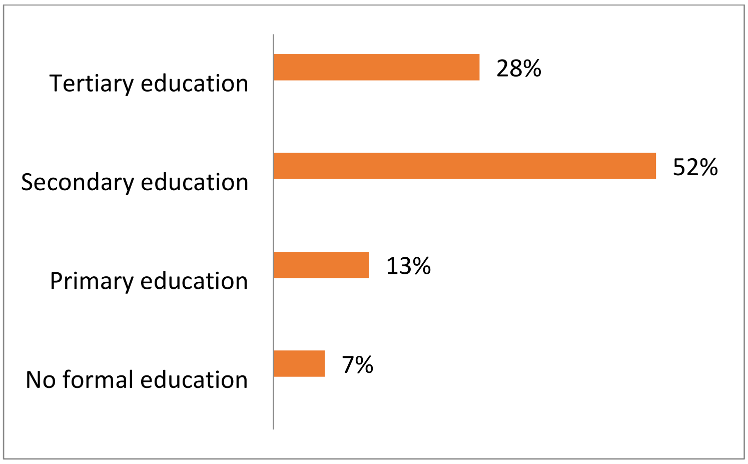


Figure 5.6: Education of the study participants

The participant's highest level of education is shown in Figure 5.6. A little over half (52%) of respondents had secondary education, followed by 28% with tertiary education. Based on a household agricultural survey by Statistics South Africa, the percentage of farmers with tertiary level education was 9% (Stats SA, 2016:4). The surveyed sample in this study showed a higher percentage supporting the predisposition that farmers with a higher level of education are likely to interact more with financial services and are likely to be recipients of government support. Participants with primary education were 13%, and those with no formal education represented 7% of the sample.

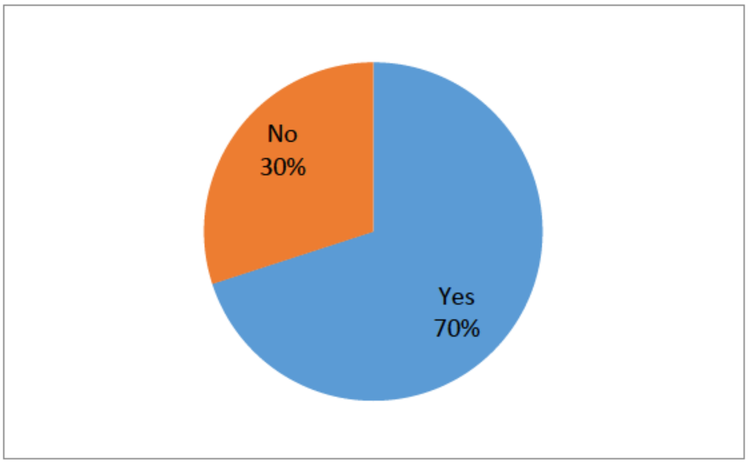


Figure 5.7: Usage of insurance by the study participants

Statistics from the 2018 FinScope Consumer Survey shed light on the application rate for insurance in South Africa, revealing that 61% of adults have at least one insurance policy. The bulk of these policies are in the form of funeral cover (Finmark Trust, 2018:3). According to Figure 5.7 the results of this study are consistent with the aforementioned consumer survey as indicated by 70% of farmers who own at least one insurance policy and the remaining 30% of farmers reporting that they are uninsured.

5.5.2 Socio-economic profile

The aim of this section is to understand the farmer's socio-economic profile as it pertains to farming activities insofar as experience, land access, turnover, and access to credit is concerned in order to assess a broad spectrum of factors that may influence index insurance purchase decisions.

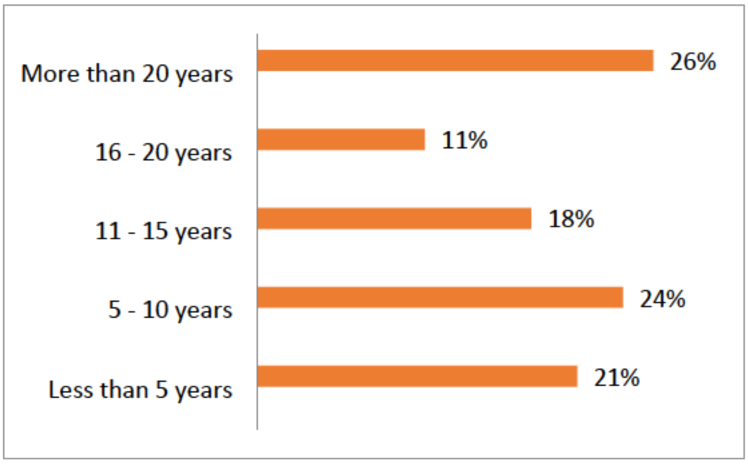


Figure 5.8: Experience of the study participants

The number of years in farming is well represented across the different experience levels, with a majority of farmers having a wealth of experience in agriculture. From a granular level, the experience is represented as follows: 26% of farmers had more than 20 years farming experience, 24% had between 5 – 10 years, 21% were fairly new participants with less than 5 years' experience, 18% had 11 – 15 years' experience, and lastly 11% of farmers had experience of between 16 – 20 years. The results are presented in Figure 5.8. In summarizing the presentation, at an aggregate level, 55% of individual farmers had more than 10 years' experience, while 45% had less than 10 years of farming experience.

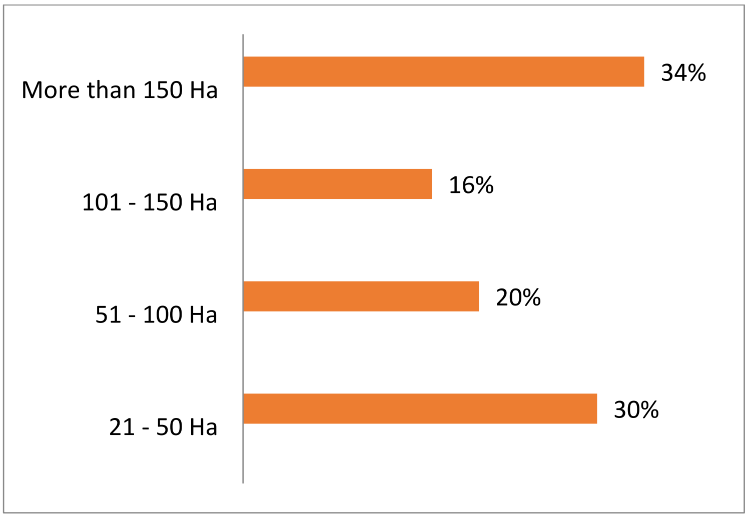


Figure 5.9: Hectares cultivated by study participants

Maize is the main cultivar and the largest produced field crop in South Africa (GCIS, 2019:10). The crop plays a central role in the livelihood strategy of most low-income farmers (Sitko, Chamberlin, Cunguara, Muyanga & Mangisoni, 2017:243) and requires mass production to achieve economies of scale that yield meaningful financial returns. From the study sample, as depicted in Figure 5.9 a little over one third (34%) of farmers produced maize on more than 150 hectares. Compared to the classic definition of small-scale farming, this is considered large. The context of this extensive agricultural holdings is that South Africa classifies over 70 per cent of its land as agricultural (Finmark Trust, 2016:76), meaning that agriculture is given space and opportunity to thrive on dedicated lands.

In comparison, other studies report landholdings of low-income farmers to be less than 5 hectares in Ethiopia (Ahmed, McIntosh & Sarris 2017:14) and Burkina Faso (Fonta et al., 2018:11). Average land size for smallholder farmers South Africa is particularly large compared to the rest of Africa where farm sizes are typically less than 2 hectares (FAO, 2015:5).

The remaining two thirds of agricultural land under cultivation is accounted for as follows: 30% of farmers planted between 21 – 50 hectares, 20% were between 51 – 100 hectares, while 16% planted lands of between 101 and 150 hectares. At an aggregate level, there was an even split of farmers who produce on more than 100 hectares and the other half below 100 hectares.

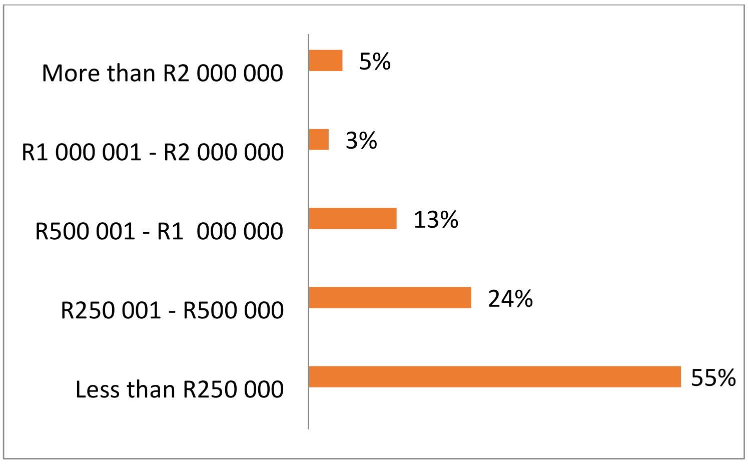


Figure 5.10: Turnover of the study participants

Low agricultural output and productivity due to climate change and variability affect revenue, creating a chronic cycle of low income. The average data in Figure 5.10 shows that most low-income farmers (55%) generated an annual turnover of less than R250 000 per annum, followed by 24% with between R250 001 – R500 000, 13% of farmers generated revenue of between R500 001 – R1 000 000 and 5% made more than R2 000 000 per year. Very few farmers (3%) indicated that they generated an annual turnover of R1 000 000 – R2 000 000. In summary, collectively nearly three fourths (74%) of low-income farmers generated revenue of R500 000 or less.

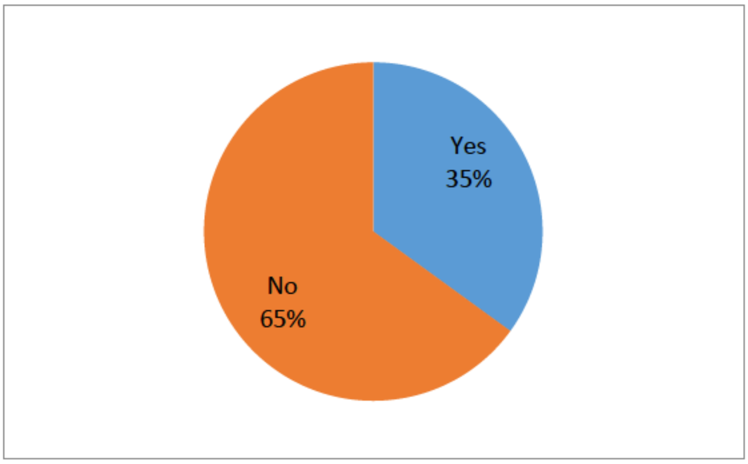


Figure 5.11: Access to credit by the study participants

Sebola (2018:5) sharply points to the fact that loan funding is difficult to access for low-income farmers. Figure 5.11 demonstrates that from the sample participants, 65% of farmers did not receive any production loans over the last 5 years, and 35% received credit to support production.

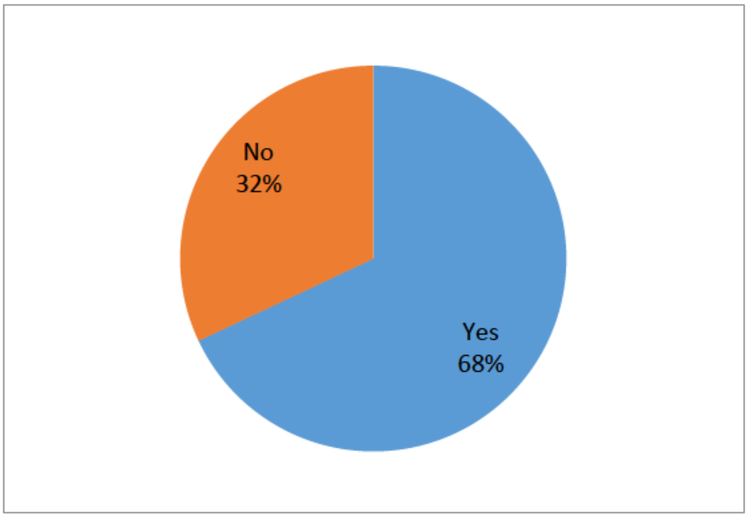


Figure 5.12: Group membership of the study participants

South Africa has a vast network of farmers associations representing a diverse group of farmers with the objectives of promoting stability and sustainability in agriculture. These associations, to name a prominent few, include Agri SA with over 28 000 members, Grain SA which provides strategic commodity support, and AFASA a united body of African farmers organized to influence agricultural policies (GCIS, 2020:7). Figure 5.12 describes 68% of farmers as members of a farming association or group and 32% as having no membership affiliation. As demonstrated in the literature review, belonging to a professional body has been found to be a perfect way to disseminate information within farming communities.

5.5.3 Farm-level risk analysis

Decision making in agriculture is complex, farming decisions throughout the production value chain are risk-laden from crop and cultivar selection, the period of planting, implementation technologies, levels of inputs to apply, plant density to even the time to harvest, and lastly they have to contend with weather issues (Domingo et al., 2015:2). Weather-related risks and their impact on farm operations as a whole are considered in this sub-section, alongside with the preferred coping strategies adopted by farmers. This is to obtain an additional understanding of the environment that farmers have to navigate and how these obstacles shape perceptions of agricultural insurance and decision making.

Table 5.2: Primary weather-related risk

Peril	Frequency	Percentage
Drought	157	70%
Low rainfall	51	23%
Hail	12	5%
High rainfall	4	2%
	224	100%

According to the World Bank (2016:9) among southern African countries, South Africa has the highest drought-affected population, estimated at more than 14 million people (25 per cent of the total population). In addition, smallholder farmers perceive high levels of drought vulnerability as threatening to their farming operations (Bahta, Jordaan & Muyambo, 2016:47). Consistent with the World Bank report, the sampled population in this study shows that 7 in 10 farmers (70%) indicated drought as the biggest source of risk affecting their livelihoods. Low rainfall which is a drought-related trait followed at 23%, with hail and high rainfall representing the remaining sources of risk at 5% and 2% respectively.

Studies show that the lower the perceived frequency of drought, the lower the likelihood of participating and purchasing index insurance. This confirms farmers' awareness and rationality in purchase decisions (Castellani, Vigano & Tamre, 2014:1683). Other scholars such as Njue, Kirimi and Mathenge (2018:10) indicate contradictory results, low-income farmers that experience drought risks have a negative outlook towards purchases of weather index insurance contracts. The result shows that even when a farmer realizes repetitive crop loss due to drought, they are less likely to take-up the cover. A plausible explanation for this finding is that repetitive shocks may prompt a household to devise other informal mechanisms to cope with weather-related hazards. Or repetitive shocks severely constrain liquidity so much that farmers no longer have the resources to afford the premiums (Adjabui, Tozer & Gray 2019:502).

Table 5.3: Percentage of crop loss following the occurrence of weather risk event

Crop Loss	Frequency	Percentage
Less than 25%	37	16%
26% - 50%	103	46%
51% - 75%	58	26%
More than 75%	26	12%
	224	100%

In the appraisal process of crop loss, a majority 46% of study participants reported losses of between 26% - 50% of their crop production consequent to the occurrence of their identified source of weather risk, this is followed by 26% of farmers who reported crop losses of between 51% - 75%, 16% of farmers reported losses of less than 25% while 12% indicated that their estimated crop losses exceed 75% per crop cycle. At an aggregate level, it is calculated that 38% of farmers lost more than half of everything that they plant in a single season. This reported loss is from a harvest perspective; however, there are other related monitory losses in respect of seed inputs, and fertilizer, pesticide, labour hours, machine hours and associated fuel costs that are not estimated as part of this analysis.

The results provide a glimpse of the unaccounted-for loss of income, and resources and brings into sharp focus the negative impact of mainly drought on small-scale farmers. Income from crop farming is a function of commodity price and yield, which have an inverse relationship with each other. When aggregate production of a commodity increases, mostly due to favourable weather, market prices tend to decrease due to excess supply, and when yields reduce, prices generally rise indicative of demand forces. This offsetting nature of price and production impacts has a somewhat mitigating impact on farmers' revenue (Gulati, Terway & Hussain, 2018:3). However, with losses in excess of 50% of crop value, the mitigating impact of price and yield relationship often fall short of compensating for crop losses of low-income farmers or at least to restore the farmer to parity. Low insurance coverage in the face of historical patterns of crop losses is not a phenomenon new to South Africa, for India's two main food crops, rice and wheat, insurance coverage is less than 5%, even though farmers record substantial crop losses of more than 25% (Aditya, Khan & Kishore, 2018:166).

Table 5.4: State of preparedness for weather risk event

Level of Preparedness	Frequency	Percentage
Prepared	37	16%
Somewhat prepared	38	17%
Neutral	39	17%
Somewhat unprepared	10	5%
Not prepared	100	45%
	224	100%

With respect to the level of preparedness in managing weather-related risk, a 50% majority of farmers indicated that they are not prepared (45% not prepared and 5% somewhat unprepared), 17% could not make a judgement, and 33% were prepared (16% prepared and 17% somewhat prepared). The high level of unpreparedness is in line with the existing theory that low-income farmers require effective financial instruments to reduce climate risk. A high number of farmers could not judge whether they were prepared or not; this speaks to the uncertainly of the current risk mitigating strategies and the effectiveness thereof.

According to Ncube and Shikwambana (2018:6) the extent to which a population could be impacted by drought risk is primarily dependent on availability of pre-drought planning scenarios both from an individual and government perspective, adequacy of response or coping strategies, and the farmer's degree of vulnerability. With respect to introducing new risk mitigating tools and plans, a study in semi-arid Namibia found that adaptation of new risk mitigating practices despite their value proposition might not be easy to introduce. The authors point to hesitance and reluctance on the part of farmers that created barriers to changing farming practices. Most farmers in that study mentioned that they would continue applying tried and tested methods, citing tradition as the main reason for not deviating to available alternatives. At the heart of these traditions is the firm belief that current approaches were the best and only way despite evidence demonstrating a progressive reduction in crop yields (Spear & Chappel, 2018:5). Holding steadfast to this set of beliefs clearly results in ambiguity in decision making. This study's research results underscore the level of ambiguity, which can be seen in 33% of farmers confirming that they are adequately prepared to manage weather risk. But 84% of the same respondents indicate losing more than 25% of their crops due to weather hazards (Table 5.3).

Kruskal-Wallis H test was conducted to examine the difference in characteristics of those that are prepared and those that are not prepared according to the extent of crop losses. Statistically significant differences (chi-square = 12.686, df (3), p=0.006) were found among the four categories of crop loss. The class with the lowest levels of preparedness in terms of crop losses is between 51% - 75% (median = 4) and crop losses in excess of 75% (median = 4).

Table 5.5: Primary coping strategy for reducing crop loss

Risk coping strategy	Gender		Risk coping strategy	
	Male	Female	Frequency	Percentage
I plant less in times of uncertainty	57	15	72	32%
I shift crop planting dates	35	10	45	20%
I diversify crops	25	3	28	13%
I rely on government support	17	6	23	10%
I use crop insurance	19	0	19	9%
I focus on off-farm income	11	1	12	5%
I utilize my savings	8	4	12	5%
I apply for loans or credit to help recover	5	2	7	3%
I rely on irrigation	4	2	6	3%
	181	43	224	100%

Most farmers (32%) opt for reducing production and planting less hectares as an effective response strategy. This is in agreement with the classic agrarian economic theory of reducing production in times of uncertainty. A further 20% of farmers change crop planting dates in attempts to find the most optimum window to navigate the particular season's challenges, 13% opt for crop diversification to minimize the impact of future losses, 10% seek government assistance following weather-related losses, 9% of farmers use crop insurance as a mitigating strategy. The remaining representation of risk coping strategies is: off-farm income (5%), utilization of savings (5%), applying for credit (3%), and irrigation (3%) in particular against drought risk.

In their study to identify farmer risk management strategies in Mpumalanga, South Africa, Mokhaukhau, Hlongwane, Chaminuka, Mayekiso, and Cholo (2020:49) find that only a small percentage of small-scale farmers have no risk management strategy in place, 87% are adopters, and 13% are non-adopters, which is contrary to this study where all sampled farmers deployed at least one strategy for crop risk management. A systematic literature review on risk management strategies covering 197 studies shows crop diversification as the main mitigating strategy employed by farmers (Duong, Brewer, Luck & Zander, 2019:6). In this study diversification is the third most considered strategy, with the reduction in crop production the leading approach, this points to risk aversion of South African farmers - a low risk-low return strategy is consistent with the classical response to uncertainly by risk averse individuals (Sulewski et al., 2020:15). In addition, high demand for insurance in indicative of high levels of risk aversion (Jusufovic, 2016:22).

Few studies have investigated socio-economic factors that influence risk perceptions among farmers (Duong et al., 2019:10). The use of crop insurance was a modest 9% considering that 50% of farmers are not prepared to contend with weather risk, and a further 84% of farmers are losing more than 25% of their crops to unfavourable weather conditions. Interestingly, further analysis of the study data reveals that all the farmers who use crop insurance are male. The most preferred coping strategy among females points to utilizing of savings. This is a cause for concern as savings alone have been found to be ineffective in smoothing consumption and minimizing catastrophic risk. About 10% of farmers rely on government assistance for relief following crop loss, a strategy used more by men than women. Singh and Agrawal (2020:472) warn that this kind of dependency can undermine intentions to develop effective insurance markets, as was the case for a weather index scheme in India.

5.5.4 Cross-tabulation of results

This section features cross-tabulation and analysis of some of the results that may have a bearing on the overall research emanating from the socio-demographic and socio-economic profiles, presented with the Chi-square test. The Chi-square test has two critical coefficients, namely the Pearson Chi-square test and Cramer's V test. Pearson Chi-square is the test of the associations while Cramer's V measures the strength of association on a range of values, where values below 0.10 indicate a weak relationship, values between 0. 10 to 0.30 indicate moderate relationship while the value above 0.30 indicate a strong relationship between the variables.

Table 5.6: Cross-tabulation between education and insurance application

Qualifications	Do you have any form of insurance?		Frequency	Percentage of the sample with insurance
	Yes	No		
No formal qualification	5	10	15	33%
Primary education	13	16	29	45%
Secondary education	87	31	118	74%
Tertiary education	52	10	62	84%
	157	67	224	70%

Table 5.6 highlights that insurance usage is most prevalent among those with tertiary education and least prevalent among those with no formal education. A Pearson Chi-Square test =24.857 (df:3), p =0.000), brings to light that there is a statistically significant association between education and general insurance application. The measure of the association as determined using Phil and Cramer's V of 0.333 which shows a strong association between the variables.

Table 5.7: Cross-tabulation between group membership and gender

		Membership in a farming association		Frequency	Percentage of the sample with membership
		Yes	No		
Gender	Male	139	42	181	77%
	Female	14	29	43	33%
		153	71	224	68%

Table 5.7 highlights that 77% of male farmers are affiliates of a farming cooperative or association when compared to 33% of female farmers that do not participate in organized agriculture to the same extent. A Pearson Chi-Square test =0.018 (df:1), p =0.893), brings to light that there is a non-statistically significant association between group membership and gender. The measure of the association as determined using Phil and Cramer's V of 0.09 shows a weak association between the variables.

5.5.5 Socio-psychological profile

The socio-psychological profile assesses constructs of insurance culture, financial capability and risk perception on a five-point Likert scale questionnaire, where the scale ranged from 1 = strongly agree to 5 = strongly disagree, indicating the extent to which they agreed with a set of behavioural statements. These statements were worded and modified to suit this study following (Ajzen, 2006; 2020) recommendation on constructing a TPB questionnaire and guidance from other studies applying TPB for insurance purchase decisions (Brahmana, Brahmana & Memarista, 2018:52; Weedige, Ouyang, Gao & Liu, 2019:20). In the interpretation of responses, the strongly agree and agree percentages were aggregated and displayed in a frequency distribution column for ease of interpretation of responses. Prior to the assessment, descriptive statistics were presented, subsequently, the scales were tested for normality, correlation as well as reliability and internal consistency, with the results is presented in the next section.

5.5.5.1 Descriptive statistics

The summary measures of the mean, standard deviation, skewness and kurtosis were computed to reflect the central tendency, dispersion of variability, overall shape and tails of the distribution of the Likert scale responses. From the structuring of the five-point Likert scale, a lower mean is associated with a higher degree of agreement, and a higher standard deviation was indicating a larger degree of dispersion in responses to items in the construct. Schrum, Johnson, Ghuy and Gombolay (2020:7) advise that the median is the most appropriate descriptive metric for Likert scale item results because of the ordinal nature of the data. The median is defined as the middle most observation if data is ordered either in ascending or descending order of magnitude (Mishra et al., 2019:68). The results as presented in Table 5.8, report a median of 2 for both insurance culture and risk perception translating to a positive leaning towards the indicators that support these construct; and a median of 3 for financial capability with is indicative of a more neutral response.

Table 5.8: Descriptive statistics

Construct	Median	Mean	Standard deviation	Skewness	Kurtosis
Insurance culture	2	2.42	0.94	0.58	-0,11
Financial capability	3	3.01	1.02	0.00	-0.99
Risk perception	2	2.10	0.76	0.65	0.31

Measures of skewness and kurtosis are used to determine if variables in a dataset have met assumptions of normality. Skewness refers to the symmetry of a distribution of a variable, or more precisely, the lack of symmetry of the normal distribution. Kurtosis refers to the flatness or peakedness of a distribution. A normal distribution has skewness and of 0 and a kurtosis of

3. Any significant deviations from these values indicate that assumptions of normality have been violated (Islam, 2019:1). Traditionally, skewness is the key criterion for the determination of normality in Likert scale data (Schrum et al., 2020:5). In this regard, a skewness range of between -1 to +1 is a guide for acceptable normality (Mishra et al., 2019:70). A positive skew value shows that the tail on the right side of the distribution is longer than the left side and that most of the values lie to the left of the mean, while a negative skew value indicates the opposite (Albers, 2017:68). Skewness values reported in the dataset range from 0.00 – 0.65. On this basis, the data meets the criteria of normality, and parametric procedures may be applied which as indicated in the previous chapter are more robust and likely to yield unbiased results than non-parametric tests (Sullivan & Artino, 2013:542). After computing the descriptive statistics, the relationships between the constructs were assessed, as outlined in the following section.

5.5.5.2 Correlation and multicollinearity analysis

Numerous statistical tests used for data analysis make assumptions about the normality of distribution, including correlation analysis (Mishra et al., 2019:70). The Pearson product-moment correlation coefficient, which is a measure of the strength of relationship or association between two variables, is typically used for normally distributed data. Correlation relationship simply says that two factors move in a synchronized manner, where a change on one variable is reflected in the other (Albers, 2017:55). Prior to conducting SEM section of the analysis, Pearson's correlation coefficients were determined for the behavioural constructs. The correlation coefficient as outlined in Table 5.9, indicates that there are weak to moderate statistically significant positive correlations between the socio-psychological constructs, specifically, weak correlation of 0.30 between insurance culture and financial capability, moderate correlation of 0.38 between insurance culture and risk perception, lastly, moderate correlation of 0.41 between financial capacity and risk perception. According to Ajzen (2020:319) these results are in line with other empirical studies using TPB, where correlations of low to moderate significance are usually observed.

Table 5.9: Correlation analysis of behavioural constructs

		Insurance culture	**Financial capacity**	**Risk perception**
Insurance culture	Pearson Correlation	1.00	0.30**	0.38**
	Sig. (2-tailed)		0.00	0.00
	N	224	224	224
Financial capability	Pearson Correlation	0.30**	1.00	0.41**
	Sig. (2-tailed)	0.00		0.00
	N	224	224	224
Risk perception	Pearson Correlation	0.38**	0.41**	1.00
	Sig. (2-tailed)	0.00	0.00	
	N	224	224	224

** Correlation is significant at the 0.01 level (2-tailed)

Daoud (2017:5) highlights that if correlation coefficients among latent constructs are large, meaning highly correlated, this could signal potential problems of multicollinearity, which is a serious issue that should be resolved prior to applying inferential statistical tests. The author lists the main concern resulting from multicollinearity as: increased standard errors of the estimated parameters of regression coefficients, which could result in wider confidence intervals and some variables being statistically insignificant when they should be significant thereby distorting research output. Yoo, Mayberry, Bae, Singh, He and Lillard (2014:9) cite literature from various scholars and provide a summation of the effects of multicollinearity as: inaccurate estimates of regression coefficients with incorrect signs and an improbable magnitude for some explanatory variables, in addition to increased redundant results, which means that what a predictor variable explains about the outcome coincides with what another predictor or a set of explanatory variables elucidates. As a rule of thumb, the authors provide guidelines that high inter-correlation between variables is a range from 0.7 to 0.9. There are no multicollinearity problems in this study as the highest correlation coefficient reported was 0.41 between financial capability and risk perception. On the basis of the low correlation structure and no existence of multicollinearity between constructs, all the predictor variables can be included in the measurement model when conducting SEM analysis.

5.5.5.3 Internal consistency reliability assessment

A poorly formed scale may result in data that does not assess the intended study hypothesis. Thus, before any inferential statistical tests are applied to a Likert scale, it is best practice to test the quality and reliability of scales adopted for research (Schrum et al., 2020:4). Scale reliability was assessed using Cronbach alpha and tested on the three socio-psychological constructs adopted to test willingness-to-pay. The common rule of thumb is that a scale with a value of Cronbach's alpha above 0.7 demonstrates acceptable internal consistency, though the closer to 1.0 this value is, the better. Cronbach's alpha below 0.7 is cause for concern, indicating that at least one of the items is adversely affecting the scale's reliability (Hinton & Platt, 2019:72).

Table 5.10: Scale reliability and validity statistics

Construct	No. of Items	Mean	Cronbach's Alpha Coefficient
Insurance culture	3	2.42	0.81
Financial capability	3	3.01	0.84
Risk perception	4	2.10	0.74
Overall Cronbach Alpha	10	2.47	0.83

Insurance culture calculated a Cronbach alpha of 0.81, the financial capability was 0.84, and risk perception 0.74. The aggregate alpha yielded a result of 0.83. This result indicates that the scales are reliable according to the measurement criteria, reporting satisfactory coefficient alpha values.

5.5.5.4 Analysis of behavioural responses

This section offers an analysis of responses from the five-point Likert scale section of the questionnaire. Likert scales should not only be checked for internal consistency, but unidimensionality as well to ensure their reliability and validity (Schrum et al., 2020:8). Items in a scale are often derived from the definition of the construct they intend to measure. This logical method of developing measurement items is meant to ensure that all items truly capture the construct. As a consequence, measurement items or indicators belonging together in a scale are believed to capture differences in the same underlying construct; this is unidimensionality (Ziegler & Hagemann, 2015:231). Exploratory factor analysis is typically used to test whether or not a set of items measure the same attribute. For this reason, the latent factor loadings are presented for all the items on the scale that measures the relevant construct alongside the aggregate response to each indicator. Higher values of this factor would depict that the item satisfactorily measures the construct it intends to measure.

Table 5.11: Insurance culture among the study participants

Insurance culture n = 224	Frequency Distribution						Descriptive		Latent Factor
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Strongly Agree/Ag	Mean	Std Dev	
I have a good understanding of how crop insurance works	22%	46%	13%	16%	3%	68%	2.32	1.07	0.84
I have considered using crop insurance to protect my assets or income	26%	45%	11%	14%	4%	71%	2.24	1.10	0.91
I understand that paying for insurance does not guarantee a payout	12%	42%	18%	22%	6%	54%	2.69	1.12	0.81
Cronbach's Alpha							0.81		

Cultural factors exert a profound and broad influence on consumer behaviour (Langat, Naibei & Getare 2017:703). A majority of low-income farmers (68%) claimed to have a good understanding of agricultural crop insurance which is currently commercially available. It was important to test the knowledge base of crop insurance in order to obtain an understanding of how respondents react to and understand the insurance. This provides a good foundation for further questions in the study where the novel alternative is presented, as it means a majority of participants can draw a comparison between the two products, which will allow them to gauge the alternative effectively. Responses to the second indicator of insurance culture show that 71% of farmers responded that they have considered using insurance to protect their crops. Responses to the first two statements indicate favourable orientation towards crop insurance, to the extent that even farmers with little understanding, have considered using the crop insurance demonstrated by the 3% differential between understanding (68%) and possible consideration of using crop insurance (71%). The last measure shows that a lower 54% of farmers indicated an understanding that payment for crop insurance premiums does not guarantee that there will be a claim pay-out. The low level of agreement to this statement is indicative of the perception that insurance has long been viewed as a grudge purchase and in the purchase consideration, consumers strongly weigh the probability of a payment as a measure of effectiveness. Based on the latent factor analysis, consideration for crop insurance use (0.91) holds the most significance in the domain of insurance culture.

Table 5.12: Financial capability of the study participants

Financial capability n = 224	Frequency Distribution						Descriptive		Latent Factor (Principal
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Strongly Agree/Ag	Mean	Std Dev	
I have access to emergency savings	7%	28%	14%	33%	19%	35%	3.29	1.25	0.92
I have sufficient funds to carry on my farming operations for the next year	5%	28%	16%	32%	19%	33%	3.33	1.20	0.93
I manage farm income and expenditure according to a planned budget	19%	43%	20%	15%	3%	62%	2.39	1.04	0.76
Cronbach's Alpha							0.84		

In measuring financial capability, only 35% of farmers indicated that they have access to emergency savings to support farming operations. According to Mbonane and Makhura (2018:7) only farmers with adequate savings have a strong preference for crop insurance and are likely to purchase the product. Another aspect of financial capability is availability of future working capital, only 33% of farmers attested to having sufficient funds to continue successful crop production next season. The first two indicators paint a bleak picture of farmer's resilience, in terms of adequate resources to continue sustainable crop production. A 62% majority of farmers indicated that they plan and actively manage their farm budget, demonstrating that the analysis provided in the first two items is on the basis of an informed analysis of the current status of their farming enterprise. Most of the farmers in the study engage financiers for purposes of capital raising, consistent with their engagements; one of the key required information is budgets and financial statements. The latent factor analysis explains which financial capability consideration are most significant for low-income farmers. Participants place significance on the ability to continue production in the future (0.93) and access to savings to respond to unforeseen events (0.92).

Table 5.13: Risk perception of the study participants

Risk perception n = 224	Frequency Distribution						Descriptive		Latent Factor
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Strongly Agree/Ag	Mean	Std Dev	
I make planting decisions based on available weather reports	29%	45%	12%	11%	4%	74%	2.17	1.07	0.86
I am careful when planning for the next crop cycle to reduce risk of low yield	33%	48%	11%	7%	1%	81%	1.95	0.89	0.91
I am more cautious because of previous crop loss experience	36%	46%	12%	6%	0%	82%	1,88	0.84	0.79
Compared to other farmer, I would say I take more risks	31%	23%	27%	14%	5%	54%	2,41	1,21	0.49
Cronbach's Alpha							0.74		

The farmers' risk preferences were assessed based on their responses to two sets of practical statements involving certain and risky farm practices as well as their own risk self-assessment. Sulewski et al. (2020:15) find that farmers attitude towards risk is strongly linked with their own risk assessment regarding the processes they follow in farm management. Most low-income farmers (74%) determined their planting dates according to weather forecasts in order to optimize production or minimize production given the prevailing conditions. 81% confirmed that they are careful and meticulous when planning for the next production cycle. Crop production is an intricate endeavour, and the farmer assumes multiple roles in this process which entails careful land preparation processes, soil conservation through leaving the fields fallow for a period of time to replenish nutrients, and crop rotation to avoid the development of pests and diseases as well as to improve soil fertility, all those aspects are critical in a normal production cycle. In assessing risk perception, historic crop loss contributed to farmers being more cautious as represented by 82% positive affirmation to the posed statement. A lower 54% indicated that compared to other farmers, they take more risk. Addressing the fact that farming in itself is a risky endeavour and the farmers themselves evaluate their level of risk-taking to be at a higher level than their counterparts. Based on the latent factor analysis, careful planning for the planting cycle (0.91) holds the most significance in the domain of risk perception. In contrast, the farmer’s comparison of their risk attitudes holds the lowest factor loading (0.49) and is indicative of a potential misfit of the item in measuring risk perception.

5.5.6 Willingness-to-pay analysis

The secondary research objectives of the study were to investigate low-income farmers’ willingness-to-pay for index insurance, and the price range they were willing to pay. The purpose of price range determination was to assess if major difference are present between the farmer’s valuation of insurance, captured by their self-reported willingness-to-pay, and the cost of insurance established on the basis of the empirical literature review. In this subsection, results are presented on willingness-to-pay according to the starting point premium as derived on the basis of the literature review and ranges based on the contingent valuation method.

Table 5.14: Willingness-to-pay by the study participants

WTP	5%		10%		2.5%		Aggregate WTP	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Yes	175	78%	77	44%	17	35%	192	86%
No	49	22%	98	56%	32	65%	32	14%
Total	224	100%	175	100%	49	100%	224	100%

Recent drought conditions in South Africa have heightened the focus on agricultural insurance as a potential intervention (World Bank, 2016:9). It was, therefore, no surprise that 86% of farmers are willing to pay for insurance to mitigate and reduce effects of weather-related risk on their livelihood, 78% of farmers indicated that they are willing to pay a 5% insurance premium based on their crop output, from this number a further 44% indicated that they would be willing to pay as much as 10%. Of the farmers that were not willing to pay the initial bid of 5%, 17 farmers indicated that a 2.5% premium would be more affordable, bringing the aggregate willingness-to-pay to 86% which was derived as follows: (175 + 17) / 224. These results are similar to a study in Kenya, where 84% of farmers indicated a willingness to take up weather index-based crop insurance for their maize production (Musya & Muttai, 2020:18).

5.5.6.1 Mean willingness-to-pay

One of the major problems government face in supporting agricultural insurance is setting optimum premiums which will encourage farmer participation in insurance schemes (Aditya, Khan & Kishore, 2018:13). In considering the optimum amount, Sadik-Rozsnyai (2016:571) cites (Dost & Wilken, 2012) in emphasizing that recent research conceptualizes willingness-to-pay as a range rather than as a single point. To this end, the secondary research objective of the study was to determine the price range low-income farmers are willing to pay for wealth--index insurance. On the basis of the contingent valuation approach, the starting bid price was set as 5% using the literature review as a base, and a price range of between 2.5% - 10% was established as derived from farmers' responses to the starting bid (section 4.6.2). A weighted mean was calculated to establish the average price respondents were willing to pay based on the number of affirmative responses. The weighted mean was determined as: Σwx/Σw; where: w = the weights; and x = the value.

Table 5.15: Weighted mean willingness-to-pay

Bid Price (w)	**No of farmers that responded "Yes" (x)**	**Σwx**
2.5 per cent	17	0.43
5 per cent	98	4.90
10 per cent	77	7.70
	192	**13.03**
Weighted Average WTP (13.03/192)		**6.8%**

The calculation featured in Table 5.15 shows that on average farmers were willing to pay 6.8% of their turnover as insurance premium. This is marginally higher than the average of 6.3% as collected from various studies researched in section 3.4 of the literature review. The high consistency of results is suggestive of smallholder farmer's appraisal of insurance across various settings. Evidence shows that the more premium increases, the less attractive the insurance will be for low-income farmers (Ellis, 2017:718). Therefore, at the higher end of the willingness-to-pay scale, it can be reasonably concluded that those farmers that are willing to pay 10% or more for insurance can be classified as risk seeking. Risk seeking farmers spend significantly more on fertilizer and improved seeds (Sibiko & Qaim, 2017:18), and are also expected to pay more for insurance.

5.5.6.2 Reasons for non-participation

A set of statements were provided to each respondent with a negative disposition to willingness-to-pay in order to establish the main reasons for non-participation in the proposed weather index insurance scheme. Table 5.16 presents a summary of responses.

Table 5.16: Reasons for not participating in weather index insurance

Explanation for non-participation	Frequency Distribution						Descriptive	
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Strongly Agree/Ag	Mean	Std Dev
Premiums are expensive	34%	28%	22%	9%	6%	63%	2.25	1.22
I have other priorities	44%	47%	6%	3%	0%	91%	1.69	0.74
I don't trust insurance	31%	13%	25%	22%	9%	44%	2,66	1.38
No one in my community uses insurance	25%	41%	25%	9%	0%	66%	2,19	0,93
My crop management plan is working well	13%	31%	13%	31%	13%	56%	3,00	1,29

From the dataset 32 farmers who represent 14% of the population not willing to pay for insurance, the most prevalent reason was that the farmers have other key priorities (91%). The secondary reasons from highest to lowest were that crop insurance is not commonly used in their community (66%) which indicates that insurance culture plays a role in purchase decisions, proposed premiums are expensive (63%) is the third reason, the current crop management plan to mitigate losses is effective (56%), and 44% of farmers do not trust insurance companies. The main reasons provided for non-participation in weather index insurance in this study are in line with previous research that suggested that farmers had other priorities, listed as the number one factor, followed by premiums being expensive as the second explanation (Jin, Wang & Wang, 2016:370). Trust, even though not among the top reasons for non-insurance purchase, plays a key role in weather index insurance purchase considerations, as evidenced in (Casaburi & Willis, 2017:40; Zhang, Ju & Zhan, 2019:2914) farmers with a higher level of trust are more likely to purchase agricultural insurance. Based on field and laboratory-experimental data from a randomized controlled trial in Kenya and consistent with theory, Dercon, Gunning and Zeitlin, (2018:23) find that limited trust in insurance providers is a critical barrier to insurance adoptation, particularly among poor households and these are precisely the households that stand to gain the most from the benefits of insurance. The authors define trust as the probability that the insurance provider fails to honour their obligation in the event of a claim. It is advised that institutions responsible for marketing index insurance should be mindful to establish trust-based relationships for successful insurance distribution. This entails establishing reputable partnerships and obtaining government accreditation.

After descriptive statistics and analysis, the next step is to use inferential statistics to test hypotheses. Test techniques applied in this study are SEM and binary logistics regression. The analysis is presented in the sections that follow.

5.6 Confirmatory Factor Analysis

In SEM, the researcher hypothesizes a set of relations that exist among a set of variables, based on a theoretical framework (Crano, Brewer & Lac, 2015:173). SEM is the preferred statistical analysis to addressing the primary research objective of developing a conceptual framework of factors that influence willingness-to-pay for weather index insurance. SEM involves the construction of two models, the measurement model specifying the relationship between latent variables and their respective indicators or measuring items and the structural model specifying inter-relations of latent variables in the analysis. The first step in SEM is to specify the measurement model and conduct Confirmatory Factor Analysis (CFA) to test for unidimensionality, validity and reliability of items measuring the latent variables or constructs (Awang, Afthanorhan, Mamat & Aimran, 2017:1434). Since the empirical data in this study were normally distributed (refer to Section 6.8 of this study), the Maximum Likelihood Estimation (MLE) method could be applied to conduct CFA. MLE is an estimation technique used to determine values for the parameters of a specified model in such a way that maximizes the likelihood that the process described by the model is consistent with the empirical data actually observed (Crisci, 2012:6). MLE has proved to be a highly robust and efficient estimation method (Awang, Afthanorhan & Asri, 2015:65).

5.6.1 Measurement model

The three latent constructs – insurance culture, financial capability, and risk perception – are measurement models; the hypothesized relationship between them is a structural model. Insurance culture was measured directly by three questions in the instrument (IC1, IC2, and IC3). Financial capability was captured by a three items scale (FC1, FC2, and FC3). Risk perception was measured by four indicators (RP1, RP2, RP3 and RP4). As a general rule, when modelling latent constructs, each latent variable requires at least two observed indicator variables, but three is desirable. It is highly recommended that CFA should be conducted on all latent variables as a single group, referred to as pooled-CFA (Awang, 2012:56). The CFA approach computes the factor loading for each item measuring latent constructs (Awang et al., 2017:1435). Error terms are modelled for each item when computing the factor loading. This allows for the elimination of items with large measurement error and/or low factor loadings, thus improving the quality of the latent constructs modelled (Hair, Gabriel & Patel, 2014:45). Using the CFA method, the model was then examined for any potential problematic estimates, specifically those with low factor loadings. The results of which are shown in Table 5.17.

Table 5.17: Factor loadings of the measurement model

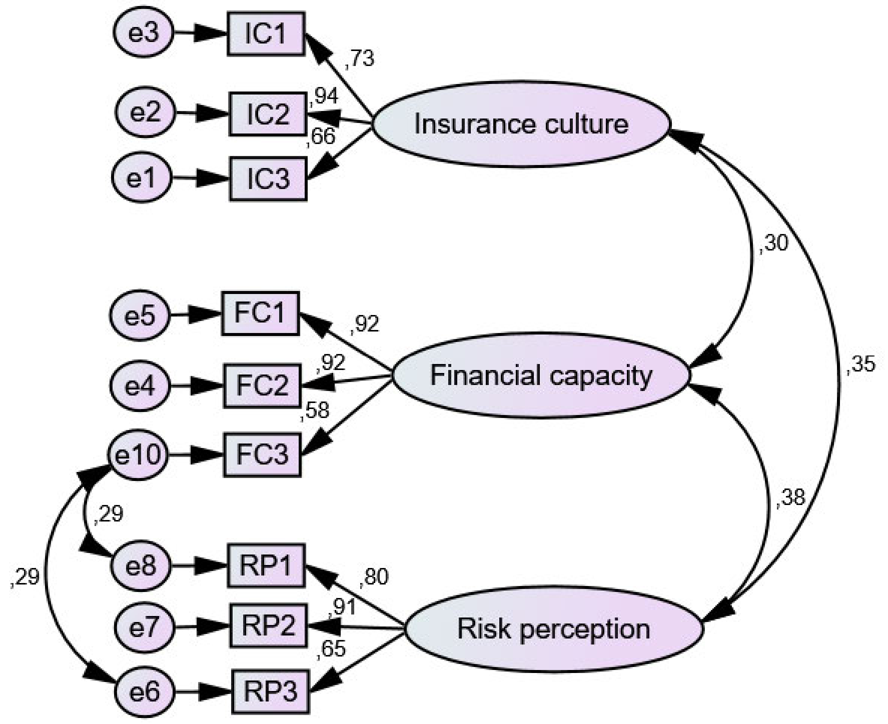
Construct	**Indicators**	**Factor loading**	**Square multiple correlations**	**Standard error**
Insurance culture (IC)	IC1	0.73	0.53	0.067
	IC2	0.94	0.88	0.077
	IC3	0.66	0.43	0.079
Financial capability (FC)	FC1	0.92	0.85	0.069
	FC2	0.92	0.84	0.064
	FC3	0.56	0.34	0.07
Risk perception (RP)	RP1	0.80	0.64	0.058
	RP2	0.91	0.82	0.044
	RP3	0.65	0.42	0.041
	RP4	0.37	0.13	0.123

The indicator weights of factor loadings are standardized to values between -1 and +1, but, in rare cases can also take values lower or higher than this range, which indicates abnormal results, either due to multicollinearity issues and/or problems associated with a small sample size. Weight close to 0 indicates a weak relationship of the factor loading with the construct, whereas weights close to +1 (or -1) indicate strong positive (or negative) factor loading (Hair, Risher, Sarstedt & Ringle, 2019:10). All factor loadings in this study were positive and above the recommended threshold of 0.50 for items that are newly developed (Awang, 2015:54), except for RP4 which measured 0.37 based on statistical outcomes and was therefore removed from the measurement model because it contributed the least to the explanation of the construct. The author cites that removing items with low factor loadings for the respective latent construct ensures that unidimensionality is achieved, which is an underlying assumption of measurement theory and a prerequisite for a valid CFA.

The only case where items with low factor loadings should be retained is when there is sufficient theoretical justification of the item in the measurement model; this was not the case in this study. No negative error variances were reported in this study nor were observations made of standardized factor loadings below -1 or above +1. An inspection of Squared Multiple Correlations (SMC) values for each indicator variable excluding the removed RP4 indicator, ranged between 0.34 and 0.88, implying that the specified indicators explain the latent constructs in the measurement model in a satisfactory manner. SMC explains the variance in a given indicator variable explained by its latent construct. It has been observed that the indicator and FC3 accounted for the least percentages of the variance and indicator IC2 accounts for the highest percentage of the variance.

As part of conducting CFA, all latent constructs should be connected using a double-headed arrow to estimate their correlations (Awang et al., 2017:1437). After doing so, the final grouped model featured 45 distinct sample moments and 23 distinct parameters to be estimated, which leaves 22 degrees of freedom (df) based on the identified model, and a chi-square value of 49.989 with a probability level equal to p=0.001. A significant chi-square value indicates that the model is not an appropriate fit for the data. It is the shared view of many scholars that a reasonable sample size, usually greater than 200, as is the case in this study, and good approximate fit as indicated and discussed further below, can alleviate concerns about the significance of the chi-square test and that a significant chi-square is not a justification for changing the model (Westland, 2015:54). The measurement model is illustrated in Figure 5.13.

Figure 5.13: Measurement model of latent constructs



5.6.2 Goodness-of-fit indices

Various goodness-of-fit indices are proposed in the literature to assess model adequacy, which addresses construct validity. Commonly reported goodness of fit indices included the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Goodness-of-fit Index (GFI) and the Root Mean Square Error of Approximation (RMSEA). As a rule of thumb if CFI and TLI are greater than 0.90, the model is deemed acceptable, while a value greater than 0.95 indicates good fit (Hox & Bechger, 1998:362). On the same basis, by convention, GFI, which measures the descriptive adequacy of the model should be equal to or greater than 0.90 for acceptability (Westland, 2015:55). Typically, RMSEA of less than 0.05 is indicative of good fit and values between 0.05 and 0.08 are considered adequate fit (Browne & Cudeck, 1993:144). Lastly, a chi-square/df ($\chi 2$/df) of between 2 and 5 is a common benchmark for goodness-of-fit (Roshani & Bagrecha, 2017:6).

Table 5.18: Acceptable and observed values of CFA indices

Model fit category	Indices	Acceptable values	Observes values	Acceptance
Parsimonious fit	$\chi 2/df$	Less than 5.0	2.27	Good fit
Incremental fit	CFI	0.90	0,97	Good fit
Incremental fit	TLI	0.90	0.95	Good fit
Absolute fit	GFI	0.90	0,95	Good fit
Absolute fit	RMSEA	0.08	0.08	Adequate fit
Overall Decision: Accept Model				

Chi-square = 49.989, Degree of freedom = 22, Probability level = 0.001

In conformance and compliance with goodness-of-fit indices, the results indicated in Table 5.18 demonstrate that the measurement model fits the data in an adequate manner. It is imperative to conduct rigorous statistical tests to identify any underlying problems within the measurement model. In this respect, the next section reports on the reliability and validity of the measurement model by determining and assessing measures such as composite reliability and construct convergent and discriminant validity in accordance with the prescribed guidelines provided in the literature.

5.6.3 Reliability of measurement model

Reliability of the measurement model was assessed through Cronbach's alpha and composite reliability. Cronbach's alpha is sensitive to the number of items in the scale and generally tends to underestimate internal consistency reliability. By applying Cronbach's alpha in conjunction with composite reliability, different indicators of reliability are considered, while avoiding the underestimation associated with Cronbach's alpha (Hair et al., 2014:111). Cronbach's alpha for all the constructs indicates acceptable internal consistency of above 0.7 (section 5.5.3.3). As a measure of internal consistency, composite reliability above 0.6 indicates reliability and internal consistency of latent variables (Awang, 2012:55). As calculated in Table 5.19, composite reliability is in excess of 0.8 for all the constructs indicating high internal reliability. Composite reliability is determined as $CR\eta = (\Sigma\lambda yi)^2/[(\Sigma\lambda yi)^2+(\Sigma\varepsilon i)]$; where $CR\eta$ = Composite reliability, $(\Sigma\lambda yi)$ = Square of the summation of the factor loadings; $(\Sigma\varepsilon i)$ = Summation of error variances (Bewick, Cheek & Ball, 2004:131).

Table 5.19: Composite reliability

Constructs and items on a scale			Estimates	$(\sum\lambda Yi)^2$	Summation of error terms		**CRη=(Σλyi)2/[(Σλyi)2+(Σεi)]**
					έi	∑έi	CR
IC	<---	IC1 IC2 IC3	0.73 0.94 0.66	5.44	0.46 0.12 0.57	1.14	0.83
FC	<---	FC1 FC2 FC3	0.92 0.92 0.58	5.84	0.15 0.16 0.67	0.98	0.86
RP	<---	RP1 RP2 RP3	0.80 0.91 0.65	5.59	0.35 0.17 0.58	1.10	0.84

Martinez-Lòpez, Gázquez-Abad and Sousa (2013:132) draw attention to the fact that reliability assessments should be followed by a comprehensive analysis of the validity of constructs in a measurement model. This is because, unless tested for reliability, the model remains questionable, insofar as its validity is concerned. The implications, therefore, in this study, were to perform statistical validity tests to assess convergent, and discriminant validity of the model. Construct validity was already established by the use of CFA which noted adequate goodness-of-fit indices, following this, the factor loading and the SMC of the indicators that comprise the measurement model showed correlation with the specified construct indicating construct validity (Ab Hamid, Mustafa, Idris, Abdullah & Suradi 2011:88).

5.6.4 Validity of measurement model

The validity of the measurement model was examined by determining convergent validity to ascertain the degree to which the socio-psychological variables were measured by the listed indicators. Support is provided for convergent validity where the AVE is 0.50 or higher. AVE of or more than 0.50 indicates that the construct explains more than half of the variance of its indicators (Hair et al., 2014:111). The AVE for all constructs as presented in Table 5.20 and was calculated as: $V\eta = \Sigma\lambda yi^2 / [(\Sigma\lambda yi)^2+(\Sigma\varepsilon i)]$; where $V\eta$ = Average Variance Extracted; $\Sigma\lambda yi$ = Summation of the squared of factor loadings; $\Sigma\varepsilon i$ = Summation of error variances; shows high levels of convergent validity for all the constructs (Bewick, Cheek & Ball, 2004:131).

Table 5.20: Average variance extracted

Constructs and items on a scale			Estimates	λyi²	∑λyi²	Summation of error terms ἑi	∑ἑi	$V\eta = \Sigma\lambda yi^2/(\Sigma\lambda yi^2+\Sigma\varepsilon i)$ AVE
IC	<--	IC1 IC2 IC3	0.73 0.94 0.66	0.54 0.88 0.43	2.33	0.27 0.06 0.34	0.67	0.78
FC	<--	FC1 FC2 FC3	0.92 0.92 0.58	0.85 0.84 0.33	2.42	0.08 0.08 0.42	0.58	0.81
RP	<--	RP1 RP2 RP3	0.80 0.91 0.65	0.65 0.83 0.42	1.90	0.20 0.09 0.35	0.64	0.75

The reported AVE ranges from 0.75 to 0.81, which is greater than the threshold of 0.6. This denotes that the indicator variables applied in this study maintained acceptable individual item validity as more than 50 per cent of each indicator's variance was shared with its respective latent construct. Therefore, the respective measures are appropriate in this study since the above-mentioned findings confirmed that the scale indicators converged in a satisfactory manner on their respective constructs.

Discriminant validity indicates that the measurement model of a construct is free from redundant items. Discriminant validity is determined by calculating the square root of AVE, which should exceed the correlation of latent constructs in the measurement model. The discriminant validity for all constructs is achieved when the squared AVE highlighted in bold in Table 5.21, is higher than the values in its row and column. Referring to the results, it can be concluded that the discriminant validity for all three constructs is achieved.

Table 5.21: Discriminant validity matrix

	Insurance culture	Financial capability	Risk perception
Insurance culture	**0.88**		
Financial capability	0.30	**0.90**	
Risk perception	0.35	0.38	**0.87**

5.6.5 Bivariate normality

Parametric procedures in SEM are premised on adequate sample size, unusually a minimum of 100 and normally distributed data (Awang, Afthanorhan & Asri, 2015:58). The normality assessment is made by evaluating the measure of skewness and kurtosis parameters for every indicator variable (Islam, 2019:2). The absolute value of skewness 1.0 or lower indicates the data the normal distribution of data. Another method for normality assessment is by looking at the multivariate kurtosis statistic. According to Safiih and Azreen (2016:47), the acceptable range for the multivariate kurtosis is a value below 50. In which, in this analysis, the result was 21.48, combined with skewness values that are reported in Table 5.21 that between -1 and +1, the data is considered normal.

Table 5.22: Normality assessment

Variable	Min	Max	Skew	c.r	Kurtosis	c.r
IC1	1	5	0.665	4.063	-0.422	-1.29
IC2	1	5	0.801	4.897	-0.198	-0.606
IC3	1	5	0.398	2.435	-0.811	-2.478
FC1	1	5	-0.191	-1.165	-1.189	-3.631
FC2	1	5	-0.142	-0.868	-1.178	-3.598
FC3	1	5	0.539	3.291	-0.42	-1.283
RP1	1	5	0.911	5.568	0.161	0.491
RP2	1	5	0.985	6.021	0.754	2.303
RP3	1	5	0.829	5.068	0.263	0.802
Multivariate					21.48	11.424

The validation procedure in CFA evaluated the unidimensionality, bivariate normality, reliability and validity of all three latent constructs. The reliability of the constructs was assessed through composite reliability, while validity was confirmed through construct, convergent and discriminant validity. On the basis of the aforementioned tests and results for the measurement model, all requirements were satisfied, and appropriate SEM analysis may proceed as set out in the next subsection.

5.7 Structural Equation Model

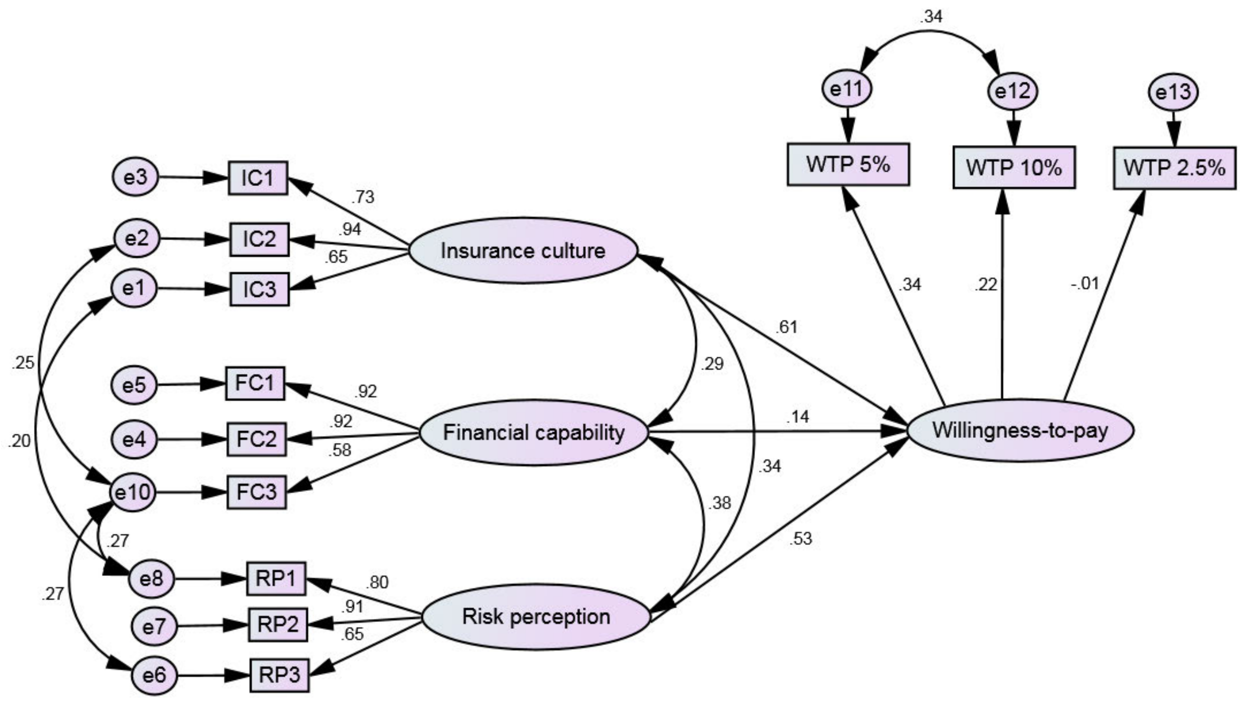
The hypothesized structural model with the visual display of estimates shows the initial measurement model of this study, with linkages between constructs in the model, the research framework and the stated hypotheses to be tested. Relationships between variables are called path coefficients which are shown by single-headed arrows in the model. If the exogenous construct, which is the independent variable is hypothesized to have a causal effect on an endogenous construct, then a single-headed arrow referred to as the structural effect should flow from an exogenous pointing to the endogenous construct. Exogenous constructs in the study are insurance culture, financial capability and risk perception. Meanwhile, willingness-to-pay is the endogenous construct. Double-headed arrows in the structural model reflect correlations between latent constructs.

The initial process commenced with observing the model fit indices for the structural paths, thereafter the hypothesized parameter estimates were interpreted and tested for statistical significance. Structural model coefficients, which is the path coefficient can be evaluated in terms of statistical significance, where the strength of the relationships between the constructs are derived from estimating a series of regression equations where the path coefficients range between -1 and +1, where higher values indicate greater explanatory power (Hair et al., 2019:11). A positive coefficient (+1) means that the unit increase in the measurement of one structure results in a direct increase in the measurement of the structure it projects to, proportional to the magnitude of the coefficient. A negative coefficient has the opposite effect, meaning that an increase in the activity measure in one structure leads to a direct, proportional decrease in the activity measure of structures it projects. All estimates are standardized, which means that the higher the path coefficient value, the greater the influence of the independent variables on the dependent variable. Standardized path coefficients with absolute values less than 0.10 reflect a small effect on the dependent variable, whilst 0.30, reflects a medium effect, and path coefficients greater than 0.50, indicate a large effect (Suhr, 2008:4).

5.7.1 Initial structural model

The identified SEM in Figure 5.14 features 78 distinct sample moments and 34 distinct parameters to be estimated, which leaves 44 degrees of freedom (df) based on the just-identified model, and a chi-square value of 161.527 with a probability level equal to p=0.000.

Figure 5.14: Initial structural model



Upon examining the values of the fitness indices, it was found that the structural model did not meet the goodness-of-fit requirements, reporting a problematic incremental and absolute fit with a low TLI of 0.85 and a high RMSEA of 0.11. Goodness-of-fit indices for the initial SEM model are presented in Table 5.23.

Table 5.23: Acceptable and observed values of the initial structural model

Model fit category	**Indices**	**Acceptable values**	**Observes values**	**Acceptance**
Parsimonious fit	$\chi 2$/df	Less than 5.0	3.7	Good fit
Incremental fit	CFI	0.90	0,90	Adequate fit
Incremental fit	TLI	0.90	0.85	Inadequate fit
Absolute fit	GFI	0.90	0,91	Adequate fit
Absolute fit	RMSEA	0.08	0.11	Inadequate fit
Overall Decision: Inadequate Model				

Chi-square = 161.527, Degree of freedom = 44, Probability level = 0.000

If a model is not adequate, it is common practice to modify the model by deleting parameters that are not significant and adding parameters that improve fit. The process is achieved by computing modification indices for each fixed parameter. Modification indices are the minimum amount that the chi-square statistic is expected to decrease if the corresponding parameter is freed. At each stage of modification, a parameter is freed that produces the largest improvement in fit, this process is repeated until adequate fit is obtained (Hox & Bechger, 1998:362). The model modification was performed using modification indices to identify and constrain the correlated items through correlating measurement errors of redundant items in order to improve fitness indices. Following modification, the model still did not represent the desired data fit, meaning that the initial model was not compatible with the data. Taking this into account, a revised model was tested on the basis of the original measurement model. The re-specification was based on both theoretical and empirical considerations to warrant valid assertions.

5.7.2 Revised structural model

Farmer's response to pay a premium of 2.5% for weather index insurance had a negative factor loading on the willingness-to-pay variable. This was identified as a problematic variable affecting the initial model. From the sample data (section 5.5.6) only 49 out of 224 farmers were asked questions in the lower category of willingness-to-pay based on their response to the initial bid, this represents 22% of overall responses, and the low response in the category may explain the resultantly low factor loading. Whereas all 224 farmers were asked and responded to the initial bid of 5% and from those that responded yes, 175 were further asked on their willingness-to-pay 10% and such data collected from these two items was sufficient for SEM analysis and retained in the willingness-to-pay construct. Following the removal of the willingness-to-pay at 2.5% item, the model was re-specified in a manner that did not compromise the hypothesis testing of the study. The revised model was assessed and goodness-of-fit indices for the SEM model presented in Table 5.24. The revised SEM was reported as identified and features 66 sample moments, with 29 estimated parameters, resulting in 37 degrees of freedom (df). Chi-square was reported as 89.423 with a significance level of p=0.000.

Table 5.24: Acceptable and observed values of SEM indices

Model fit category	Indices	Acceptable values	Observes values	Acceptance
Parsimonious fit	χ2/df	Less than 5.0	2.41	Good fit
Incremental fit	CFI	0.90	0.95	Good fit
Incremental fit	TLI	0.90	0.93	Good fit
Absolute fit	GFI	0.90	0,93	Good fit
Absolute fit	RMSEA	0.08	0.08	Adequate fit
Overall Decision: Accept Model				

Chi-square = 89.423, Degree of freedom = 37, Probability level = 0.000

Although the p=0.000 generated from the chi-square test is significant indicating a non-statistically fit model, scholars agree that chi-square test is not a good indicative measure because of its sensitivity to sample size (Roshani & Bagrecha, 2017:6). The larger the sample size, the greater the probabilities of obtaining a statistically significant chi-square. Given that SEM should only be conducted with large sample sizes, the chi-square test is all but guaranteed to be significant. Because of this, other measures of fit needed to be considered. Table 5.24 summarizes model fit measures and indicates that the model is acceptable supported by fitness indices that meet the required levels under various model fit categories. Having established the validity of the structural model and having met the criteria for goodness-of-fit, the next step was to examine the path coefficients and to test the theoretical relationships.

5.7.3 Testing for covariance

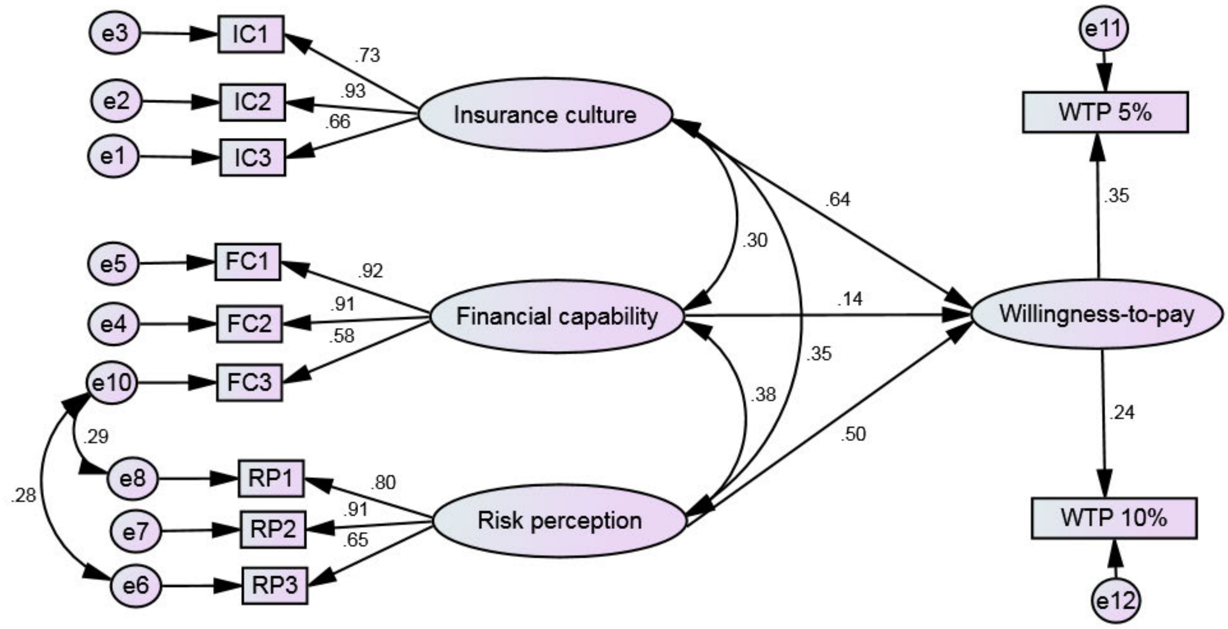
In the revised structural model, the model fits the data and assumptions that insurance culture, financial capability and risk perception have a direct positive influence on willingness-to-pay for weather index insurance at a premium of 5% and 10% based on annual farm turnover. In addition, the covariance between latent constructs (Table 5.25), insurance culture and financial capability is 0.24; financial capability and risk perception is 0.22 and insurance culture, and risk perception is 0.12. These show low levels of correlation, meaning that, discriminant validity is achieved and that constructs are not redundant and may be treated separately. Covariance is a measure of how much two random variables change together. If the variables appear to exhibit similar behaviour, the covariance is a positive number; otherwise, if the variables lean towards contrary behaviour, the covariance is negative. The sign of the covariance describes the linear relationship between the variables (Westland, 2015:28). Low covariance between latent constructs indicates that there is no multicollinearity—a condition which, if it was found to exist, can distort SEM results (Niemelä-Nyrhinen & Leskinen 2014:13).

Table 5.25: Testing for covariance between latent constructs

Constructs			**Estimate**	**S.E.**	**C.R.**	**P**
Insurance culture	<-->	Financial capability	0.24	0.06	3.661	0.000
Financial capability	<-->	Risk perception	0.22	0.05	4.373	0.000
Insurance culture	<-->	Risk perception	0.12	0.03	3.933	0.000

Nomological validity was tested by examining whether or not the covariances between the constructs in the measurement model demonstrate the relationships shown to exist based on theory. Lee (2019:137) collates various definitions and summarizes nomological validity as a concept relating to whether the correlations among variables reflect the theoretical relationships of the variables or not. Support for the nomological validity of the latent constructs is found where the covariances are significant and positive (Hair, Wolfinbarger, Bush & Ortinau, 2013:317). The construct covariances in Table 5.25 are used to assess this. All the covariances, as reported in this study were positive and significant, therefore, confirming nomological validity. Thus, it was confirmed that the scale developed had adequate psychometric soundness for measuring willingness-to-pay for weather index insurance in South Africa.Appropriateness of covariances and achievement of nomological validity was confirmed. This study depicts the hypothesized path estimates of the structural model using a visual display of the estimates, as shown in Figure 5.15.

Figure 5.15: Structural model with standardized regression weights



As shown in Figure 5.15, the standardized beta estimate for the effect of insurance culture on willingness-to-pay is 0.64, financial capability has a standardized beta estimate of 0.14 on willingness-to-pay, while the standardized beta estimate for risk perception is 0.50. Insurance culture (path estimate=0.64, p=0.001), and risk perception (path estimate=0.50, p=0.01), determinants both have a statistically significant (p<0.01) positive influence on willingness-to-pay. While financial capability (path estimate=0.14, p=0.44), is identified in the structural model, but this is neither substantial nor statistically significant. The positive sign though implies that farmers who have the financial capability are likely, to a lesser extent as compared to other constructs tested in the study, to consider index insurance as a solution.

Standardized beta estimates provide for an understanding of relationships expressed in terms of standard deviations (Grace & Bollen, 2005:290). In these units, we observe that if insurance culture were increased by one standard deviation, willingness-to-pay would be expected to increase by 0.64 standard deviations; similarly, if risk perception increased by one standard deviation willingness-to-pay would increase by 0.50 standard deviations.

Hypothesis tests present a simplified model of the real world that can either be ‘confirmed’ or ‘ejected’ through analysis and summarization of data relevant to the underlying theory

(Westland, 2015:145). Results of the study hypotheses testing based on the structural model show that study hypotheses H_1 and H_3 are supported and have a large positive effect on willingness-to-pay. There was a small non-significant effect of financial capability on willingness-to-pay. On these grounds, it can be concluded that H_2 is not supported by the study results. This is contrary to findings by Abd Aziz et al. (2015:241), deploying multiple regression analysis, the authors suggest that perceived behavioural control, which reflects the ability and opportunity both financially and otherwise, has the highest impact as a predictor on the intention to participate in agricultural insurance in Malaysia, with a standardized beta coefficient of 0.44.

Table 5.26: Hypotheses test results

Constructs				Hypothesis	P	Effect
H_1	Insurance culture	-->	Willingness-to-pay	Confirmed	0.001	Large
H_2	Financial capability	-->	Willingness-to-pay	Rejected	0.44	Small
H_3	Risk perception	-->	Willingness-to-pay	Confirmed	0.01	Large

5.7.4 Multinormality testing

Multinormality is one of the considerations in performing SEM to ascertain the validity of results. Multivariate normality refers to the situation in which, in addition to the normality of each variable, each variable is also normally distributed for each other variable. Although bivariate normality with respect to skewness and kurtosis is achieved for all the variables in the data (Table 5.22), multinormality kurtosis shows a critical ratio of 11.242 established on the basis of Mardia's normalized estimate of multivariate kurtosis. Scholars, Bentler (2005:109), among others, suggests that to achieve multinormality, the critical region should be less than 5.

Since the multinormality criterion was not achieved, a variety of options are available such as deploying the Mahalanobis distance measure, which is a multivariate distance metric to identify and subsequently delete outlier observations in the data or applying bootstrapping techniques, which in essence is a resampling method which provides an estimation of the standard error. The limitation of applying Mahalanobis distance is that the sample having a multinormality distribution is reduced and does not include some of the observations which may have other rich and meaningful data. The general rule of thumb in data analysis is to not ignore or delete outliers. Deleting data introduces selection bias; therefore, outliers should be handled by applying other techniques (Albers, 2017:177). For this reason, bootstrapping procedures, with their associated significance test were performed to assess whether multinormality had an effect on the model results or not. In particular, whether or not measurement errors were affected and consideration of their impact on significance test results was considered. The underlying concept behind bootstrapping is that the sample data is often the closest approximation of the shape of the population from which the sample was drawn. Thus, it can be assumed, without actually gathering further data, that future data will come from this empirical distribution, and that, therefore, more data can be generated artificially (Westland, 2015:109).

Table 5.27: Bollen-Stine bootstrap standardized regression weights

Constructs			**Estimate**	**Lower**	**Upper**	**P**
Willingness-to-pay	<--	Insurance culture	0.64	0.197	0.927	0.015
Willingness-to-pay	<--	Financial Capability	0.14	-0.209	0.548	0.429
Willingness-to-pay	<--	Risk perception	0.50	0.055	0.91	0.034

The Bollen-Stine bootstrap was conducted with an additional 1 000 samples at a 95% confidence level adopted to accommodate for the nonnormal properties of the data. Results of the bootstrap showed direct effects where significance was achieved at 0.01 for insurance culture and risk perception, while financial capability remained non-significant confirming results of the MLE. These results indicate that the associated biases for the estimates of parameters and standard errors of the parameter estimates were minimal and had little to no effect on the overall results. Awang, Afthanorhan and Asri (2015:63) find that implementation of MLE in SEM testing provides high consistency in obtaining of parameter estimates and accurate hypotheses testing.

5.8 Logistic Regression

Binomial logistic regression was estimated to identify the specific socio-demographic and socio-economic factors influencing willingness-to-pay. Logistic regression is applied when analyzing relationships between multiple independent variables and a categorical dependent variable and estimating the probability of occurrence of an event by fitting data to a logistic curve (Park, 2013:155). The outcome variable in logistic regression is a dichotomous variable, in this case, Yes (0) or No (1) to willingness-to-pay for weather index insurance.

According to Ranganathan, Pramesh and Aggarwal (2017:149), the key to a meaningful logistic regression model is the choice of appropriate predictor variables to include in the model. The inclusion of as many variables as possible can dilute true associations, lead to large standard errors with wide and inaccurate confidence intervals. Therefore, a chi-square test presented in Table 5.28, was performed on all categorical variables to identify factors with significant associations with the dependent variable for inclusion in the logistic regression. The authors advise that a more liberal statistical test of significance ($p<0.2$) should be applied for setting the inclusion criteria since the purpose is to identify potential predictor variables rather than hypothesis testing. Moreover, an association may change to significant in a logistic regression model given the compounding effect of other variables in the model. On the basis of this consideration, the significance threshold is increased from $p<0.05$ to $p<0.2$.

Table 5.28: Chi-square test of inclusion criteria in logistic regression

Data type	**Treatment**	**Independent variables**	**Pearson Chi-square**
Categorical	Factor	Gender	0.007
		Age	0.240
		Marital status	0.905
		Qualification	0.003
		Household size	0.610
		Access to credit	0.006
		Turnover	0.051
		Farming experience	0.905
		Farm size	0.279
		Group membership	0.009
		Risk coping strategy	0.558

Agricultural insurance is one of the largest and fastest growing speciality lines of insurance (Hohl, 2019:21), therefore, the identification of the relevant factors that drive this growth is key. A rich understanding of the underlying elements will lay the foundation for long-term planning of directed marketing efforts (Langat, Naibei & Getare, 2017:705). Pearson chi-square was used to test the significance of variables that influence willingness-to-pay for insurance in the study. To make a conclusion about the predictor variables at 80% confidence level, the p-value of the Chi-Square statistic should be less than 0.2, which is the alpha level associated with the related confidence interval.

A Pearson chi-square test at a statistically significant level ($p<0.2$) indicated that as independent variables: gender, qualification, access to credit, group membership and turnover have a significant association with willingness-to-pay. These were the variables that were included in the final logistic regression model. Where the p-value is more than 0.2, then it was concluded that the variables are independent of willingness-to-pay and have no significant statistical association. Previous investigations reviewed for this research suggested that the adoption of weather index insurance schemes would be influenced by age, marital status, household size, farm size, farming experience and preferred risk coping strategy, all the mentioned were not significant determinants in this study at a significance level of 20%.

Following the selection criteria of items included in the final model the logistic regression is presented in Table 5.29 as a table showing regression coefficients (Beta), standard errors (S.E), Wald chi-square test (Wald test), significance levels (P) and an equation for log (odds) containing regression coefficients for each variable (Exp(B). The equation provides a model which can be used to estimate the likelihood of an event occurring for a particular person, in this case the farmer, given the predictor factor profile (Ranganathan, Pramesh & Aggarwal, 2017:149).

Table 5.29: Variables in logistic regression

Variables	Beta	S.E	Wald Test	P (Significant)	Exp(B)
Gender	0.814	0.415	3.848	0.050	2.256
Qualification			8.728	0.033	
Primary education	-1.720	0.749	5.276	0.022	0.179
Secondary education	-1.875	0.641	8.550	0.003	0.153
Tertiary education	-1.531	0.685	5.001	0.025	0.216
Turnover			7.354	0.118	
R250 001 – R500 000	-1.083	0.549	3.886	0.049	0.339
R500 001 – R1 000 000	-0.73	0.626	0.77	0.782	0.841

R1 000 001 – R2 000 000	0.311	0.902	0.119	0.730	1.365
More than R2 000 001	1.077	0.729	2.183	0.140	2.935
Access to credit	0.833	0.454	3.373	0.066	2.301
Group membership	0.677	0.375	3.258	0.071	1.967
Constant	-2.920	1.271	5.281	0.22	0.540

The logistic regression was statistically significant, chi-square = 33.876, df = 10, p=0.000 and the model satisfactorily fits the data as evidence in Hosmer and Lemeshow test results (chi-square = 7.325, 8 degrees of freedom, p=0.289). A non-significant Hosmer and Lemeshow chi-square in this regard indicates that the data fit the model well (Wuensch, 2020:9). The model explained 21.6% (Nagelkerke R^2) of the variance in willingness-to-pay and correctly classified 79.5% of the variance. These values are acceptable and within the region of other willingness-to-pay studies applying the contingent valuation method (Abdullah et al., 2014:26).

From the results reported in Table 5.29, Gender (p=0.05) and education (p=0.03) were statistically significant factors influencing willingness-to-pay at a 5% confidence level. Access to credit (p=0.066) and group membership (p=0.071) were statistically significant at a 10% confidence level. Males were twice (2.256) as likely to purchase index insurance compared to females, similarly, access to credit (2.301) and group membership (1.967) increases the chances of willingness-to-pay by twice as much while education decreases the likelihood of willingness-to-pay for index insurance. Although the variable turnover was hypothesized in the model to have an influence, there was no significant effect on willingness-to-pay. This is similar to results in Ellis (2017:713), where income has an insignificant relationship with farmers' willingness to purchase insurance.

5.9 Conclusion

Chapter five presented the research findings and analysis of data using parametric and non-parametric tools. Descriptive statistics regarding the population were presented for better understanding and contextualization of the research results, thereafter data pertaining to latent constructs of the study were presented and assessed for normality and the relevant indicator items tested for reliability and validity. This formed the basis for selecting appropriate statistical tools to support the study objectives. A conceptual framework of factors that influence low-income farmers' willingness to pay was derived using an integrated approach of SEM and logistic regression. Prior to conducting SEM analysis, CFA was performed on the measurement model to test its adequacy. The measurement model yielded satisfactory results in terms of unidimensionality, relevant measures of validity and composite reliability setting the foundations for the structural model to follow. The initial structural model reported poor goodness-of-fit value. After re-specifying the model and eliminating items with poor factor loadings based on empirical justification, the modified structural model demonstrated acceptable fitness indices, consistent with the study data. The conceptual framework provided a rich characterization of the determinants of take-up with special attention being given to the role of behavioural traits in addition to sociodemographic and economic considerations. The results of the statistical tests showed that the hypothesized path relationship between insurance culture and willingness-to-pay and the relationship between risk perception and willingness-to-pay, were both statistically significant, consistent with the conjecture that culture and risk aversion influence insurance uptake. The relationship between financial capability and willingness-to-pay was not significant. Overall, farmers showed strong interest in weather index insurance and willingness to purchase the index insurance solution, evidenced by 86% positive affirmations from sampled respondents. Using logistic regression, from a socio-demographic analysis, gender and education are statistically significant predictors of willingness-to-pay, and socio-economic drivers of access to credit and group membership are statistically significant predictors of willingness-to-pay. The mean Willingness-to-pay using a weighted average approach was calculated at 6.8% with a premium price range of between 2.5% to 10%.

The next chapter will discuss the main findings of the study in line with the research objectives.

CHAPTER SIX: DISCUSSION OF FINDINGS

6.1 Introduction

Chapter Six discusses the study findings which were presented in the previous chapter in terms of the research objectives as set out in chapter one. The chapter commences with a summary of the demographic profile of respondents, after which empirical findings of the study are interpreted based on the literature review and considerations are balanced with ongoing progress and research reports from various index insurance implementing institutions in efforts to bridge the gap between academic and practitioners' standpoints. The role of insurance in agricultural development and the role of agriculture in economic development cannot be viewed in isolation. The literature review reveals that insurance is one of the key farm risk mitigating controls in an environment constrained by climate variability. Its application can lead to adoption of technology for improving crop yields opening access to both local and international markets. It is estimated that if Africa were to increase agricultural exports by 1%, this would increase its GDP by up to $70 billion (Finmark Trust, 2016:46); therefore the discussion of the results is intended to stimulate conversation around a clearer understanding of farmers' views towards insurance. The findings of this study provide insight into socio-psychological considerations in index insurance purchase decisions, following the application of the Theory of Planned Behaviour (TPB), which is mainly used as a predictor for willingness-to-pay intentions by identifying references that underlie economic behaviour. In so doing, allowing economics to extend outside its conventional dependency on price and income fluctuations as well as the expected utility thereof as the primary explanation of economic behaviour (Carter, 2016:85). In addition, the findings contribute to existing research on the role of socio-demographic and socio-economic considerations that influence decision making in insurance purchase.

6.2 Summary Profile of Low-income Farmers

A summary of the demographic variables reveals that most of the participants in the study were married, Black African males, living in a household of 5 (five) members or less. The majority of participants were between the ages of 45 and 54. They are highly experienced farmers with more than 10 years' experience and have at least completed secondary education. The farmers are members of a farming group, who typically have at a minimum one insurance policy, be it personal or commercial. The majority of the low-income farmers' operations generate less than

R500 000 annual turnover, on cultivated farmlands of more than 50 hectares, where expansion efforts are limited due to inability of the farmers to access credit. The farmers are highly exposed to drought conditions, suffering losses of not less than 25% of crop output per season as such, most farmers self-classify as unprepared to contend with the effects thereof. In response, their preferred coping mechanism is to reduce crop production in times of uncertainty.

6.3 Willingness-to-pay Findings

Farmers use a wide array of alternative farming practices that affect the sensitivity of their crops to weather risk, such methods include crop diversification, shifting planting dates and application of seed inputs with improved resilience to specific natural hazards. This study reports that farmers' primary response to weather risk is to curtail production in times of uncertainly to essentially reduce potential losses. This risk return spectrum is effectively the belief that farmers hold that lower levels of production reduce the farm into a more manageable unit where close monitoring and a higher degree of control can be effected, thus ensuring that a variety of risk response strategies can be implemented for better tactical farm management to improve yield, albeit on a small-scale. This is perfectly illustrated in investigations that show that farmers cultivating smaller lands apply more fertilizer per hectare to improve yields (Sibiko & Qaim, 2017:17).

Risk management is at the heart of sustainable, long-term agriculture. In addition, to weather fluctuations, more structural characteristics may substantially affect a farmer's exposure to risks (Ceballos & Robles, 2020:4). Within these existing dynamics, the study reports that a large number of farmers would welcome a novel risk transfer solution to alleviate some of their challenges and concerns. This is underscored by 86% of surveyed farmers reporting a willingness-to-pay for crop-index insurance as an innovative hedging instrument. Positively, the responses are a direct translation of not only underlying demand but intention as well among a heterogeneous group of farmers who are unique in their intrinsic and extrinsic motivations but despite their uniqueness, all commonly search for an additional element to supplement existing risk mitigating strategies, in this case, that component is market-based weather index insurance.

The research reported here strongly complements other willingness-to-pay studies such as Fonta et al. (2018:11) reporting willingness-to-pay of 88%; Nyaaba, Nkrumah-Ennin and

Anang (2019:369) reporting willingness-to-pay of 91%; Adjabui, Tozer and Gray (2019:498) reporting 70% in Ghana and to a lesser extent Ellis (2017:707) with a reported willingness-to-pay of 52%. Interestingly, the gender composition in the last cited author's research is 74% male and 26% female, relatively similar to the 81% male and 19% female representation in this study. But the results on the extent of willingness-to-pay were largely different, especially in the context that both studies also tested the same crop commodity.

6.4 Willingness-to-pay Price Range Findings

Insured farmers intrinsically transfer risk to insurance providers and offset the transfer by seeking higher risk in farming operations which can increase overall crop yield (Aditya, Khan & Kishore, 2018:170). For example, weather index insurance uptake among farmers increases investment in maize seeds by 65% and reports record an improved yield in the region of 60%. These are very substantial results that underscore the degree to which farmers' input use is affected by weather risk (Sibiko & Qaim, 2017:22). Such studies necessitated a valuation of the extent to which farmers are willing to part with monetary resources for risk transfer solutions in the light of resource constraints within this price-sensitive farming subsector. The results were that on average low-income producers who are interested in weather index insurance were willing to pay 6.8% of the value of their crop yield as insurance premium, determined as a percentage of annual crop turnover. The pricing options range on a scale; at the lower boundary of the scale, 2.5%, the mid-point was 5%, and the upper limit was 10%. The mid-point was the starting point of the questionnaire, established upon investigations of similar empirical studies, market practice and juxtaposed with the commercial rate for crop insurance. Through the establishment of a credible mid-point, the contingent valuation approach for soliciting information based on studies of non-market goods was applied. The technique was used to determine the lower and upper bound; effectively, this represents the price range of willingness-to-pay at between 2.5% and 10%. The upper limit as determined in this study is consistent with the ceiling on the current Ghana Agricultural Insurance Programme (GAIP) where the maximum premium charged is 10% (Adjabui, Tozer & Gray, 2019:495).

The establishment of the mean and price range is a critical guideline in setting overall market acceptable prices and assessing commercial viability, with or without government support of index insurance initiatives in key agro-ecological zones, both under dryland and irrigation cultivation in South Africa. It should be noted that although the average rate of 6.8% is higher than the commercial crop insurance rate estimated between 4% and 5% traditional indemnity crop insurance is not tailored for smallholder farmers, and premiums would need to increase exponentially to compensate for low levels of the sum insured, on-field assessment costs, administrative and intermediary costs as well as technical underwriting considerations relating to pricing of risk for farmers mostly in rural homelands where intra-regional climate variations are among the most volatile in the country.

Price is an important variable which can undermine or promote an insurance scheme. It can serve as an attractive proposition to maintain existing clientele and bring in new clients, even those with low levels of trust when it comes to insurance companies. In a field and laboratory experiment, Dercon Gunning and Zeitlin (2018:16) finds that when the cost of insurance is varied, individuals with a low level of trust are positively responsive to the changes in price. Meaning that when priced correctly, not only risk averse farmers will prefer insurance, but those who have low levels of trust are likely to reconsider their decision. In their experiment on price versus quality, Ulbinaite, Kucinskiene and Le Moullec (2014:16) find that when insurance was presented as affordable, individuals have a higher inclination to purchase the product without extensively interrogating its qualities. In presenting affordable insurance, insurers have the option of structuring deductible levels to reduce the final insurance premium; the caveat though is a reduced level of coverage for the farmer. For a low-income market, there are nuances in setting optimum deductibles.

First, given farmer's liquidity constraints, insurance purchase on its own is a significant acquisition. The expectation that when claims arise, a resource-constrained farmer would have sufficient reserves to settle the deductible would need to be considered. Second, index insurance products have an inherent uncovered (basis) risk element which if presented and explained well is considered the first layer of risk that is retained by the farmer. To include a second layer of deductibles in addition to the underlying basis risk may potentially render the scheme unattractive due to the lower coverage for farmers despite well-priced premiums. The average low-income farmers might not fully grasp these financial complexities for several reasons: (1) the price proposition may be attractive; (2) cognitively, farmers may select high deductibles because events of major disasters are rare, and the lure of price reduction is greater; (3) the relief of accessing additional risk mitigating tools to cope with stressors associated with weather risk; (4) low level of financial literacy and experience with financial products. Providers of index insurance, thus have a moral obligation to educate the market on these intricacies, but more importantly, to keep the product simple and easy to understand. If farmers purchase the product on the basis of price, with complicated deductible incentives that reduce the cost of insurance, the implication may only be fully realised at claim stage when the indemnity is less than what the farmer expects. This is likely to reduce buyer confidence and undermine future demand since the product would not have performed at the level of expected coverage. According to (Du, Feng, & Hennessy 2014:19) when farmers make a choice on renewing insurance, a careful decision making process takes place, high satisfaction is placed on previously favourable outcomes and low consideration on past outcomes where insurance failed to fulfil its anticipated obligation. An equally important consideration in pricing-quality design is the powerful element of word-of-mouth. If the product is highly complicated, the likelihood of farmers sharing positive experiences is reduced simply because the user cannot in clear and simple language explain the offering to others that might be interested.

6.5 Findings on Socio-psychological Factors

According to Carter et al. (2014:29), uptake of index insurance depends on farmer behaviour toward risk, and products need to be designed in response to behavioural attributes. Therefore, the use of socio-psychological models becomes important to explain the low demand for insurance in agricultural economics. The TPB is one of the leading theories in explaining psychological control processes of purchasing insurance (Mai et al., 2020:1694). In their study, using TPB as a base, López-Mosquera and Sánchez (2012:251) observed that the theory has a strong influence on willingness-to-pay because psycho-social factors strongly determine positive intentions and subsequent behaviour. To this end, reported behavioural results under this study were as follows:

Study hypothesis: H_1- insurance culture has a significant positive relationship with willingness-to-pay;

Study hypothesis: H_2 – financial capability does not have a significant relationship with willingness-to-pay,

Study hypothesis: H_3 – risk perception has a significant positive relationship with willingness-to-pay, Both study hypothesis: H_1 and study hypothesis: H_3 was confirmed in this study. While study hypothesis: H_3 was not supported. According to Ajzen (2020:316) in such instances, the TPB indicates that there is strong motivation towards enact a behaviour to the extent that people feel that they have the resources and skill to carry out the desired action. The results of the hypothesis testing are further discussed below:

6.5.1 Insurance culture

These study findings confirmed the *a priori* expectation that insurance culture has a significant, direct effect on willingness-to-pay for index insurance. Consistent with insurance literature, culture has an influence on participation in insurance markets (Zhong et al., 2015:41) and cultural considerations should be understood before entering a market because cultural differences produce different insurance participation outcomes. This is because consumers respond to insurance solicitations according to their cultural beliefs and not only according to economic rationality (Park & Lemaire, 2012:501). These subjective, cultural norms are informal rules followed by most of the community members (Buzatu, 2013:38). For example, in rural India, long-term research across 60 villages shows that individuals are more likely to purchase index insurance if co-residents purchased insurance (Cole, Stein & Tobacman, 2014:289).

In another study, following a qualitative discussion, it was found by Ceballos et al. (2015:61) that almost all farmers that took out insurance made the decision because of peer influence among community members. Most of the participation was found among relatives, friends and people of the same social class. In their study on Indonesian farmers of factors that inform intentions to participate in crop insurance based on SEM analysis, Ibrahim et al. (2020:49) report subjective norms, that is, cultural influences as the only behavioural variable influencing intention to purchase insurance. The authors reported a path coefficient of 0.74 for subjective norms which are comparable to 0.64 reported in this research. There are similarities in Ibrahim et al. (2020) and this study, in both studies when it comes to demographic profile, for instance, the majority of respondents are male, married, have less than five dependents, and more than five years farming experience. In both enquiries, the farmers operate on large parcels of land. The research proves that society and its influences, including personal relationships and experiences all which form the cultural fibre have an enormous impact on intentions to purchase insurance.

Previous TPB studies within an agricultural context are consistent on the effect of subjective norms (insurance culture) on purchase decisions. Daxini, Donoghue, Ryan, Barnes, Buckley and Daly (2018:16) find positive non-significant association on farmers' intentions to adopt soil nutrient management plans. In exploring intentions to adopt conservation agriculture in Mozambique for sustainable production intensification, Lalani, Dorward, Holloway and Wauters (2016:26) find that subjective norms have a significant positive influence on these intentions. Senger, Borges and Machado (2017:37) also report significant positive intentions by rural farmers to diversify crop production. Based on their finding, the authors conclude that important social motivations and peer influence can prompt farmers to diversify agricultural production even when they demonstrate an unfavourable attitude towards this behaviour, social pressure is an element strong enough to encourage uptake behaviour. This is unsurprising, Aziz, Husin and Husin (2017:390) in their literature review on cultural influences and purchase intentions demonstrate that in certain instances, social pressure from referent groups is a significant determinant of attitude towards performing a certain behaviour. Lastly, the findings of this study on insurance culture are consistent with general findings across consumers of technological innovations which show that social culture has a statistically significant effect on willingness-to-pay for such innovations, especially among low-income consumers (Sadik-Rozsnyai, 2016:582).

6.5.2 Financial capability

It is when financial knowledge and financial inclusion meet that financial capability is created. Financial capability integrates a person's ability to act with their opportunity to act. It requires knowledge and skill to use financial resources to good effect (Sherraden, 2013:3). Therefore, it is no surprise that financial knowledge and product accessibility have a positive statistically significant effect on insurance purchase intentions; accounting for an much as 55 per cent of the variance that explains consumer insurance purchase behaviour (Mai et al. 2020:1698). For low-income individuals, financial capability requires optimized decision making in the wake of financial constraints. When the risk is clearly identified, and there is a true desire to effectively manage the risk, financial capability is likely to have proactive effects on risk mitigation efforts. The challenge is that farmers in South Africa are severely financially constrained, and their resilience is already low. Perpetual risk events create an environment of below-par financial agricultural risk management (Choudhury et al., 2016:170). A case study in the Western Cape province of South Africa reveals that the recovery time of farmers to disaster events has significantly increased over the years because of the now repeat nature of extreme occurrences, made worse by limited access to disaster risk insurance along with scant disaster relief and post-disaster recovery support from the government (GreenAgri, 2020:4). It is likely because of this diminishing resilience that financial capability is seen as having no effect on willingness-to-pay for weather index insurance. Farmers have little alternatives and are unequivocal in their need for climate risk solutions regardless of their financial status, financial knowledge and financial literacy. The need for effective solutions cuts across all classes of farmers regardless of age, farm size or farm experience. The results in this study prove that insurance is viewed as essential to agricultural survival and not only to increased productivity. The results further demonstrate that there is a direct relationship between financial capability and intentions to purchase weather index insurance; however, this relationship is not statistically significant. This means that financial challenges and unavailability of products make are a barrier to purchasing insurance intentions. A direct path coefficient of 0.14 is reported which is relatively similar to result found in Ibrahimi et al. (2020:49), where non-significant perceived behavioural control, that is, financial capability is identified with a path coefficient of 0.35. Daxini et al. (2018:13) report a significant positive association with purchase intentions recording a direct path coefficient of 0.40. In their study, the author concludes that farmers who perceived it to be easy, meaning those that have a high level of self –efficacy to perform behaviour were more likely to perform that behaviour. Self-efficacy defines the ability to complete a task and achieve a goal (Aziz, Husin & Husin, 2017:393). In line with other studies, Senger, Borges and Machado (2017:39) record positive and statistically significant perceived behavioural control, this was measured in terms of the availability of time to perform a behaviour. While Lalani et al. (2016:26) also record significant positive effect with a standardized regression coefficient of 0.35.

6.5.3 Risk perception

This study reinforces the standard theoretical model of farmer behaviour under risk, which states that risk preferences play an important role in decision making processes. Risk perception was found to have a significant and direct influence on willingness-to-pay. For every unit increase in risk perception, willingness-to-pay is expected to increase. These results are similar to those reported in other agricultural insurance studies that risk perception significantly influences insurance purchase decisions (Adjabui, Tozer & Gray, 2019:501; Lyu & Barré, 2017:76). The findings also agree with studies in other fields of insurance where risk perception was assessed using TPB as the underlying framework and found to have significant positive effects on consumer purchase behaviour (Lalani et al., 2016:26; Mai et al., 2020:1699).

To the contrary, Awel and Azomahou (2015:3) report no evidence of risk preference effect on demand for weather index insurance. While Ibrahimi et al. (2020:49) report a negative non-significant relationship between attitude, that is, risk perception and intentions to purchase crop insurance.

Based on the findings of this study, it can reasonably be concluded that the majority of farmers who participated in the survey are risk averse. This conclusion was drawn based on the farmers reporting a willingness-to-pay of 5% which is aligned to the commercial rate for agricultural insurance, and also on the basis of activities, they undertake in managing their farm operations. Albeit, when asked about their own risk inclination in relation to other farmers, responses are more mixed. On the bias of the literature review, under the expected utility framework, a risk averse or even in some cases a risk neutral economic agent facing no liquidity constraints would be willing to purchase index insurance at what they perceive to be an actuarially fair price (Smith, 2016:282).

Risk aversion is correlated with increased participation in weather index insurance (Sibiko & Qaim, 2017:13) as risk averse farmers take more effective measures to secure themselves from unexpected losses (Fahad et al., 2018:456). For sustainability and accurate pricing of weather index insurance, it becomes important to classify farmers according to their risk preferences as risk seeking farmers are traditionally willing to pay an extra margin for insurance premiums to compensate for their risk taking activities. Risk seeking farmers would need to be priced separately not to create a situation where risk averse farmers are subsidizing premiums for those that are risk seeking.

Although recent research has failed to explain adequately the low demand for index insurance within the neoclassical utility maximization framework (Würtenberger, 2019:22) it may be unreasonable to expect such a high degree of competence and rationality on the part of insured farmers confronted with the purchase of very complex and abstract products. These study findings are consistent with economic literature, and they also take into account cultural considerations which they find to be significant in purchase considerations as well. Carter (2016:95) explains that recognizing how individuals systematically respond or deviate from the predictions of the standard expected utility model may have immediate positive implications for the design of innovative insurance solutions (Carter, 2016:95).

6.6 Findings on Socio-demographic Factors

The study results identified gender as a positively significant factor associated with willingness-to-pay, and education was identified as a negatively significant factor influencing index insurance purchase decisions.

6.6.1 Gender

Gender was identified as a positive and statistically significant factor influencing willingness-to-pay. In particular, male farmers were shown to have an increased propensity for weather index insurance, and this is consistent with literature from other settings highlighting that participation of female farmers in weather index insurance is lower (Delavallade et al., 2015:3; Nyaaba, Nkrumah-Ennin & Anang, 2019:372). Male and female farmers usually display different personality profiles, particularly in terms of their level of risk aversion (Akter et al., 2016:219). This influences their participation in insurance programmes and how much they are willing-to-pay, as reported by Abugri, Amikuzuno and Daadi (2017:7) where female farmers are willing to pay, the amount is lower than the male counterparts.

In South Africa, male farmers have a stronger orientation for commercial agriculture, where anecdotal evidence suggests that male farmers are more efficient in maize production assessed in terms of optimal land use, technical efficiency and production efficiency (Obi & Ayodeji, 2020:13). In a productivity analysis by gender in sub-Saharan Africa, the difference are noted in productivity levels favouring male farmers. The gender differentials observed in Nigeria, Tanzania and Uganda range from 15% to 30% in productivity. Due to structural constraints, evidence suggests that female farmers use much less inputs in comparison to their male counterparts (Sheahan & Barrett, 2017:20). Evidence in the form a quantitative assessment suggests that if restrictions on land, finance and inputs are resolved, then female farmers could be as efficient as their male counterparts (Mukasa & Salami, 2015:28). In light of commercialization, male farmers would take a greater interest in adopting insurance as part of their risk mitigating strategies to stabilize income and to promote sustainability. This is supported by findings in section 5.10, where only male respondents affirmed their use of crop insurance. On the other hand, female farmers engage more in subsistence farming with a view to providing domestic food security (NGPF, 2002:16). This perspective remains unchanged, originating from the pre-apartheid undermining of women’s rights to agricultural land.

Similar results on gender roles are found in Uganda where male and female farmers are equally exposed to climate change, but prevailing cultural norms in the region predispose women to be responsible for household food production focusing on subsistence agriculture, with no access to productive resources (finance, information, technology). Consequently, the adaptive capacity of women to respond to weather hazards is relatively low (Bamanyaki & Aogon, 2020:5). So too appears to be the level of awareness of index insurance products. In Ghana, Ellis (2017:709) reports that over 70% of females were not aware of index insurance, as opposed to 38% of males who were not aware of such products.

The findings presented in this study, coupled with others, highlight that gender disparity and inequality in farming remains a prevalent unresolved social issue. As cited in the National Policy Framework for Women's Empowerment and Gender Equality, female farmers in South Africa lack access to credit, land, technology and information, thus reducing their contribution to agricultural production (NGPF, 2002:16). Researchers such as Aheeyar et al., 2019:15) caution that if gender-specific disparities are not addressed, weather index insurance could deepen existing inequities rather than promote inclusive climate adaptation. According to Born, Spillane and Murray (2018:6):

> "It is critically important that gender-related agricultural factors in South Africa be included in planning or initiatives for smallholders, including insurance provision".

Among many reasons for inclusive representation, evidence shows that empowering women is the best way to multiply societal well-being. FAO (2017:9) report suggests that when women are given equal access to resources, income opportunities, insurance and education, overall agricultural output and food security increases. Especially in sub-Saharan Africa were women make-up nearly 50% of the labour force in agriculture (Mukasa & Salami, 2015:5). But land allocation in terms of ownership is unevenly distributed, for example, in their analysis of over 4 000 farms, the authors find that males manage over 80% of agricultural lands in Nigeria; and over 70% in Uganda based on the analysis of data for over 2 000 farms in that country (Mukasa & Salami, 2015:18).

6.6.2 Education

Education was a negative and statistically significant factor influencing willingness-to-pay. The negative association is also found in Swaziland, where Mbonane and Makhura (2018:10) find that higher levels of education have a considerable marginal effect on decreasing probability of interest in crop insurance. A farmer who has attained a higher level of education is 20% less likely to be interested than one with no formal education. These results are in stark contrast to the literature amassed regarding the participation of low-income farmers in insurance schemes. The existing narrative in the literature (Ali et al., 2020:544; Ellis, 2017:713; Fahad et al. 2018:464; Hountondji et al., 2019:322) is that better educated farmers are more likely to receive and understand the insurance offering with its complexities and are thereby more willing to purchase index insurance, this is also the case for the purchase of traditional indemnity-based crop insurance (Aditya, Khan & Kishore, 2018:171).

A possible explanation for the surprising variance comes from Myeni, Moeletsi, Thavhana, Randela and Mokoena (2019:12). In their analysis of determinants of adoption of Sustainable Agricultural Practices (SAP), the authors assess that smallholder farmers in the Free State province of South Africa with a higher level of education have an increased likelihood of adopting modern practice such as minimum-tillage, cover cropping, tied ridging to improve production and mitigate climate change. Most of the farmers with a higher level of formal education have the ability to understand these initiatives which require formal education and training. This could be a possible reason explaining the lack of interest in index insurance among the participants in this study. Moreover, farmers with a higher level of education may have a firm grasp of the concept and of the limitations of index insurance as it pertains to the basis risk component. Basis risk has been found to negatively impact the insurance demand of farmers who understand the mechanics of the insurance contract. In this case, it is necessary to reduce the deviation of the indemnity payment from the actual loss. This means improving the overall quality of index insurance (Lampe & Würtenberger, 2019:14). Similarly, Gaurav and Chaudhary (2020:11) find that farmers with a higher level of education have significantly lower willingness to participate and purchase weather index insurance as they are more likely to understand the relevance of basis risk on the insurance proposition than less educated farmers.

As an interesting contrast, though, this study finds that farmers with no formal education are also negatively and significantly associated with willingness-to-pay. Limited understanding of weather index insurance could translate into different misconceptions within the farmer's decision making (Ceballos & Robles, 2020:21). In support, of this notion, there is a great deal of literature that points to farmers limited understanding of a product as the leading factor in their reduced demand for weather index insurance contracts, for example, Sibiko and Qaim, (2017:13) among others. To delve further, when it comes to general insurance application among the study population as illustrated in Table 5.6, insurance usage is the lowest among those with no formal education and the highest among those with formal education. This is consistent with literature findings that farmers with a higher level of education are more inclined to use indemnity-based insurance. This points to the effect of basis risk in educated farmer's decision making. The results offer insight where it could reasonably be concluded that at levels of no formal education, there is limited understanding which deters farmers from using insurance and at the higher end of tertiary education, there is an understanding of basis risk intricacies, which also limits participation. In addition, the availability of other modern mitigating techniques lower index insurance demand.

6.7 Findings on Socio-economic Factors

The study results identified access to credit and group membership as positively significant factors influencing willingness-to-pay.

6.7.1 Access to credit

Access to credit was a positively significant determinant of willingness-to-pay. Corroborative findings come from Fahad et al. (2018:464) where access to credit is a positive coefficient which is statistically significant. Credit customarily attaches to existing assets as collateral; therefore, farmers generally have a greater interest in taking insurance against unfavourable weather variations to reduce the risk of loan defaults. Relevant studies support this credit-insurance assertion and find that access to credit where insurance is available minimizes default risk (Shee, Turvey & You, 2018:2). In their research, Aditya, Khan and Kishore (2018:166) find that less than 1% of farmers voluntarily take up crop insurance if it is not linked to credit. This points to the liquidity-constraints of farmers. The welfare gains from improving financial markets and easing liquidity challenges through credit could be substantial. If investment is discouraged by either risk or insufficient access to credit, the marginal return on investment could be higher. Mitigating risks would result in higher yields, and credit accessibility would increase the hectares planted (Karlan et al., 2014:598)

Only a moderate number of farmers (35% as reported in sub-section 5.5.2) reported receiving credit over the last five years, a situation which points to credit rationing, undermining development efforts. A case that also demonstrates farmers risk rationing as a result of onerous collateral requirements. Effects of low access to credit are further corroborated in findings in various studies in South Africa, for instance, Myeni et al. (2019:12) and Okunlola et al.

(2016:7) both report very low levels of farmers with access to credit. This is a fundamental aspect undermining sustainable crop production, yield improvements and sectoral innovation by means of new technologies. There is clear evidence across sub-Saharan Africa that suggests a close relationship between improved productivity, technology adoption and credit. Theoretically, the provision of insurance removes barriers to investing in emerging technologies while credit, on the other hand, allows such technologies to be accessible and affordable (Ndegwa et al., 2020:748). Moreover, substantial evidence exists in South Africa that access to credit is a crucial determinant of low-income farmer's decisions to adapt to climate change. This as a direct result of the capital-intensive nature of adaptation strategies (Thinda et al., 2020:8).

6.7.2 Group membership

Group membership was found in this study to be a positively significant factor influencing willingness-to-pay. The findings are consistent with Adjabui, Tozer and Gray (2019:498) based on their study in Ghana; also finding are consistent with Sibiko and Qaim (2017:11) who report that insured maize farmers in Kenya exposed to erratic rainfall and frequent droughts are more likely to be members of an organized farming group, and this group membership increases the likelihood of weather index insurance uptake by an estimated 10 percentage points. Group membership is a critical institutional arrangement for knowledge-sharing, information dissemination, learning platforms for innovation and building social capital, which can improve awareness and knowledge on index-based insurance. The positive impact of knowledge on uptake of weather index insurance has been well documented, and repeatedly found to increase demand (Würtenberger, 2019:18). For example, Ahmed, McIntosh & Sarris (2017:30) find that weather index insurance offered through an organized farming group in Ethiopia increased uptake, especially if the products are inter-linked with credit. The author's further report that, of all 108 cooperative members in the study who applied for loans linked to insurance, the approval rate was 100% and mostly for full funding.

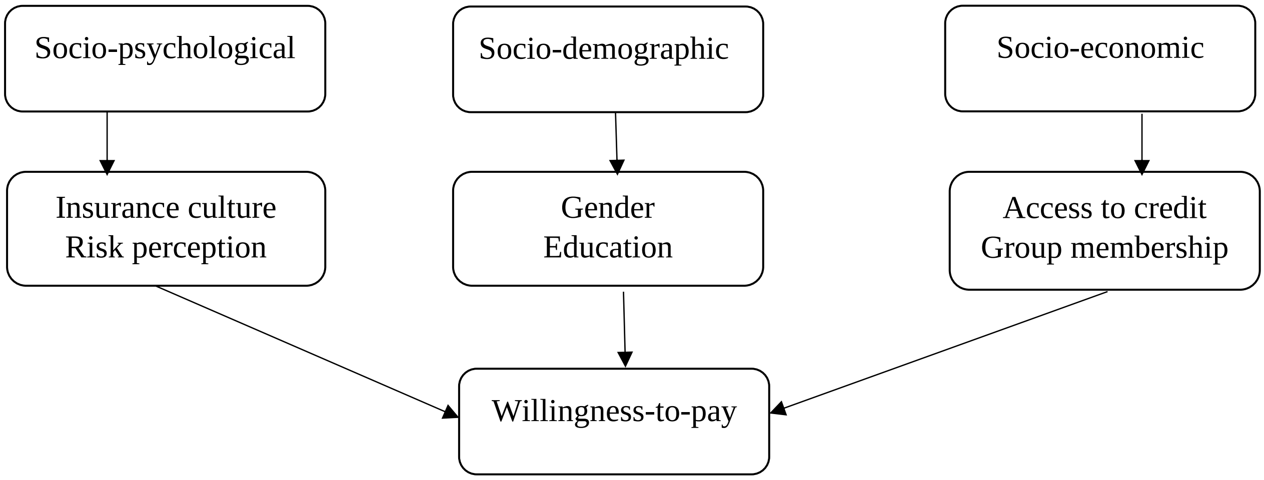
Further analysis of group membership in this study indicates that males (77%) show substantially more participation in organized farming groups than females (33%), see Table 5.7. Manda et al. (2020:2) cite (Abebaw & Haile, 2013) that female farmers across Africa participate less in organized agriculture. This is a potential area for development to improve the overall transmission of information across gender lines. The results may be read in conjunction with the strong participation of male farmers in traditional and index insurance reported in this study which demonstrates how beneficial organized agriculture in the form of cooperatives and associations is in supporting awareness of risk management in addition to their main objectives which are advocacy-related. Research shows that there are statistically significant differences between group and non-group members with respect to the preference for technology, efficient use of irrigation systems, and agricultural input application, with group members benefitting mostly (Ofori, Sampson & Vipham, 2019:222). In the study area, the authors find that group members attend more workshops on the latest technology trends and practices, experiment much more in terms of their farming practices and their food production systems are more secure. In addition, group membership is an important driver of farm performance with respect to maize production (Obi & Ayodeji, 2020:14). Therefore, efforts and policies to improve gender participation in organized groups could possibly have enormous benefits for the farming sector with regard to technology adoptation, insurance usage and improved agricultural productivity.

6.8 Conceptual Framework

Many regions report very low uptake rates of index insurance, usually estimated at less than 10% penetration (Belissa et al., 2020:13; Sibiko & Qaim, 2017:5); even through crop insurance has positive effects on farm income (Cariappa, Mahida, Lal & Chandel, 2020:13). According to Tadesse, Shiferaw and Erenstein (2015:16) sociologists and business professionals have a big role to play in the creation of approaches and instruments that improve demand for weather index insurance. Steps to address market failure and to promote insurance solutions for low-income farmers are centred-around a comprehensive empirical understanding of the market and decision making processes. The identification of demographic, behavioural and economic determinants of insurance participation is key to maximize scheme effectiveness, improve design processes and to determine product and marketing distribution efforts. With all of this in mind, it is the main objective of this study to present a conceptual framework for factors that influence the willingness of low-income farmers to pay for weather index insurance. Such a framework represents a necessary and hitherto missing step to move from problem analysis to an informed and structured pathway incorporating farmer's profile, preferences, touchpoints and influences into future weather index insurance initiatives in South Africa.

The conceptual framework, as presented in the illustrative form in figure 6.1, identifies insurance culture and risk perception as key behavioural determinants of insurance purchase decisions. Gender and education are identified as the main demographic characteristics, and lastly, the framework provides a useful understanding of economic drivers and identifies access to credit and group membership as key factors.

Figure 6.1: Conceptual framework for factors that influence willingness-to-pay



Source: Author's compilation

The conceptual framework is a crucial starting point providing useful guiding principles to stakeholders intending to provide index insurance in South Africa. The current guiding theories and models vary across different regions and countries mostly incorporating only economic drivers; and the literature mostly from developing countries has remained somewhat inconclusive on the common factor that influence willingness-to-pay (Olum, et al., 2020:2). This necessitated developing a model suited for the South African environment. South Africa is unique in its historical agricultural architecture influenced by atypical economic factors, a legacy of racist land possession policies, inhospitable climatic conditions, especially rainfall patterns, lack of agricultural education among many other things, all of which form the societal culture and a basis for the current agricultural enterprise. However, this does not mean that there are no mutual challenges among the developing economies where index insurance is currently applied. Hence the design and development of this conceptual framework were based on a collection of factors identified as relevant in other countries but only those that were significant in the South African context formed part of this model.

Of the many stakeholders interested in agricultural insurance as a whole, the government is among the most interested. Through its NDP, the South African government prioritizes the elimination of extreme poverty, reduction of inequality and the growing of an inclusive economy by 2030, especially in rural areas. NDP goals are aligned to Sustainable Development Goals (SDGs) and to the African Union Agenda 2063 and are integrated into government planning systems and processes at all three spheres of national, provincial and local levels. SDGs are 17 sustainability targets adopted by 169 countries. The goals aim to respond to climate change while achieving inclusive growth, to build resilient communities and to reduce extreme poverty, hunger and malnutrition (FAO, 2017:4). Various short and long-term mechanisms can be applied to curb poverty, hunger and malnutrition, including subsidization of stable foods, and reduction of import tariffs to make prices more affordable as a short-term strategy. While in the long-term, efforts can be directed towards improving the level of disposable income through sustainable employment and improving access to finance and credit (van Wyk & Dlamini, 2018:7). Insurance, as demonstrated in the literature review section, is an additional mechanism to maintain price stability over basic food by directly encouraging production in agriculture. With steady levels of food supply, inflationary increases are likely to be within a manageable range, thus maintaining household welfare. The direct impact of increased investment in agriculture is expected to have positive effects on employment. Therefore, insurance uptake, given fiscal constraints arising from the current health crises and shrinking economic growth, can be an effective indirect approach in the government's objectives of improving the welfare of its citizens.

Among the goals, SDG 2 targets doubling agricultural productivity and incomes of small-scale farmers in particular for women and ensuring sustainable food production systems. To achieve this goal, a systemic approach to build farmer adaptive capacity and resilience is required, this features a list of tools for risk mitigation, risk coping, and risk transfer, including insurance. Financial inclusion in the form of insurance, credit and savings has been found to improve the resilience of low-income farmers to climate hazards (Moore et al., 2019:3). It is projected that less than 3% of smallholder farmers in sub-Saharan Africa have access to agricultural insurance (Shakhovskoy & Mehta, 2018:5). Development of functioning insurance markets for small-scale agriculture is therefore critical to achieving these goals in a financially prudent and cost-effective manner. Thus, the understanding of future market participants and the factors that drive these participants becomes paramount. The conceptual framework provides an in-depth understanding that is expected to facilitate the development of appropriate and effective strategies and technologies for reaching markets and to aid in achieving SDGs.

Underpinning product design is a strong need for continued technological innovation to reduce complexities and cost as well as refining knowledge of market participants, especially in understanding how they react to these innovations and the level of adoption of new technologies. The development and deployment of supportive technology are essential to overcoming the physical and economic barriers to weather insurance participation by low-income farmers. A core part of these technology improvements relates to the underwriting, premium collection, claim settlement and data analysis to support product design, pricing, and claims processing (Shakhovskoy & Mehta, 2018:20).

6.9 Conclusion

In Chapter Six, the discussion focussed on a critical evaluation of aspects relating to the main study findings, which were presented in the previous chapter. The focus of this chapter was on the discussion and interpretation of the results consistent with the research objectives and aligned to the context of existing theory and evidence. The conceptual framework proposed for enhancing insurance uptake among low-income farmers employing an understanding of the underlying factors that are central to decision making in the realm of index insurance was presented. In the framework, behavioural factors that influence willingness-to-pay were noted as insurance culture and risk preference. Findings on the role of insurance culture and risk preferences have very significant implications for the development of weather -index insurance solutions and the subsequent attraction of farmers to these type of insurance initiatives. First, the behaviour of farmers cannot be neglected in product design or insurance distribution and secondly culture plays an integral role in forming and shaping farmers' perceptions. Gender and education were modelled in the framework as demographic considerations and access to credit and group membership were identified as socio-economic drivers. These findings support other findings from the existing body of studies in developing economies to provide a clear view of the factors that are prevalent in the South African context. An empirical understanding of the target market in South Africa should better direct efforts to introduce what is theoretically a viable risk management option premised on improving agricultural intensification especially in the context of 86% of the sampled farmers reporting a willingness-to-pay for weather index insurance at an average price of 6.8%, which serves as an estimated guideline for pricing models. It is cautioned to use the guideline in conjunction with the different risk preferences of farmers and to price in margins for those that are risk seeking. Products developed at price ranges that are not within farmer's reach, where the additional premium charge is not subsidized, will most likely suffer from low uptake, given that farmers have already developed cost-effective, even though production-reducing risk management techniques. The findings of this study have important implications for policy development for low-income farmers which will be discussed further in the last chapter.

The last chapter provides a summary of the main findings, conclusions and recommendation of the research study.

CHAPTER SEVEN: CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

Although weather risks are largely irrepressible, they can be managed or transferred through insurance. In principle, there are two main characteristics that constitute successful insurance; this is the law of large numbers, and the provision of economically feasible premiums (Addey, Jatoe & Kwadzo, 2020:13). For this reason, among the objectives of this study was an investigation of farmers' interest in weather index insurance, to assess the criteria of the law of large numbers; and the subsequent willingness-to-pay insurance premiums, which addresses economic feasibility. Willingness-to-pay is influenced by a range of situational, attitudinal and economic factors. There are rich streams of research on economic considerations and related concepts covered in this study, but psychological contributors to willingness-to-pay remain relatively scarce in the literature (Dixit, Hall & Dutta, 2014:238). A firm grip on these factors could have crucial implications for product development, pricing optimization and product distribution. The identified gaps in psychological factors in the literature, and the broad range of demographic and economic variabilities found in various studies, make a strong case for the study of the psychological and contextually specific factors that influence willingness-to-pay in their setting, given the considerable emerging interest in index insurance solutions. Against this backdrop, chapter seven offers the conclusion and recommendations of the study founded on the empirical research results and on the literature review. The chapter commences with a description of the overall picture of the research findings, underlining each finding in relation to the research objectives. Following this, recommendations are put forward in terms of intricacies of product distribution, education and marketing as well as product design considerations. Next, suggestions are then submitted for areas of future research, which preceded the conclusion for this study.

7.2 Main Findings and Conclusions of the Study

The primary research objective of this study was to develop a conceptual framework for factors that influence low-income farmers' willingness to pay for weather index insurance in South Africa. In this regard, a comprehensive study of prevalent socio-psychological, socio-demographic and socio-economic drivers founded on literature and theory was undertaken. Through this investigating, insurance culture and risk perception were critical components from a psychological standpoint. Culture was among others, defined in the form of farmers understanding of crop insurance and contemplation of insurance utilization in their farming operations. Whilst, risk perception was considered on the basis of the farmers' own categorization of their risk attitude, pre-planting planning activities and attitude towards previous loss. Financial capacity, which is firmly linked to financial literacy, was found not to have a significant influence on farmers purchase decisions. This finding was contrary to literature which suggests that financial literacy significantly affects demand for index-based insurance (Aditya, Khan & Kishore, 2018:12).

Socio-demographic analysis and testing uncovered gender and education as significant positive and negative determinants, respectively. Whilst socio-economic drivers are access to credit and group membership. Credit improves the liquidity position of farmers and association membership advances levels of awareness and access to information, both of which have a positive, significant influence on insurance participation. Diverse factors, as identified in previous studies such as age, marital status, household size, experience, turnover, farm size, and other risk coping strategies were concluded to have no significant effect on South African maize farmers' willingness to take up crop weather-based index insurance.

7.2.1 Willingness-to-pay

In response to secondary research objective one: to investigate low-income farmers willingness-to-pay for weather index insurance:

A structured questionnaire in the form of a survey was employed to ask respondents directly of their purchase intentions of weather index insurance. The product functionality and model of insurance was explained, and illustrative examples were given on how the product responds in the event of a claim. To premise the willingness-to-pay enquiry, farm-specific questions were asked to obtain an understanding of the farming activities and related weather risks in the area of operation. Such questions entailed gathering information on the farm size, pertinent weather risk, historical crop loss and level of preparedness to manage weather risk. This data would provide a wealth of insight into what informs purchase decisions. From the engagement, 86% of the sampled population of low-income farmers expressed a positive inclination to purchase weather index insurance. The overwhelming affirmation makes a compelling case for weather index insurance application in South Africa. It is well documented and researched that low-income farmers are resource and cash-constrained, this study demonstrates that in between the restraints that exist rests a need for alternative or reconsidered risk management solutions in the form of insurance, for which a majority of farmers are willing to purchase. Demand for risk mitigating tools is on the increase, including demand for comprehensive advisory support, as indicated in Loki, Mudhara and Pakela-Jezile (2020:96) where farmers in the Eastern Cape and KwaZulu-Natal provinces of South Africa reported a willingness-to-pay for different sources of extension services.

7.2.2 Willingness-to-pay price range

Secondary research objective two was to determine the price range low-income farmers are willing to pay for weather index insurance.

Where index insurance schemes are promoted, they are often initially funded partially or in full by way of government subsidies, examples being schemes in China, India, Nepal, Uganda and the United States to name a few, wherein the promotion strategy is implemented to directly influence farmers awareness, demand and take-up in the form of support for affordable and accessible insurance premiums. Where full subsidization is offered, it is relatively easy to determine subsidization, which in this case is the full costs of providing insurance in that particular region. Where partial subsidization is proposed, the challenge is to determine the optimum level of subsidies. The end-goal is to support farmers and improve financial inclusion by making sure that farmers also contribute a meaningful portion of the insurance premium. Partial subsidization is a more realistic alternative in light of the governments' budgetary constraints, and slow pace of economic growth, especially in the context of a world-wide pandemic, which is the outbreak of the novel Covid-19 virus, which has seen a redirection of funds from other strategic sectors to healthcare and social grants.

Literature was examined from a diverse range of studies to obtain the average premium rate smallholder farmers are willing-to-pay for index insurance solutions. An average rate of 6.3% was computed and adjusted for relevant factors in the South African environment to arrive at a final rate of 5%; this formed the starting bid price for this study. Logic dictates that there should be high demand for weather-based index insurance in arid and semi-arid areas such as South Africa, but even here the insurance has to be competitively priced relative to available options for managing risk. Application of the double-bounded contingent valuation approach determined the price range as 2.5% to 10% on the basis of the initial bid price.

On the basis of the initial bid price, 175 of surveyed farmers stated that they would be willing-to-pay 5%; from the initial 175, a further 77 farmers expressed a willingness-to-pay up to 10%; lastly, 17 farmers confirmed a willingness-to-pay 2.5% of their annual turnover towards insurance (Table 5.14). Cumulatively, this resulted in an overall weighted average premium of 6.8% that low-income farmers in South Africa are willing-to-pay towards weather index insurance (Table 5.15). Once the price has been determined, Fonseca (2016:21) suggests that stakeholders should consider other different constraints that prevent farmers from purchasing index insurance. These are highlighted in the factors below that restrict insurance participation.

7.2.3 Factors influencing willingness-to-pay

The empirical research objectives number three, four and five were stated as follows:

To identify socio-demographic factors that influence willingness-to-pay for weather index insurance;
To identify socio-economic factors that influence willingness-to-pay for weather index insurance; and
To identify socio-psychological factors that influence willingness-to-pay for weather index insurance;

Considerable literature exists studying factors influencing index insurance purchase decisions from an expected utility maximization theorem point of view. Carter (2016:95) advises that identifying how individuals systematically diverge from the predictions of the standard expected utility model can have immediate implications for the design of innovative insurance solutions. As a relatively new concept, weather index insurance is different from conventional crop insurance, so the factors that determine farmers' acceptance decisions should be different as well (Jin, Wang & Wang, 2016:367). Hence, this study researched prevalent factors which could influence uptake decisions in South Africa, applying a different methodological approach in order to overcome the existing gap in the knowledge of market participants, a vacuum which has proven to undermine insurance innovation and expansion efforts.

The conceptual model developed in this study addressed three dimensions that are antecedent conditions to willingness-to-pay. As far as the author is aware, studies of psychological traits in conjunction with demographic and economic drivers are rare. Therefore, the study made contributions to literature in this regard. By means of SEM with the TPB as the underlying theoretical framework, it was found that behavioural traits of insurance culture and risk perception had a direct effect on willingness-to-pay. Principally SEM relates constructs to one another and represents the theory specifying how these constructs are related (In'nami & Koizumi, 2017:25). In the form of a binary logistic regression, gender and education were identified as socio-demographic factors at a 95% confidence level that significantly influence willingness-to-pay; and access to credit and group membership were identified as socio-economic factors at a 90% confidence level that significantly influence willingness-to-pay.

7.3 Recommendations

The empirical research objective number six was to recommend aspects to include in the product design of weather index insurance solutions in South Africa.

Agricultural insurance markets have been in existence in Europe for over 200 years (Reyes et al., 2017:5). Over the last two decades, an increasing number of national governments, academic researchers, insurers, reinsurers, specialists in development economics and agricultural finance along with international NGOs have shown great interest in weather index insurance (Jin, Wang & Wang, 2016:366). The empirical results of this study should offer meaningful insights and guidance for policymakers and local insurers into development index insurance solutions and should attract farmers' participation in the respective schemes. The recommendations are unpacked in the subsections that follow:

7.3.1 Pilot scheme initiation

Prior to the full implementation of any index insurance programme in South Africa, it is recommended to initiate a government-endorsed pilot scheme for purposes of gathering sufficient actual data. This study was premised on a hypothetical market scenario; it is for this reason that actual monetary-backed commitment, ground-proofing validations, experience and research would uncover the extent of demand, costing and practicality of a nation-wide index insurance scheme. There is currently no reliable information on low-income producers in South Africa, including number, location, and farming practices, a situation that poses significant challenges in the design of agricultural insurance (World Bank, 2016:7). For this reason, a pilot would also serve a dual purpose of providing large scale accurate data collection which could be used for long-term sectoral strategic planning in conjunction with insurance structuring.

As actors interested in weather index insurance, the government represented by the National Treasury and DALRRD in the PPP working group should consider piloting for a period of 18 – 24 months, this would allow for phases of product refinement wherein a final product could be modelled with suitably calibrated indices that correlate as closely as possible to crop loss as well as allowing sufficient time for market understanding, orientation and buy-in from low-income farmers. Moreover, a pilot would provide a litmus test and an opportunity to interrogate the current legislative framework's ability to regulate weather index insurance as an approved class of insurance. Through this testing, licensing criteria could be determined and in so doing this would open the market to interested role players for approval to underwrite index insurance.

7.3.2 Gender-specific focus

The conceptual framework delivered an appraisal of factors influencing willingness-to-pay. One of the critical factors highlighted was gender, and the evidence suggested that female farmers participate less in crop insurance and are less interested in adopting weather index insurance. Unequal gender relations continue to marginalize the participation of females in agriculture. Therefore, a concerted effort should be made to improve women‘s participation in risk mitigating alternatives; otherwise, there is an increased risk of bolstering inequality and failure to unlock women's productive capacity in agriculture. Gender-transformation initiatives are required; these can be achieved through direct education and training workshops tailor-made for woman farmers to assist in risk identification and present various options on effective risk reduction. Presenting information on climate change, weather forecasts and documented impacts on crop yield may increase risk awareness and reduce understatement of risk events (Dougherty, et al., 2019:40). A consideration of packaging insurance with a savings component may prove to be a more attractive proposition as female farmers have shown that they have a strong preference for savings as a risk mitigating tool. Overall, integrating a gender-specific focus is vital to enhancing agricultural production and productivity, as well as household food security and income (Bamanyaki & Aogon, 2020:5).

The study further reported that every 3 out of 10 women participate in farming associations or cooperatives, in comparison to 7 out of 10 for the male counterpart. The low participation creates barriers to accessing new information and technologies that can improve inclinations towards insurance application. Such barriers can be removed by considering alternative ways of information dissemination suited to female farmers either via social media, targeted marketing and collaboration with existing niche programmes that explicitly target women. This as a direct response to communication and information networks that appear to be different from those preferred by male farmers. Structural disadvantages and information asymmetry across gender lines continue to place restrictions on female farmer's commercialization aspirations. A greater attempt to remove these barriers is likely to improve social welfare with respect to indirect benefits in the area of health, nutrition and education for rural farmers (Mukasa & Salami, 2015:38).

7.3.3 Credit-insurance bundling approach

It was found in this study that liquidity betters the prospects of index insurance purchase. Access to credit has long been heralded as a gateway to exponentially increasing agricultural insurance uptake, this as farmers seek an additional layer of security to enable repayment of debts in the event of weather-related hazards. An approach followed in many established index insurance markets is to leverage this link and to bundle the provision of credit with insurance (Aditya, Khan, Kishore, 2018:170), which has demonstrated numerous developmental benefits such as financial inclusion and technology adoptation. According to Hansen et al. (2017:17) insurance is most effective when it is integrated into the agricultural value chain — owing to its ability to improve efficiencies and to unlock the economic potential in agricultural production (Stoppa & Manuamorn, 2017:5). For this reason, risk-contingent credit is the recommended distribution channel based on the findings of this study. In applying this method, weather-related perils are transferred from farmer to financier via insurance and reinsurance markets. Herein serving a twofold purpose, whereby the financier is protected (meso-level), and the farmer is covered (micro-level). The bundling approach, or risk-contingent credit, takes care of product distribution, where a financier with existing infrastructure and client base can package insurance cost-effectively. In addition, this should open the market to a wider pool of customers because index insurance has the capability to serve as surrogate collateral that improves the creditworthiness of clients backed by a cession agreement on claim payouts. In view of the fact that financiers deal with complex financial models, index insurance, adopted at the level of risk and credit modelling, would benefit improved credit product packages and stimulate demand for insurance.

Moreover, fit for purpose credit-insurance bundling has the desirable effect of making insurance premium more affordable because premiums can be collected in monthly instalments along with loan repayments, thus eliminating one of the shortcomings of standalone index insurance, where farmers are asked to pay premiums upfront when disposable income is at its lowest and the marginal utility of cash is at its highest (Belissa et al., 2020:11). Survey respondents who were not interested in weather index insurance cited other priorities (91%) and expensive premiums (63%) as the main reasons. The recommended approach should, to an appreciable extent, alleviate the concerns and improve participation in future index insurance schemes. Few schemes have reached scale without leveraging pre-existing distribution channels or without the bundling approach with other relevant services to reduce distribution costs. Over 90 per cent of all index insurance services are either bundled or offered together with credit or inputs (Shakhovskoy & Mehta, 2018:11).

7.3.4 Promoting insurance: education and training

A recent review by Ceballos and Robles (2020:34) found that most index insurance programmes demonstrate anecdotal evidence of farmers complaining about a lack of payouts after experiencing farm-level crop damage, being under the impression that the index should respond to idiosyncratic loss. However, idiosyncratic risk is outside the bounds of the index insurance contract. For example, perils such as poor soil condition and pests and disease are uninsured under index contracts (Hill et al., 2019:3). Therefore, effective communication is necessary for clients and stakeholders to understand the covered risk and plan for the possibility of a basis risk event (Greatrex et al., 2015:7). To reduce negative perceptions, reputational damage and perceptions of product failure that can undermine index insurance success, education and training efforts should be undertaken pre- and post-selling index insurance solutions.

Educational campaigns are essential for consumer awareness of the inner workings of index insurance; providing clarity on the inclusions and exclusions of the insurance policy (Coleman et al., 2017:128). Scholars such as Musya and Muttai (2020:21) agree that undercutting the educational process has detrimental effects on insurance participation. Market education is so important that in their study King and Singh (2018:24) find that without proper education, even government-led and subsidized index insurance schemes suffer from low demand. Lampe and Würtenberger, (2019:14) uncovered similar results and proceeded further to analyze that even subsidies as high as 50% are ineffective in the absence of product awareness and education. Financial education improves household welfare and overall soundness of financial systems

(Carpena et al., 2015:2). It also enhances financial skills giving individuals the confidence to search for financial products that will address their needs (Refera, Dhaliwal & Kaur, 2016:9).

Market education will ensure that the product's main attributes which are geared towards out-of-cycle, less frequent but high-value losses, in the form of covariate shocks such as regional drought, are well understood by the target audience. Farming associations and cooperatives offer an excellent platform for rolling-out educational initiatives. These groupings often organize themselves into manageable units for collaborative study purposes with the aim of sharing farming techniques, identifying service providers for collective, and entering into collective bargaining agreements with suppliers. For example, farmers in organized groups show significant savings in fertilizer and seed purchase, calculated to be as much as 14 percentage point difference when compared to non-members (Tolno et al., 2015:132). Cooperatives can build economies of scale and thus promote welfare by combining various resources such as labour, knowledge and financial resources among participants (Wossen et al., 2017:224). For this reason, organized farming groups are largely used as a way of encouraging advanced agriculture technology and mitigating food shortages and poverty. (Manda et al., 2020:2). This study has demonstrated that being part of such an association increases prospects of participating in weather index insurance schemes, and it stands to reason that this is the optimum and cost-effective platform for educational initiatives.

Through education and training, insurance culture is further cultivated, which this study has shown is a precursor for improving prospects of insurance purchase. It is culture that guides behaviour and reinforces certain belief systems. Smaller subcultures are present in each culture. Nationalities, sects, ethnic classes and regional areas have subcultures. These subcultures make up an important market segment, and effective marketing means designing products and marketing programmes tailored to the specific needs of a subculture (Langat, Naibei & Getare 2017:703). In the short-term a synchronized effort, with education as a tool and farming cooperatives as a platform, is expected to increase insurance awareness, interest and probability of uptake. For instance, Sibiko and Qaim (2017:13) determined that participation in at least one training session increases the likelihood of weather index insurance purchase by 15 percentage points.

Training in agriculture, which is also a proxy for exposure to extension services, is a positive and statistically significant determinant of crop insurance adoption (Aditya, Khan & Kishore, 2018:168). This education should fall under the broad umbrella of farm-level management practices, where extension services can play a key role in education, training and awareness raising, primarily because of their outreach capacity and existing relationships with farming communities. Extension services have been proved to improve the rate of technology adoptation in agriculture (Manda et al., 2020:10) and are available for free to South African Farmers (Loki, Mudhara & Pakela-Jezile, 2020:84). Farmers who engage extension officers are more likely to purchase index insurance products (Ellis, 2017:708). This is because extension agents are among the main sources of information for most small-scale farmers in rural communities (Nyaaba, Nkrumah-Ennin & Anang, 2019:370).

Radio broadcasts are also an effective way of disseminating information to a large audience. Radio transmissions provide a sense of information credibility, and radio is usually the primary source of news for many farmers in remote rural locations. In their study, Abugri, Amikuzuno and Daadi (2017:5) found that 60% of smallholder farmers acquired knowledge on index insurance through radio stations and that farmers who own a radio have increased prospects of weather index insurance purchase. Similarly, Ellis (2017:709) finds statistically significant relations between radio ownership and willingness-to-pay.

In their study of South African smallholder farmers, Thinda et al. (2020:6) report similar findings in this regard. Access to radio improved probabilities of farmers utilizing climate change adaptation strategies, including insurance. On the strength of these findings and on the literature featured in this study in term of access to information, it is recommended that radio be one of the mediums of communication to be adopted at a local scale to provide targeted educational information on index insurance workings, using local indigenous languages for understanding and clarity.

7.3.5 Product-specific initiatives

In this study, 70% of respondents referred to drought as the main source of risk affecting crop yield, a further 23% of farmers noted that although drought is scarce in their respective areas, low rainfall is of particular concern. The response indicates that rain-deficit index insurance products reflect the true needs of South African farmers. Intuitively, the response is in conformity with South Africa's relatively low annual rainfall and exposure to El Niño elements. It is thus recommended that a drought index product would be the ideal solution that would resonate with low-income farmers. The design should be based on rainfall satellite data which the literature review indicated is more accurate, readily available with no missing time series and providing complete coverage over space and time. This will provide architects of index insurance with sufficient data to design comprehensive solutions to mitigate weather risk. A drought indicator matrix as adopted by the national government when declaring provincial and regional drought should be used as a critical component for calibrating the index. Where the drought index is triggered with sufficient early warning prior to government declaration this will allows farmers to receive timely payouts to enable them to take farm-level tactical corrective action, including replanting if time permits, as well as early planting preparations for the next crop production cycle. Early warning detection is key in drought recovery processes; late detection thereof has proved to very costly (GreenAgri, 2020:7). An efficient early warning system entails spatial determination of the scope of drought, anticipated duration and intensity thereof. The current response by the government to drought has room for much improvement; currently, each province manages its own drought response plan where some plans have been in place for more than 20 years without being adjusted to reflect climate change challenges. Drought impacts farmers differently, and policy makers should give recognition to these variances, which will inform different response strategies (Ncube & Shikwambana, 2018:3).

It is recommended to encourage farmers to adopt drought-tolerant seed varieties by discounting insurance premiums where drought resistant cultivars are applied. Drought resilient crops have intrinsic features of minimizing plant water loss and maximizing water intake (Ncube & Shikwambana, 2018:25). Although more expensive, drought-tolerant varieties improve farmer resilience and show positive results in years of no drought or instances of moderate drought. The pairing of these products offers better risk management solutions against adverse climate shocks, allowing index insurance contracts to respond only to cases of severe drought, where the risk of basis risk is minimized substantially. In so doing, index insurance accomplishes its objectives of building resilience, reducing vulnerability and encouraging agricultural development in addition to stimulating investments by low-income farmers in revenue generating activities (Stoeffler et al., 2020:4).

Weather index insurance should be sold to the market prior to the commencement of the planting season, with clear cut-off dates for enrolment in order to avoid adverse selection by ensuring that at policy commencement date there is information symmetry between the insured and insurer. If farmers are able to predict the weather, they will only insure in years of high risk, and if insurers can predict the weather, they will raise premiums and limit insurance coverage. Both situations can undermine index insurance efforts. Thus, an early cut-off period will solve the problem. Another critical aspect to consider in insurance provision is the existence of insurable interest. Insurable interest will have to become an integral part of weather index insurance validation to comply with principles of insurance law and to avoid speculation by those with non-farming interest or farmers who simply fail to plant crops for the season but speculate on weather variations. Satellite imagery from NDVI can be used to locate the farm and remotely assess the existence or cropping activity or government extension officers who routinely support farmers are also able to confirm existence.

Underwriting index insurance on a group basis for a specific farming association or cooperative can additionally be an effective way of achieving large scale uptake provided that the grouping is homogenous, plants the same crop and are within a similar geographical area, which is mostly the case. Group members, as documented in the literature, would be more inclined to participate and tend to display more confidence in a group set-up both to interrogate and appreciate the product offering. This approach leverages already organized groups, in this way, the strategy also addresses the issue of product understanding, because of the knowledge sharing that typically takes place, ensures ease of administration, reduces education and marketing costs. This form of group underwriting also goes a long way to cultivate positive insurance culture and heighten risk perception. The combined effect of lowered administrative costs, distribution and sales would result in a more affordable insurance premium split proportionately between participating members in the group scheme.

7.3.6 Policy interventions

It is well documented that the government's spending over the last decade in the agricultural sector has been of epic proportions with limited transformational and economic impact for the majority of smallholder and subsistence farmers. It is clear that the key challenge remains to improve agricultural production for low-income farmers in South Africa (Ncube, 2018:89). Given the slow pace of land reform in relation to government's targets, disenfranchised low-income farmers remain voiceless on the side-lines and frustrated with the unrealized promises thus far as chartered in the New Growth Path. For land reform beneficiaries who in the main, primarily receive once-off standalone grant funding as a forerunner to sustainable farming operations, these grant funds counterproductively and counterintuitively increase frustration and discourage future farming endeavours, in light of perpetual weather shocks in addition to other agricultural price and production risks to which capacity constrained low-income farmers are routinely exposed.

The standalone, once-off grant funding model, as well as ad hoc, reactionary disaster relief funding, appears to be unsustainable, impractical for the cyclical nature and weather-risk exposed agricultural environment, as well as limited in its reach. In recognition of these shortcomings, DALRRD has in recent time commenced working on compiling a comprehensive farmer's register to respond directly to questions of identification and reach of low-income farmers. In addition to policy reforms that reduce dependency on grant funding by introducing a blend of loan financing with a grant component. This blended finance option is expected to leverage funding from commercial banks and grants from the government to provide more comprehensive funding packages to farmers (Aliber, 2020:19). Agricultural insurance in the role of risk transfer, with effects of economic development and sustainability, can play a critical role in ensuring that at a minimum, grant disbursements for crop production has an insurance component. In the event of crop failure, the farmer is not left to stranded and waiting for another round of potential funding, instead of insurance as a cushion, to a great extent, is able to reinstate the farmer in a timely manner, to a position prior to planting in order to ensure sustainable production with risk transferred from the farmer, to insurance markets, to global reinsurance markets and furthers retrocession programmes.

It is recommended that agricultural crop insurance with its subsets finds resonance in the national policy agenda and integration into the agricultural policy framework among the many government programmes such as the Comprehensive Agricultural Support Programme (CASP). This targeted support programme explicitly enlists financial services as a priority action item in supporting smallholder farmers. 'Financial services' is a broad term encompassing grants, credit and insurance. It is, therefore, under the insurance aspect, which has been perennially underfunded that agricultural insurance should be robustly explored, discussed and implemented for its ability to support farmers in a sustainable manner, specifically, with weather index insurance which is more suited for covariate risks such as drought that plagues farmers in South Africa. Climate change is expected to continue over the next decade, and unsurprisingly, so too farmer's interest in crop-based index insurance products is expected to increase (Guo & Bohara, 2015:17). By integrating insurance in government programmes through policy, a sustainable, holistic risk management system can be established, where a system approach of comprehensive financial services and non-financial support in the form of extension services runs parallel to address farmers' challenges. In addition to facilitating better access to credit, inputs and markets. In this portfolio approach, insurance can be used to largely respond to catastrophic risk, while credit can be used for intermediate and less covariate shocks and farmer's individual savings can be used for the more frequent and smaller shocks that can be absorbed within a farmers risk retention capacity (Carter et al. 2014:29). This would be in line with most developed countries who in their disaster risk management and financing initiatives opt for a combination of extending credit, providing index insurance and reserving resources for post disaster relief (Cia, de Janvry & Sadoulet, 2016:5), and use crop insurance as a climate change mitigation tool and adaptation strategy (Reyes et al., 2017:29). According to Herbold (2014:200) there are no other economic activities that are as vulnerable to natural threats as crop production. Therefore, government contingency and disaster management plans, infrastructure build programmes such as boreholes and irrigation need to be comprehensive in response to the inherent challenges.

Agricultural insurance is noticeable for its absence in the national policy agenda, as both a social safety net and a management instrument in response to catastrophic risk. This study calls upon an open dialogue for discussions around partial premium subsidization guided by stringent administrative procedures for new insurance products aimed at smallholder farmers. Subsidization is associated with ex-ante risk management which contributes to more reliant agricultural insurance systems where there is an efficient and transparent flow of funds to beneficiaries underpinned by insurance policies (Herbold, 2014:202). Various studies demonstrate that subsidies and discounts positively influence willingness-to-pay for weather-index insurance in the presence of state intervention (Hill, Robles & Ceballos, 2016:1259; Jin, Wang & Wang, 2016:370; McIntosh, Sarris & Papadopoulos, 2013:414; Zhang, Brown & Waldron, 2017:18). Furthermore, subsidies increase the depth of insurance coverage in terms of the sum insured (Aditya, Khan & Kishore, 2018:168). According to Kunreuther and Pauly (2014:3) it as necessary to adopt stringent policy tools such as premium subsidization to induce farmers to utilize insurance and move from suboptimal resource utilization. In light of the positive emerging evidence on the welfare effects of weather insurance in developing world agriculture (Gaurav & Chaudhary, 2020:13).

7.4 Contributions

The motivations behind designing smallholder insurance products vary and can include climate resilience, poverty reduction, and protection for financiers, catastrophe risk protection, social safety-net provision, commercial orientation or a combination of different objectives. Central to each of the objectives is the end consumer, which is the farmer. According to Langat, Naibei and Getare (2017:706) the first step in tapping into an insurance market's true potential is the understanding of the consumer's attitude towards insurance. The second step is to segment consumers on the basis of insurance perceptions, rather than simply on the income, commercial orientation, farm size and so forth. This study contributes to the present knowledge gaps as identified in chapter one by presenting a conceptual framework on the basis of empirical research involving factors that influence willingness-to-pay for weather index insurance in South Africa. The framework identified specific demographic and economic drives unique to the South African environment and contributes to the existing body of literature on risk transfer and mitigation in developing countries. It was noted that the standard economic framework ignores the behavioural inputs from the cognitive and socio-psychological perspectives (Jurkovicova, 2016:184). In response, this study takes into account these previously ignored elements in constructing a comprehensive framework. The novelty of the study is that it is one of the few studies assessing low-income farmer's willingness-to-pay for weather index insurance from a psychological, demographic and economic consideration in a single study, thus contributing to theoretical knowledge. The study further provides preliminary evidence of latent demand for index insurance solutions in South Africa and establishes a mean price that can guide insurance pricing decisions. The fact that low-income farmers can contribute to so many different developmental agendas is a unique aspect of the sector. This study sets the scene for dialogue among stakeholders to provide effective risk mitigating solutions in response to climate change and contributes to the current policy discourse between the government, industry and academia to finding appropriate and adequately priced solutions for low-income farmers.

7.5 Limitations of the Study

Index insurance is a new concept for South African farmers as it is a non-market product in the country which was hypothesized in this study based on similar products piloted in developing countries for low-income farmers. As such farmers might respond differently to a real-life product scenario. Especially in consideration of the complex realities of smallholder agriculture in contemporary South Africa where there is no previous experience with insurance. In addition, from a consumer-orientation perspective, the valuation of any commodity is complex and can vary depending on multiple variables, some associated with the product itself and others related to the special circumstances of the consumer, such as current financial position as well as the availability of alternatives (Dixit, Hall & Dutta, 2014:242). The availability of other options, grant funding and other innovations in the low-income farmer space is a likely reality, given that more government initiatives are being directed towards stimulating the sector. Therefore, the main limitation is that the study is based on a hypothetical market, and there may exist an intention-action gap. However, this limitation does not invalidate the results of the study because of the use of appropriate econometric methods such as contingent valuation in the analysis where it is common practice to assess willingness-to-pay for non-market goods. Furthermore, research on the relationship between intention and behaviour uncovers very positive results with strong correlations, with some studies reporting direct path coefficients of 0.97 (Ibrahim et al., 2020:52).

This study was limited to farmers within the sampling frame and who have engaged financial services offerings (grants and/or credit) over the last four years from 2015 – 2019 through the Land Bank. The sample was limited to three provinces, although covering a shade over 80% of maize production there may be attitudinal differences towards weather index insurance from farmers in other provinces and districts that were not sampled in the study. Agricultural risk comes from diverse sources, and it is experienced to varying degrees across different political and regional circumstances (Duong et al., 2019:1). Therefore, results can be generalized to a limited degree, based on areas with similar characteristics and agro-economic conditions and where farmers are active participants in the financial services market. Lastly, 224 responses were received from the study sample of 326. A lower sample implies that the minimum confidence criteria of α = 5% (or a confidence level of 95%) is not achieved. Even though the minimum criteria for SEM analysis has been achieved, the inferential results should be interpreted with caution.

7.6 Future Study

As sophistication levels of agricultural production systems in South Africa mature, so too will the demand for insurance solutions. For future architects of weather index insurance initiatives in South Africa, it is recommended that forthcoming studies take a closer look at understanding barriers to crop insurance adoption for female farmers. In this study, a large response rate was received from males; this makes it difficult intensively to assess differences in gender preference. However, from the limited data, reasonable inferences could be made that there are statistical differences. Overall, data on gender distribution in agricultural insurance in South Africa is lacking, and if collected would be extremely valuable for tackling challenges and barriers to scaling of agricultural insurance products (Born, Spillane & Murray, 2018:12). Beyond that, understanding how female farmers' access information would be integral to educational efforts and to establish the most optimum gender-sensitive distribution channels.

As a growing phenomenon of interest, index insurance has different elements and can be structured in a variety of ways to achieve better reliability and validity of statistics regarding crop losses. An expanding body of international literature and emerging index insurance pilot schemes are exploring alternative indices such as Area Yield Index insurance based on actual historical yield data and Soil Moisture Index, where the level of moisture in the ground taken by satellite, measured and used as a proxy to anticipate crop loss. Lastly, a hybrid model can be explored of weather index insurance and indemnity-based insurance co-existing as the first level of notification of claims in a region, that is, the initial qualifying criteria for assessment, prompting traditional loss adjusting. The fixed cost element associated with validating claims for a large number of small farms makes indemnity-based insurance unaffordable, but using weather index insurance in combination can greatly reduce the number of inspections undertaken (Boucher et al. 2020:4). These options are among other forms of crop index insurance that can be explored further within the South African dynamic. Interviews from farmers in Ghana highlight that having a larger portfolio of products is critical to guarantee wide scale adoption of agricultural insurance (Lence, 2015:32).

More studies on weather index insurance and how it can enhance farm risk management are required. Especially if a pilot programme is initiated, actual pilot results can influence analysis and data could be studied further to ensure product enhancement, to assess benefits of marketing and educational expenditure on take-up, and to study optimum distribution channels and evaluate if index insurance delivers its promise as a solution for vulnerable, low-income farmers. This study utilized a quantitative research approach. Although robust in its statistical approach, future research using a qualitative or mixed-method approach may contribute to creating a more in-depth understanding of the purchase decisions of small-scale farmers. In qualitative research, it is possible to gain new insights into consumer thoughts, demographic, behavioural patterns, and emotional reasoning processes, thus generating new concepts and theories (Mohajan, 2018:20). The limitations of this work raise new research problems that can be addressed in future studies.

7.7 Conclusion

The need for effective alternative solutions such as weather index insurance cannot be ignored for much longer since weather-related hazards are increasing in severity and frequency. Where weather- index insurance has been adopted, numerous benefits in poverty reduction, improved investment and technology adoption have been observed; therefore the need is clear, but the financial commitment of farmers towards insurance purchase remains uncertain in light of the structural, and exogenous factors affecting farm operations, as well as the presence of product basis risk. The fact that one is trying to solve an agronomical problem with a mathematical solution creates room for basis risk. In essence, the existence of basis risk represents a trade-off for lower premiums, reduced administration costs and many positive developmental impacts of weather index insurance. The study investigation revealed that drought is the main risk affecting low-income farmers, with most farmers reporting annual production losses of between 26% - 50%. A majority of low-income respondents indicated that their preferred risk mitigation options which are mainly reducing production, shifting planting, and crop diversification plans are inadequate to contend with weather vagaries, as observed in their declaration of unpreparedness in managing weather risk. Only a few farmers were noted as using crop insurance. When presented with the prospects and offering of index insurance, 86% of farmers were willing-to-pay for index insurance if it addressed their identified main peril, which in this instance is drought. Employing a weighted average pricing methodology, a pricing guide of 6.8% average premium was determined, this price offers a crucial acceptance and compromise starting position, with a pricing range of 2.5% to 10% providing a reasonable range within farmers' spending appetite. Pricing at the upper boundary of the range may have downward effects on-demand as insurance purchase is price elastic.

In determining factors that influence willingness-to-pay, a mixed approach was applied founded on behavioural theory and economic literature. SEM was applied to identify socio-psychological constructs that have a direct impact on willingness-to-pay. Prior to conducting SEM, confirmatory factor analysis was carried out, and the results confirmed the existence of convergent and discriminant validity. Insurance culture and farmers' risk perception were both found to be predictors of farmer's purchase intentions towards weather index insurance. The impact of financial capacity as a construct was not a direct predictor of farmers' intentions to adopt weather index insurance as was originally hypothesized prior to the investigation. Logistic regression was applied to socio-demographic and socio-economic facts that have been researched to determine their impact on tactical farm-level decisions. Gender, access to credit and group membership were identified as positively significant factors, and education was found to be a negatively significant factor influencing willingness to pay. In promoting index insurance in South Africa, recommendations are mainly focused on (1) gender-specific initiative in order to avoid reinforcing gender disparities in insurance participation, (2) packaging insurance with credit as this has been shown to be able to stimulate both aspects of the credit-insurance complex, intersecting the divide of business risk and financial risk, (3) targeted marketing and education through organized groups and cooperatives, and lastly (4) calling for the piloting of index insurance in South Africa. The final call of this study is for insurance to feature in the national agricultural policy framework as part of a portfolio of tools applied to reduce the triple threat of poverty, unemployment, and equality. In summation, to echo the sentiments of National Treasury (2020:46):

> "A functioning insurance market is a key instrument to support the resilience of a country given the increased weather risk exposures that are anticipated".

REFERENCES

Abdallah, A., Ayamga, M. & Awuni, J.A. (2018). Impact of agricultural credit on farm income under the Savanna and Transitional zones of Ghana. *Agricultural Finance Review*, 79 (1), pp. 1 – 26.

Abdullah, A.M., Auwal, A.G., Darham, S. & Radam, A. (2014). Farmers Willingness to pay for crop Insurance in North West Salangor Integrated Agricultural Development Area (IADA), Malaysia. *Journal of International Society for Southwestern Asian Agricultural Sciences*, 20(2), pp. 19 – 30.

Abd Aziz, N.A.B., Abd Aziz, N.N.B., Aris, Y.B.W. & Abd Aziz, N.A.B. (2015). Factors influencing the paddy farmers' intention to participate in agriculture Takaful. *Procedia Economics and Finance*, 31(2015), pp. 237 - 242.

Abebe, H.T. & Bogale, A. (2015). Willingness to pay for rainfall based insurance by smallholder farmers in Central Rift Valley of Ethiopia: The Case of Dugda and Mieso Woredas. *African Journal of Agricultural Research*, 10(28), pp. 2738 – 2747.

Abugri, S.A., Amikuzuno, J. & Daadi, E.B. (2017). Looking out for a better mitigation strategy: Smallholder farmers' willingness to pay for drought-index crop insurance premium in the Northern region of Ghana. *Agriculture and Food Security*, 6(71), pp. 1 – 9.

Ab Hamid, M.R., Mustafa, Z., Idris, F., Abdullah, M. & Suradi, N.M. (2011). Measuring value-based productivity: A Confirmatory Factor Analytic (CFA) approach. *International Journal of Business and Social Science*, 2(6), pp. 85 - 93.

Accenture. (2018). *Assessing the Demand for Agricultural Insurance Targeting Smallholder Farmers in South Africa. Initial Research Report*. Pretoria: Accenture.

Addey, K.A., Jatoe, J.B. & Kwadzo, G.T. (2020). Adoption of crop insurance in Ghana: An application of the complementary log-log truncated Poisson double-hurdle model. *Agricultural Finance Review*. DOI: 10.1108/AFR-06-2019-0062.

Adegoke, J., Aggarwal, P.K., Rüegg, M., Hansen, J., Cuellar, D., Shaw, R., Greatrex, H., Hellin, J., Diro, R. & Zougmoré, R.B. (2017). *Review of index-based insurance for Climate-Smart Agriculture: Improving climate risk transfer and management for Climate-Smart Agriculture—A review of existing examples of successful index-based insurance for scaling up*. Rome: Global Alliance for Climate-Smart Agriculture.

Aditya, K.S., Khan, M.T. & Kishore, A. (2018). Adoption of crop insurance and impact: insights from India. *Agricultural Economics Research Review*, 31(2), pp. 163 – 174.

Aditya, K.S., Khan, M.T. & Kishore, A. (2018). Willingness to pay for Weather Based Crop Insurance in Punjab. In: *30th International conference of Agricultural Economists*. Vancouver, 28 July – 2 August, 2018.

Adiku, S.G.K., Debrah-Afanyebe, E., Greatrex, H., Zougmore, R. & MacCarthy, D.S. (2017). *Weather index based crop insurance as a social adaptation to climate change and variability in the upper west region of Ghana: Developing a participatory approach*. Working paper no.

189. Copenhagen: CGIAR Research Program on Climate Change, Agriculture and Food Security.

Adjabui, J.A., Tozer, P.R. & Gray, D.I. (2019). Willingness to participate and pay for index-based crop insurance in Ghana. *Agricultural Finance Review*, 79(4), pp. 491 – 507.

African Centre for Biodiversity. (2017). *Against the odds: Smallholder farmers and agricultural biodiversity in South Africa*. Johannesburg: African Centre for Biodiversity.

African Centre for Biodiversity. (2018). *Input supply in South Africa's smallholder farmer support programmes: A tale of neo-apartheid plans, dodgy dealings and corporate capture*. Johannesburg: African Centre for Biodiversity.

Afriyie, L., Zabel, A. & Damnyag, L. (2017). Index-Based Insurance for Cocoa Production in Ghana: just a mirage? In: *Conference on International Research on Food Security, National Resource Management and Rural Development*. Bonn, 20-22 September, 2017. Boon: University of Bonn.

Afroz, R., Akhtar, R. & Farhana, P. (2017). Willingness to pay crop insurance to adopt flood risk by Malaysian farmers: An imperial investigation of Kedah. *International Journal of Economics and Financial Issues*, 7(4), pp. 1 – 9.

AgriSA. (2016). *A paindrop in the drought: Report to the multi-stakeholder task team on the drought Agri SA's status report on the current drought crisis*. Pretoria: AgriSA

Aheeyar, M., de Silva, S., Senaratna-Sellamuttu, S. & Arulingam, I. (2019). Unpacking barriers to socially inclusive weather index insurance: Towards a framework for Inclusion. *Water*, 11(2235), pp. 1 – 19.

Ahmed, S., McIntosh, C. & Sarris, A. (2017). The Impact of commercial rainfall index insurance: experimental evidence from Ethiopia. Retrieved 12/10/2019 from https://ferdi.fr/dl/df-7531fFCqqV5WL5LSA4SrdZBz/publication-the-impact-of-commercial-rainfall-index-insurance-experimental.pdf.

Aina, I., Ayinde, O.E., Thiam, D. & Miranda, M. (2018). Willingness to pay for index-based livestock lnsurance: Perspectives from West Africa. In: *30th International conference of Agricultural Economists*. Vancouver, 28 July – 2 August, 2018.

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational behavior and Human Decision Processes*, 50(2), pp. 179 – 211.

Ajzen, I. (2006). *Constructing a Theory of Planned Behavior Questionnaire*. Retrieved 15/09/2019 from: http://people.umass.edu/~aizen/pdf/tpb.measurement.pdf.

Ajzen, I. (2011). The Theory of Planned Behavior: reactions and reflections. *Psychology & Health*, 26(9), pp. 1113 – 1127.

Ajzen, I. (2015). Consumer attitudes and behavior: the theory of planned behaviour applied to food consumption decisions. *Rivista di Economia Agraria*, 70(2), pp. 121 – 138.

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Hum Behavior & Emerg Tecnologies*. 2020(2), pp. 314 – 324.

Ajzen, I. & Dasgupta, N. (2015). Explicit and implicit beliefs, attitudes, and intention: The role of conscious and unconscious processes in human behavior. In: P. Haggard & B. Eitam (Eds.). *The sense of agency* (pp. 115 - 144). New York, NY: Oxford University Press.

Akhtar, I. (2016). *Research Design*. In: Research in Social Science: Interdisciplinary Perspectives, pp. 68 – 84.

Akter, S., Krupnik, T.J. & Khanam, F. (2017). Climate change skepticism and index versus standard crop insurance demand in coastal Bangladesh. *Regional Environmental Change*, 17(8), pp. 2544 – 2466.

Akter, S., Krupnik, T.J., Rossi, F. & Khanam, F. (2016). The influence of gender and product design on farmers' preferences for weather indexed crop insurance. *Global Environmental Change*, 38(2016), pp. 217 – 229.

Akyüz, N.C. & Theuvsen, L. (2020). The impact of behavioral drivers on adoption of sustainable agricultural practices: The case of organic farming in Turkey. *Sustainability*, 12(17), pp. 1 - 20.

Albers, M.J. (2017). *Introduction to quantitative data analysis in behavioral and social sciences*. 1st edition. Hoboken, NJ: John Wiley & Sons.

Alhassan, A.L. & Biekpe, N. (2019). Pricing power in insurance markets: Evidence from South Africa. *International Journal of Bank Marketing*, 37(5), pp. 1371 – 1392.

Al Hasan S, Muzumdar, J.M, Nayak, R. & Wu, W.K. (2020). Using the theory of planned behavior to understand factors influencing South Asian consumers' intention to seek pharmacist-provided medication therapy management services. *Pharmacy*, 7(3), pp. 1 - 18.

Ali, E., Egbendewe, A.Y., Abdoulaye, T. & Sarpong, D.B. (2020). Willingness to pay for weather index-based insurance in semi-subsistence agriculture: Evidence from northern Togo. *Climate Policy*, 20(5), pp. 534 -547.

Aliber, M. (2020). Thematic study: Conceptualising finance to support labour-intensive land redistribution. GTAC/CBPEP/ EU project on employment-intensive rural land reform in South Africa: policies, programmes and capacities. Retrieved 06/05/2020 from http://repository.uwc.ac.za/xmlui/bitstream/handle/10566/5233/20200331%20FINAL%20GTAC%20Thematic%20Study_Finance%20branded.pdf?sequence=1&isAllowed=y.

Aliber, M. & Mdoda, L. (2015). The direct and indirect economic contribution of small-scale black agriculture in South Africa. *Agrekon*, 54(2), pp. 18 -37.

Alvi, M. H. (2016). *A Manual for selecting sampling techniques in research*. MPRA Paper No. 70218. Munich Personal RePEc Archive.

Antony, J. & Rao, A. (2010). *Contingent Valuation: A review with emphasis on estimation procedures*. Retrived 17/09/2019 from https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.599.7032&rep=rep1&type=pdf.

Apostolakis, G., van Dijk, G. & Drakos, P. (2015). Microinsurance performance–a systematic narrative literature review. *Corporate Governance*, 15(1), pp.146 - 170.

Arshad, M., Amjath-Babu, T.S., Kächele, H. & Müller, K. (2016). What drives the willingness to pay for crop insurance against extreme weather events (flood and drought) in Pakistan? A hypothetical market approach. *Climate and Development*, 8(3), pp. 234 – 244.

Aslam, M., Maqbool, M.A. & Cengiz R. (2015). *Drought stress in maize (Zea mays L.): Effects, resistance mechanisms, global achievements and biological strategies for improvement*. Cham: Springer Publishing.

Atsiaya, G.O., Wati, L.N., Ingasia, O.A. & Lagat, J.K. (2018). Smallholder farmers' willingness to pay for Insurance against climate variability effects in arid land areas of Kenya. *Journal of Environmental and Earth Science*, 8(11), pp. 52 – 59.

Awang, Z. (2012). *A Handbook on SEM*. 2nd Edition. Terengganu: Universiti Sultan Zainal Abidin.

Awang, Z. (2015). *SEM made simple: a gentle approach to learning Structural Equation Modelling*. Bandar BaruBangi: MPWS Rich Publication.

Awang, Z., Afthanorhan, A. & Asri, M.A.M. (2015). Parametric and non parametric approach in structural equation modeling (SEM): The application of bootstrapping. *Modern Applied Science*, 9(9), p.58 – 65.

Awang, Z., Afthanorhan, A., Mamat, M. & Aimran, N. (2017). Modeling structural model for Higher Order Constructs (HOC) using marketing model. *World Applied Sciences Journal*, 35(8), pp. 1434-1444.

Awel, Y.M. & Azomahou, T.T. (2015). *Risk preference or financial literacy? Behavioural experiment on index insurance demand*. UNU-MERIT Working Papers: ISSN 1871-9872. Maastricht: Maastricht Economic and Social Research Institute on Innovation and Technology.

Awondo, S.N., Kostandini, G., Setimela, P. & Erenstein, O. (2015). Multi-Site bundling of drought tolerant maize varieties and index insurance. *Journal of Agricultural Economics*, 71(1), pp. 1 – 21.

Aziz, S, Husin M.M, Hussin N. (2018). Conceptual framework of factors determining intentions towards the adoption of family takaful - An extension of decomposed Theory of Planned Behaviour. *International Journal of Organizational Leadership*, 6(2017), pp. 385 – 399.

Bahta, Y.T., Jordaan, A. & Muyambo, F. (2016). Communal farmers' perception of drought in South Africa: Policy implication for drought risk reduction. *International Journal of Disaster Risk Reduction*, 20(2016), pp. 39-50.

Baiyegunhi, L.J., Majokweni, Z.P. & Ferrer, S.D. (2019). Impact of outsourced agricultural extension program on smallholder farmers' net farm income in Msinga, KwaZulu-Natal, South Africa. *Technology in Society*, 57(2019), pp. 1 – 7.

Balaban, M., Simeunović, I. & Markovic, M. (2018). Problems of crediting and insurance in agriculture. *Economics of Agriculture,* 57(2), pp. 419 - 427.

Balmalssaka, Y., Wumbei, B.L., Buckner, J. & Nartey, R.Y. (2016). Willingness to participate in the market for crop drought index insurance among farmers in Ghana. *African Journal of Agricultural Research*, 11(14), pp. 1257 - 1265.

Bamanyaki, P. & Aogon, G. (2020). *Unpacking impacts of climate change and variability on agriculture, food security and incomes in Northern Uganda: A gender standpoint*. Info Note. Wageningen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Braimoh, A., Mwanakasale, A., Chapoto, A., Rubaiza, R., Chisanga, B., Mubanga, N., Samboko, P., Giertz, A. & Obuya, G. (2018). Increasing Agricultural Resilience through Better Risk Management in Zambia. Washington D.C.: World Bank Group.

Barham, B.L., Chavas, J.P., Fitz, D., Ríos-Salas, V. & Schechter, L. (2015). Risk, learning, and technology adoption. *Agricultural Economics,* 46(1), pp.11-24.

Barnett, B. (2014). Multiple-peril crop insurance: successes and challenges. *Agricultural Finance Review,* 74(2), pp. 200 – 216.

Bartlett, J.E., Kotrlik, J.W. & Higgins, C.C. (2001). Organizational research: Determining appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal*, 19(1), pp. 43 – 50.

Bastagli, F. & Harman, L. (2015). *The role of Index-Based Triggers in Social Protection Shock Response*. London: Overseas Development Institute.

Baudoin, M., Vogel, C., Nortje, K. & Naik, M. (2017). Living with drought in South Africa: lessons learnt from the recent El Niño drought period. *International Journal of Disaster Risk Reduction,* 23(2017), pp. 128 – 137.

Belissa, T.K., Bulte, E., Cecchi, F., Gangopadhyay, S. & Lensink, R. (2019). Liquidity constraints, informal institutions, and the adoption of weather insurance: A randomized controlled trial in Ethiopia. *Journal of Development Economics*, 140(2019), pp. 269 – 268.

Belissa, T.K, Bulte, E, Cecchi, F, Gangopadhyay, S. & Lensink R. (2020). *Improving trust and relaxing liquidity constraints to enhance uptake of weather insurance in Ethiopia*. 3ie Formative Evaluation Report. New Delhi: International Initiative for Impact Evaluation (3ie).

Belissa, T.K., Lensink, R. & van Asseldonk, M. (2019). Risk and ambiguity aversion behavior in index based insurance uptake decisions: Experimental evidence from Ethiopia, *Journal of Economic Behavior and Organization,* 3(37), pp. 1 – 13.

Belissa, T.K, Lensink, R.,& Winkel, A. (2020). Effects of index insurance on demand and supply of credit: Evidence from Ethiopia. *American Journal of Agricultural Economics*, 00(00), pp. 1 – 21.

Bentler, P. M. (2005). *EQS 6 Structural equations program manual*. Encino: Multivariate Software.

Berg, E., Blake, M. & Morsink, K. (2017). *Risk sharing and the demand for insurance: Theory and experimental evidence from Ethiopia*. Oxford: Centre for the Study of African Economies, University of Oxford.

Bettany-Saltikov, J. & Whittaker, V.J. (2013). Selecting the most appropriate inferential statistical test for your quantitative research study. *Journal of Clinical Nursing*, 23(11-12), pp. 1 – 11.

Bewick, V., Cheek, L. & Ball, J. (2004). One-way analysis of variance critical care. *Statistics Review*, 8(2), pp. 130 - 136.

BFAP. (2016). *Policy brief on the 2015/2016 drought*. Pretoria: Bureau for Food and Agricultural Policy.

BFAP. (2018). *Agricultural outlook 2018 - 2027*. Pretoria: Bureau for Food and Agricultural Policy.

BFAP. (2018a). *Income & cost budgets: Summer crops – 2018/19*. Pretoria: Bureau for Food and Agricultural Policy.

BFAP. (2020). BFAP baseline: Agricultural outlook 2020 – 2029. Pretoria: Bureau for Food and Agricultural Policy.

Bhattacherjee, A. (2012). *Social science research: Principles, methods, and practices*. Tampa Bay Open Access Textbooks Collection. Book 3. Tampa: University of South Florida,

Binswanger-Mkhize, H.P. (2012). Is there too much hype about index-based agricultural insurance? *Journal of Development Studies*, 48(2), pp. 187 – 200.

Boucher, S., Carter, M., Erenstein, O., Flatnes, J.E., Lybbert, T., Malacarne, J., Marenya, P. & Paul, L. (2020). Bundling innovative risk management technologies to accelerate agricultural growth and improve nutrition. 2015-2018 Project report. Feed the Future. Retrieved 06/07/2020 from https://basis.ucdavis.edu/sites/g/files/dgvnsk466/files/2019-11/MRR%20Innovation%20Lab%20-%20DTM%20project%20report.pdf.

Bokusheva, R. (2018). Using copulas for rating weather index insurance contracts. *Journal of Applied Statistics*, 45(13), pp. 2328 – 2356.

Bokushevaa, R., Kogan, F., Vitkovskaya, I., Conradt, S. & Batyrbayeva, M. (2016). Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses. *Agricultural and Forest Meteorology*, 220(2016), pp. 200 – 206.

Born, L., Spillane, C. & Murray, U. (2018). Integrating gender into index-based agricultural insurance: a focus on South Africa. *Development in Practice*, 29(11), pp. 1 – 15.

Braun, A., Schmeiser, H. & Schreiber, F. (2016). On consumer preferences and the willingness to pay for term life insurance. *European Journal of Operational Research,* 253(3), pp. 761 – 776.

Brick, K. & Visser, M. (2015). Risk preferences, technology adoption and insurance uptake: A framed experiment. *Journal of Economic Behavior & Organization*, 118(c), pp. 383 – 396.

Browne, M. W. & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.). *Testing structural equation models* (pp. 136 − 162). Newbury Park, CA: Sage.

Bryman, A. (2014). *Social Research Methods*. 4th Edition. New York, NY: Oxford University Press.

Budhathoki, N.K., Lassa, J.A., Pun, S. & Zander, K.K. (2019). Farmers' interest and willingness-to-pay for index-based crop insurance in the lowlands of Nepal. *Land Use Policy*, 85(2019), pp. 1 – 10.

Bueno, J., Dinis, B., Kotanko, B., Maggiora, D. & Neves, R. (2019). *Bancassurance: It's time to go digital*. McKinsey & Company. Retrieved 12/10/2019 from https://www.mckinsey.com/industries/financial-services/our-insights/bancassurance-its-time-to-go-digital.

Bukve, O. (2019). *Designing social science research*. Cham: Palgrave Macmillan.

Bulut, H (2016). *U.S. farmers' insurance choices under Expected Utility Theory and Cumulative Prospect Theory*. Agricultural and Applied Economics Association, Annual Meeting, July 31-August 2, 2016, Boston, Ma.

Buzatu, C. (2013). The Influence of behavioral factors on insurance decision a Romanian approach. *Procedia Economics and Finance*, 6(2013), pp. 31 – 40.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. & Ringler, C. (2014). Climate change and agriculture: Impacts and adaptation options in South Africa. *Water Resources and Economics*, 5(2014), pp. 24 – 48.

Cameron T.A., & James M.D. (1987). Efficient estimation methods for closed-ended contingent valuation surveys. *Review of Economics and Statistics*, 69(2), pp. 269 - 276.

Cameron, T. A. & Quiggin, J. (1994). Estimation using contingent valuation data from a "Dichotomous choice with follow-up" questionnaire. *Journal of Environmental Economics and Management*, 27(3), pp. 218 – 34.

Cariappa, A.A., Mahida, D.P., Lal, P. & Chandel, B.S. (2020). Correlates and impact of crop insurance in India: evidence from a nationally representative survey. *Agricultural Finance Review*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/AFR-03-2020-0034.

Carlos, A. (2016). *Comparative assessment of weather index insurance strategies*. Vuna research report. Pretoria: Vuna. Retrieved 05/01/2020 from https://www.ccardesa.org/knowledge-products/literature-review-comparative-assessment-weather index-insurance-strategies.

Carpena, F., Cole, S., Shapiro, J. & Zia, B. (2015). The ABCs of financial education: experimental evidence on attitudes, behavior, and cognitive biases. Policy research working paper no. 7413. Washington, D.C.: World Bank. https://openknowledge.worldbank.org/handle/10986/22669 License: CC BY 3.0 IGO.

Carson, R.T. & Hanemann, W.M. (2005). Contingent valuation. *Handbook of environmental economics*, 2(1), pp. 821 - 936.

Carson, R.T. & Louviere, J.J. (2011). A common nomenclature for stated preference elicitation approaches. *Environmental and Resource Economics*, 49(4), pp. 539 - 559.

Carter, M.R. (2016). What farmers want: the "gustibus multiplier" and other behavioral insights on agricultural development. *Agricultural Economics*, 47(S1), pp. 85 – 96.

Carter, M.R. (2019). Testing agricultural index insurance for minimum quality. Markets, Risk and Resilience Innovation Lab. Retrieved 15/06/2020 from https://basis.ucdavis.edu/sites/g/files/dgvnsk466/files/2019-02/Feed%20the%20Future%20AMA%20Innovation%20Lab%20-%20Spotlight%20-%20Testing%20Index%20Insurance%20with%20MQS.pdf.

Carter M.R., Janzen S.A., & Stoeffler Q. (2018). Can insurance help manage climate risk and food insecurity? Evidence from the pastoral regions of East Africa. In: G. Lipper, L. McCarthy, N. Zilberman, D. Asfaw. & S. Branca (Eds.). *Climate smart agriculture: Building resilience to climate change* (pp. 201– 225). 52nd Edition. Cham: Springer.

Carter, M.R, de Janvry, A., Sadoulet, E. & Sarris, A. (2014). *Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling*. Background document for the workshop: "Microfinance products for weather risk management in developing countries: State of the arts and perspectives". Paris: Agence Francaise de Developpement.

Carter, M.R. (2016). What farmers want: the "gustibus multiplier" and other behavioral insights on agricultural development. *Agricultural Economics*, 47(S1), pp. 85 – 96.

Carter, M.R. & Chiu T. (2018). *The state of microinsurance 2018: Inclusive insurance for a sustainable future*. Luxembourg: Microinsurance Network.

Carter, M.R. & Chiu T. (2020). *The state of microinsurance 2018: Inclusive insurance for a sustainable future*. Luxembourg: Microinsurance Network.

Carter, M.R., Cheng, L., & Sarris, A. (2016). Where and how index insurance can boost the adoption of improved agricultural technologies. *Journal of Development Economics*, 118(2016), pp. 59 - 71.

Casaburi, L. & Willis, J. (2017). *Time versus state in insurance: Experimental evidence from contract farming in Kenya*. Retrieved 17/05/2020 from https://scholar.harvard.edu/files/jwillis/files/jmp_20170420.pdf.

Castellani, D. & Vigano, L. (2015). An Analysis of the demand of weather index-based insurance with flexible attributes in a risk management framework. *European Scientific Journal*, 11(16), pp. 1 – 22.

Castellani, D. & Vigano, L. (2017). Does willingness-to-pay for weather index-based insurance follow covariant shocks? *International Journal of Bank Marketing*, 35(3), pp. 516 – 539.

Castellani, D., Vigano, L. & Tamre, B. (2014). A discrete choice analysis of smallholder farmers' preferences and willingness' to pay for weather derivatives: Evidence from Ethiopia. *The Journal of Applied Business Research*, 30(6), pp. 1671 – 1692.

Castillo, M.J., Boucher, S. & Carter M. (2016). Index insurance: Using Public data to benefit small-scale agriculture. *International Food and Agribusiness Management Review*, 19(A), pp. 93 – 114.

Ceballos, F., Manuel, R.I., Robles, M. & Butler, A. (2015). *Smallholder access to weather securities in India: demand and impact on production decisions*. 3ie Grantee Final Report. New Delhi: International Initiative for Impact Evaluation (3ie)

Ceballos, F. & Robles, M. (2020). Demand heterogeneity for index-based insurance: The case for flexible products, *Journal of Development Economics*, 2020(102515), pp. 1 – 41.

Ceballos, F; Ulimwengu, J.M., Makombe, T. & Robles, M. (2017). Insurance opportunities against weather risks for smallholder farmers in Africa. In: A. De Pinto. & J.M. Ulimwengu (Eds.). *A thriving agricultural sector in a changing climate: Meeting Malabo Declaration goals through climate-smart agriculture* (pp. 69 - 85). Washington, D.C.: International Food Policy Research Institute.

Chigada, J.M. & Hirschfelder, B. (2017). Mobile banking in South Africa: A review and directions for future research. *South African Journal of Information Management*, 19(1), pp. 1 – 9.

Chitiyo, F.E. (2017). *Demand for non-life insurance: Evidence from select insurance markets in Africa*. Unpublished dissertation. University of Cape Town.

Choudhury, A., Jones, J., Okine, A. & Choudhury, R. (2016). Drought-triggered index insurance using cluster analysis of rainfall affected by climate change. *Journal of Insurance Issues*, 39(2), pp.169 - 186.

Cia, H., Chen, Y., Fang, H. & Zhou, L. (2015). The effect of microinsurance on economic activities: Evidence from a randomized field experiment. *The Review of Economics and Statistics*, 97(2), pp. 287 – 300.

Cia, J., de Janvry, A. & Sadoulet, E. (2015). Social networks and the decision to insure. *American Economic Journal: Applied Economics*, 7(2), pp. 81–108.

Cia, J., de Janvry, A. & Sadoulet, E. (2016). *Subsidy policies and insurance demand Social networks and the decision to insure*. Cambridge, MA: National Bureau of Economic Research

Clarke, D.J. & Kumar, N. (2016). Microinsurance decisions: Gendered evidence from rural Bangladesh. *Gender, Technology and Development*, 20(2), pp. 218 – 214.

Clement, K.Y., Botzen, W.W., Brouwer, R. & Aerts, J.C. (2018). A global review of the impact of basis risk on the functioning of and demand for index insurance. *International Journal of Disaster Risk Reduction*, 28(2018), pp. 845 - 853.

Cole, S., Giné, X. & Vickery, J. (2013). *How does risk management influence production decisions? Evidence from a field experiment*. Working Paper, No. 13–08. Boston, Ma: Harvard Business School.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to household risk management: evidence from India. *American Economic Journal: Applied Economics*, 5(1), pp. 104 – 135.

Cole, S., Stein, D. & Tobacman, J. (2014). Dynamics of demand for index insurance: Evidence from a long-run field experiment. *American Economic Review*, 104(5), pp. 284 - 290.

Coleman, E., Dick, W., Gilliams, S., Piccard, I., Rispoli, F. & Stoppa, A. (2017). *Remote sensing for index insurance findings and lessons learned for smallholder agriculture*. International Fund of Agricultural Development. Impact Insurance. Retrieved 01/10/2019 from http://www.impactinsurance.org/practitioner-lessons/giif/planetguarantee.

Cousins, B. (2017). Land reform in South Africa is failing. Can it be saved? *Transformation: Critical Perspectives on Southern Africa*, 92(1), pp. 135 – 157.

Crano, W.D., Brewer, M.B. & Lac, A. (2015). *Principles and Methods of Social Research*. 3rd Edition. New York, NY: Routledge.

Creswell, J.W. (2014). *Research design: Qualitative, Quantitative, and Mixed Methods approaches*. 4th Edition. Los Angeles, Ca: Sage Publications.

Creswell, J.W. & Creswell, J.D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches*. 5th Edition. Los Angeles, Ca: Sage Publications.

Crisci, A. (2012). Estimation methods for the Structural Equation Models: Maximum Likelihood, Partial Least Squares and Generalized Maximum Entropy. *Journal of Applied Quantitative Methods*, 7(2), pp. 3 – 17.

DAFF. (2013). *Strategic plan for smallholder support – 2011 – 2014/15*. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2014). *Agricultural Policy Action Plan (APAP)* – 2015 – 2019. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2015). *2015/16 to 2019/20 Strategic Plan*. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2018a). *Trends in the Agricultural Sector 2017*. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2018b). *National Policy on comprehensive producer development support: Draft 5 ver. 3*. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2019). Comprehensive Agricultural Support Programme (CASP), and Ilima/Letsema conditional grants (focus on 2019/20 business plan). Presentation to the Portfolio Committee on Agriculture, Land Reform and Rural Development. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DAFF. (2020). *Trends in the Agricultural Sector 2019*. Pretoria: Department of Agriculture, Forestry, and Fisheries – Republic of South Africa.

DALRRD. (2020). Media Statement - Minister Didiza Announced the release of state land. Department of Agriculture, Land Reform and Rural Development. Retrieved 01/11/2020 from https://www.dalrrd.gov.za/docs/media/MEDIA%20STATEMENT%20-%20MINISTER%20DIDIZA%20ANNOUNCED%20THE%20RELEASE%20OF%20STATE%20LAND.pdf.

Daninga, P.D. & Qiao, Z. (2014). Factors influencing holding of drought insurance contracts by smallholders in Bunda. *International Journal of Development and Economic Sustainability*, 2(5), pp. 16 – 30.

Danso-Abbeam, G., Addai, K.N. & Ehiakpor, D. (2014). Willingness to pay for farm insurance by smallholder cocoa farmers in Ghana. *Journal of Social Science for Policy Implications*, 2(1), pp. 163 – 183.

Daoud, J. (2017). Multicollinearity and regression analysis. *Journal of Physics: Conference Series*, 949(2017), pp. 1 – 5.

Darker C. (2013). Risk Perception. In: M.D. Gellman. & J.R. Turner (Eds). *Encyclopedia of Behavioral Medicine*. New York, NY: Springer.

Daron, J.D. & Stainforth, D.A. (2014). Assessing pricing assumptions for weather index insurance in a changing climate. *Climate Risk Management*, 1(2014), pp.76 - 91.

Davis-Reddy, C.L. & Vincent, K. (2017). *Climate Risk and Vulnerability: A Handbook for Southern Africa*. 2nd Edition. Pretoria: Council for Scientific and Industrial Research (CSIR).

Daxini, A., O'Donoghue, C., Ryan, M., Buckley, C., Barnes, A. P. & Daly, K. (2018). Which factors influence farmers' intentions to adopt nutrient management planning?. *Journal of Environmental Management*, 224(2018), pp. 1 - 23.

de Klerk, M., Fraser, F. & Fullerton, K. (2013). *The Status of Agricultural and Rural Finance in South Africa*. Johannesburg: Finmark Trust.

de Leeuw, E., Suzer-Gurtekin, T. & Hox, J. (2018). How to design and implement mixed-mode surveys in cross National Surveys: Overview and guideline. In: *Second International*

Conference on Survey Methods in Multinational, Multiregional and Multicultural Contexts (3MC). Chicago, Ma: October, 2016.

de Leeuw, J., Vrieling, A., Shee, A., Atzberger, C., Hadgu, K.M., Biradar, C.M., Keah, H. & Turvey, C. (2014). The Potential and Uptake of Remote Sensing in Insurance: A Review. *Remote Sensing*, 2014(6), pp. 10888 – 10912.

de Nicola, F. (2015). *Handling the Weather: insurance, savings, and credit in West Africa*. Policy Research working paper; no. WPS 7187. Washington, DC: World Bank Group.

DEA. (2013). *Long-Term Adaptation Scenarios Flagship Research Programme for South Africa. Climate Change Implications for the Agriculture and Forestry Sectors in South Africa*. Pretoria: Department of Environmental Affairs.

DEA. (2017). *National Climate Change Adaptation Strategy Republic of South Africa: 2nd draft for public comments*. Retrieved on 24/08/2019 from Department of Environmental Affairs. https://www.environment.gov.za/sites/default/files/reports/nationalclimate_changeadaptation_strategyforcomment_nccas.pdf.

DEFF. (2019). *National Climate Change Adaptation Strategy Republic of South Africa*. Retrieved on 12/12/2019 from Department of Environment, Forestry & Fisheries. https://www.environment.gov.za/sites/default/files/docs/nationalclimatechange_adaptationstrategy_ue10november2019.pdf

Delavallade, C., Dizon, F., Hill, R.V. & Petraud, J.P. (2015). *Managing risk with insurance and savings: experimental evidence for male and female farm managers in the Sahel*. Policy Research Working Paper No. 7176. Washington, D.C: World Bank.

den Hartigh, W. (2016). *SA's dire need for agricultural insurance subsidies*. Retrieved 21/10/2019 from Farmer's weekly. https://www.farmersweekly.co.za/bottomline/sas-dire-need-for-agricultural-insurance-subsidies/.

Dercon, S., Gunning, J.M. & Zeitlin, A. (2018). *The demand for insurance under limited trust: Evidence from a field experiment in Kenya*. CSAE Working Paper WPS/201906. Oxford: Centre for the Study of African Economies.

Dillman, D.A., Smyth, J.D. & Christian, L.M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method*. 4th Edition. Hoboken, NJ: John Wiley & Sons.

Dixit, A., Hall, K.D. & Dutta, S. (2014). Psychological influences on customer willingness to pay and choice in automated retail settings - context effects, attribute framing, and perceptions of fairness. *American Journal of Business*, 29(3/4), pp. 237 – 260.

Domingo, S.N., Parton, K.A., Mullen, J. & Randall, J. (2015). *Risk aversion among smallholder high-value crop farmers in the Southern Philippines*. PIDS Discussion Paper Series, No. 2015-03. Makati City: Philippine Institute for Development Studies (PIDS).

Dougherty, J.P., Flatnes, J.E., Gallenstein, R.A., Miranda, M.J. & Sam, A.G. (2019). Climate change and index insurance demand: Evidence from a framed field experiment in Tanzania. Retrieved 31/08/2020 from https://aede.osu.edu/sites/aede/files/imce/files/Miranda/Dougherty%20et%20al%20-%20Climate%20Change%20and%20Index%20Insurance.pdf.

DRDLR. (2015). *Department of Rural Development and Land Reform Strategic Plan 2015 – 2020*. Pretoria: Department of Rural Development and Land Reform.

DRDLR. (2017). *Land Audit report*. *Phase ii: Private land ownership by race, gender and nationality*. Pretoria: Department of Rural Development and Land Reform.

Du, X., Feng, H. & Hennessy, D.A. (2014). *Rationality of choices in subsidized crop insurance markets*. Working Paper 14-WP 545. Ames, IA: Center for Agricultural and Rural Development, Iowa State University.

Du Plessis, J. (2003). *Maize production*. Pretoria: Department: Agriculture - Republic of South Africa.

Dubey, U., Kothari, D.P. & Awari, G.K. (2017). *Quantitative techniques in business, management and finance: A case-study approach*. Boca Raton: CRC Press.

Dubreuil, M. & Tabegna, A. (2018). *Achieving zero hunger through integrated climate risk management*. Luxembourg: Microinsurance Network.

Duong, T.T., Brewer, T., Luck, J. & Zander, K. (2019). A global review of farmers' perceptions of agricultural risks and risk management strategies. *Agriculture*, 9(10), pp. 1 – 16.

Dzanku, F.M. (2018). Rational but poor? An explanation for rural economic livelihood strategy. *Journal of Agricultural Economics*, 69(2), pp. 365 - 381.

Edmonds, W.A. & Kennedy, T.D. (2017). *An applied guide to research designs: Quantitative, qualitative, and mixed Methods*. 2nd Edition. Los Angeles, Ca: Sage Publications.

Ehrlinspiel, M. (2017). *Under the weather? Uptake of index-based weather insurance in Santa Lucia*. Berlin: Endeva.

Eitzinger, A., Binder, C.R. & Meyer, M.A. (2018). Risk perception and decision-making: do farmers consider risks from climate change?. *Climatic Change*, 151(2018), pp. 507–524. https://doi.org/10.1007/s10584-018-2320-1.

Elabed, G. & Carter, M.R. (2015). Compound-risk aversion and the demand for microinsurance: Evidence from a WTP experiment in Mali. Journal of Economic Behavior & Organization, 118(2015), pp. 150 – 166.

Ellis, E. (2017). Willingness to pay for index based crop insurance in Ghana. *Asian Economic and Social Society*, 7(7), pp. 700-721.

Elum, Z.A. Modise, D.M. & Marr, A. (2017). Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa. *Climate Risk Management*, 16(2017), pp. 246 – 257.

Elum, Z.A., Nhamo, G. & Antwi, M. A. (2018). Effects of climate variability and insurance adoption on crop production in select provinces of South Africa. *Journal of Water and Climate Change*, 9(3), pp. 500 - 511.

Emerick, K., de Janvry, A., Sadoulet, E. & Dar, M.H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6), pp. 1537 – 1561.

Endres, C., Ncube, S., Hougaard, C. & van As, L. (2014). *Regaining momentum? Update on microinsurance in South Africa*. Cape Town: The Centre for Financial Regulation & Inclusion.

Estelami, H. (2009). Cognitive drivers of suboptimal financial decisions: Implications for financial literacy campaigns. *Journal of Financial Services Marketing*, 13(4), pp. 273 – 283.

Fahad, S. & Wang, J. (2018). Evaluation of Pakistani farmers' willingness to pay for crop insurance using contingent valuation method: The case of Khyber Pakhtunkhwa province. *Land Use Policy*, 72(2018), pp. 570 – 577.

Fahad, S., Wang, J., Hu, G., Wang, H., Yang, X., Shad, A.A., Huong, N.T. & Bilal, A. (2018). Empirical analysis of factors influencing farmers crop insurance decisions in Pakistan: Evidence from Khyber Pakhtunkhwa province. *Land Use Policy*, 75(2018), pp. 459 – 467.

FAO. (1996). Rome Declaration on World Food Security and World Food Summit Plan of Action. In: *World Food Summit*, 13-17 November 1996. Rome: Food and Agricultural Organization of the United Nations.

FAO. (2015). *The economic lives of smallholder farmers. An analysis based on household data from nine countries.* Rome: Food and Agricultural Organization of the United Nations.

FAO. (2017). *Food and agriculture driving action across the 2030 Agenda for Sustainable Development.* Food and Agricultural Organization of the United Nations. Retrieved 19/07/2019 from http://www.fao.org/3/a-i7454e.pdf.

FAO. (2018). *2018/19 El Niño: High risk countries and potential impacts on food security and agriculture*. Food and Agricultural Organization of the United Nations. Retrieved 10/08/2019 from http://www.fao.org/3/CA2530EN/ca2530en.pdf.

Farrin, K., Miranda, M.J. & O'Donoghue, E. (2016). *How do time and money affect agricultural insurance uptake? A new approach to farm risk management analysis*. ERR-212, US Department of Agriculture, Economic Research Service, August 2016.

Fincham, J.E. (2008). Response rates and responsiveness for surveys, standards, and the Journal. *American journal of pharmaceutical education*, 72(2), pp. 1 – 2.

Finmark Trust. (2016). *Agricultural subsidies in SADC countries: Current status and impact*. Johannesburg: FinMark Trust.

Finmark Trust. (2017). *Research report on mobile money in South Africa*. Johannesburg: FinMark Trust.

Finmark Trust. (2018). *How South Africans are leveraging informal and formal financial markets - FinScope SA 2018 Fact Sheet*. [Online]. Retrieved 22/05/2020 from http://finmark.org.za/wp-content/uploads/2019/01/FMT_Fsc_Leavebehind_CB4.pdf.

Flatø, M., Muttarak, R. & Pelser, A. (2017). Women, weather, and woes: The triangular dynamics of female-headed households, economic vulnerability, and climate variability in South Africa. *World Development,* 90(2017), pp. 41–62.

Fonseca, C. (2016). *Helping farmers understand index insurance: Guidelines for consumer education interventions*. Paper No. 45. Geneva: International Labour Organization.

Fonta, W.M., Sanfo, S., Kedir, A.M. &Thiam, D.R. (2018). Estimating farmers' willingness to pay for weather index-based crop insurance uptake in West Africa: Insight from a pilot initiative in Southwestern Burkina Faso. *Agricultural and Food Economics,* 6(11), pp. 1-20.

Frey, U.J. & Pirsche, F. (2019). Distinguishing protest responses in contingent valuation: A conceptualization of motivations and attitudes behind them. *PLoS ONE,* 14(1), pp. 1 -20.

FSCA. (2018). *Short-Term Insurance Act, 1998: Amendment of Policyholder Protection Rules Prescribed Under Section 55*. Government Gazette, 28 September 2018. Pretoria: Financial Sector Conduct Authority.

Gallenstein, R. A., Mishra, K., Sam, A. G. & Miranda, M. J. (2019). Willingness to pay for insured loans in Northern Ghana. *Journal of Agricultural Economics,* 70(3), pp. 1 - 20.

Gaurav, S. & Chaudhary, V. (2020). Do farmers care about basis risk? Evidence from a field experiment in India. *Climate Risk Management*, 27(2020), pp. 1 – 15.

GCIS. (2017). *South African Yearbook 2016/17*. 24th Edition. Pretoria: Government Communications Information Services.

GCIS. (2019). *South African Yearbook 2018/19*. 26th Edition. Pretoria: Government Communications Information Services.

GCIS. (2020). *South African Yearbook 2019/20*. 27th Edition. Pretoria: Government Communications Information Services.

Gebrehiwot, D.B. (2015). Impact of weather index insurance on household demand for fertilizer in Tigray region. *Ethiopian Journal of Business and Economics,* 5(1), pp. 81 – 122.

Geyer, H. (2016). Poverty traps in South African agriculture*. Agrekon,* 55(4), pp. 356-376.

Gibson, K. (2011). Case study: Strengthening consumer protection in the South African microinsurance market. Johannesburg: Finmark Trust.

Giertz, A., Caballero, J., Galperin, D., Makoka, D., Olson, J. & George, G. (2015). *Malawi - Agricultural sector risk assessment*. Agriculture global practice technical assistance paper. Washington, D.C.: World Bank Group.

Gliner, J.A., Morgan, G.A. & Leech, N.L. (2017). *Research methods in applied settings: An integrated approach to design and analysis*. 3rd Edition. New York, NY: Routledge.

Gogtay, N.J. & Thatte, U.M. (2017). Principles of Correlation Analysis. *Journal of the Association of Physicians of India*, 65(3), pp. 78 – 81.
Goodrich, B.K., Yu. & Vandeveer, M. (2018). Risk preferences and the participation pattern of rainfall index insurance. In: *selected paper prepared for presentation at the 2018 Agricultural and Applied Economics Association Annual Meeting*, Washington D.C, 05 – 07 August.

Government Gazette. (2018). *Agriculture, Forestry and Fisheries Grants*. No. 41704. Pretoria: Republic of South Africa.

Grace, J.B. & Bollen, K.A. (2005). Interpreting the results from Multiple Regression and Structural Equation Models. *The Bulletin of the Ecological Society of America*, 86(4), pp.283-295.

Gray, D.E. (2017). *Doing Research in the Business World*. London: Sage Publication Ltd.

Greatrex, H., Hansen, J., Garvin, S., Diro, R., Blakeley, S., Le Guen, M., Rao, K. & Osgood, D. (2015). *Scaling up index insurance for smallholder farmers: Recent evidence and insights*. CCAFS Report No. 14. Copenhagen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

GreenAgri. (2020). Disaster risk reduction & management. The need for joint systematic planning and proactive reduction of extreme weather risks. Retrieved 09/08/2020 from https://www.greenagri.org.za/assets/documents-/SmartAgri/Case-Studies/DISASTER-RISK-REDUCTION-MANAGEMENT.pdf.

GreenCape. (2017). *Agriculture: Market intelligence report 2017*. Cape Town: GreenCape.

GreenCape. (2018). *Sustainable agriculture: Market intelligence report 2018*. Cape Town: GreenCape.

GreenCape. (2021). *Sustainable agriculture: Market intelligence report 2021*. Cape Town: GreenCape.

Grill, G. & Notaro, S. (2019). Exploring the influence of an Extended Theory of Planned Behaviour on preferences and willingness to pay for participatory natural resources management. *Journal of Environmental Management*, 232(2019), pp. 902 – 909.

Gulati, A., Terway, P. & Hussain, S. (2018). *Crop insurance in India: Key issues and way forward*. Working Paper No. 352. New Delhi: Indian Council for Research on International Economic Relations.

Gulseven, O. (2014). Estimating the demand factors and willingness to pay for agricultural insurance. *Australian Journal of Engineering Research*, 1(1), pp. 13-18.

Gunjal, K. (2016). *Agricultural risk management tools: Resource for the e-learning curriculum course on "Agricultural risk assessment and management for food security in* *developing countries*. Capacity Development Module 3. Platform for Agricultural Risk Management.

Guo, G., Wen, Q. & Zhu, J. (2015). The impact of aging agricultural labor population on farmland output: From the perspective of farmer preferences. *Mathematical Problems in Engineering*, 25(4), pp. 1 - 7.

Guo, W. & Bohara, A. (2015). *Farmers' perception of climate change and willingness to pay for weather index insurance in Bahunepati, Nepal*. Retrieved 27/01/2020 from https://digitalrepository.unm.edu/cgi/viewcontent.cgi?article=1073&context=hprc.

Gyrd-Hansen, D., Jensen, M.L. & Kjaer, T. (2014). Framing the willingness-to-pay question: impact on response patterns and mean willingness to pay. *Health Economics*, 23(5), pp.550-563.

Haile, K.K., Nillesen, E.E. & Tirivayi, N. (2019). *Impact of formal climate risk transfer mechanisms on risk-aversion: Empirical evidence from rural Ethiopia*. CESifo Working Paper No. 7717. Munich: Munich Society for the Promotion of Economic Research.

Hair, J. F., Gabriel, M. & Patel, V. (2014). AMOS covariance-based structural equation modeling (CB-SEM): Guidelines on its application as a marketing research tool. *Brazilian Journal of Marketing*, 13(2), pp. 44 – 55.

Hair, J.F., Risher, J.J., Sarstedt, M. & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), pp. 2 – 24.

Hair, J.F., Sarstedt, M., Hopkins, L. & Kuppelwieser, V.G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool for business research. *European business review*, 26(2), pp. 106 – 121.

Hair, J.F., Wolfinbarger, M., Bush, R.P. & Ortinau, D.J. (2013). *Essentials of marketing research*. International Edition. Boston, MA: McGraw-Hill.

Hansen, J.W., Araba, D., Hellin, J. & Goslinga, R. (2017) A roadmap for evidence-based insurance development for Nigeria's farmers. Wageningen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Haruna, B., Sohngen, B., Yahaya, I. & Wiredu, A.N. (2017). Effects of weather index insurance: the case of smallholder maize farmers in Northern Ghana. *International Journal of Food and Agricultural Economics*, 5(1128-2018-042), pp.75 - 85.

Hart, T. & Aliber, M. (2012). *Inequalities in agricultural support for women in South Africa*. Policy brief. Pretoria: Human Sciences Research Council of South Africa.

Hasan, M.T. (2019). Prospects of weather index-based crop insurance in Bangladesh. *International Journal of Agricultural Economics*, 4(1), pp. 32 - 40.

Hausman, J. (2012). Contingent Valuation: From dubious to hopeless. *Journal of Economic Perspectives*, 26(4), pp. 43 – 56.

Hazell, P., Sberro-Kessler, R. & Varangis, P. (2019). *When and how should agricultural insurance be subsidized?* : Issues and good practices. Washington, D.C.: World Bank Group.

Hazelton, D.G., Pearson, I. & Kariuki, A.W. (1994). *Development of drought response policy options for the cost-effective provision of water supply to rural communities subject to recurring droughts*. Pretoria: Report to the Water Research Commission by the Development Services and Technology Programme Division of Water Technology CSIR, No. 506/1/94.

He, J., Zheng, X. (2017). Does crop insurance really reassure farmers? A puzzle and its explanations based on field data. In: *Selected Papers prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting*, Chicago, Illinois, July 30-1 August, 2017.

Helamo, E.M. (2018). Review on smallholders farm risk and management strategies in Ethiopia. *Journal of Poverty, Investment and Development*, 44(1), pp. 24 -31.

Hellin, J., Hansen, J., Rose, A. & Braun, M. (2017). *Scaling up agricultural adaptation through insurance: Bringing together insurance, big data and agricultural innovation.* Wageningen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Herbold, J. (2014). New approaches to agricultural insurance in developing economies. In: D. Köhn (Ed.). *Finance for food: Towards new agricultural and rural finance*. Berlin: Springer.

Hess, U. & Hazell, P. (2016). *Innovations and emerging trends in agricultural insurance: How can we transfer natural risks out of rural livelihoods to empower and protect people*? Bonn and Eschborn: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH.

Hess, U., Hazell, P. & Kuhn, S. (2016). *Innovations and emerging trends in agricultural insurance*. Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH.

Hilbe, J. M. (2009). *Logistic regression models*. Boca Raton: Chapman & Hall/CRC.

Hill, R. V., Robles, M., & Ceballos, F. (2016). Demand for a Simple Weather Insurance Product in India: Theory and Evidence. *American Journal of Agricultural Economics*, 98(4), pp. 1250–1270.

Hill, R.V., Hoddinott, J. & Kumar, N. (2013). Adoption of Weather index Insurance: learning from willingness to pay among a panel of households in rural Ethiopia. *Agricultural Economics*, 44(2013), pp. 385 – 398.

Hill, R.V., Kumar, N., Magnan, N., Makhija, S., de Nicola, F., Spielman, D.J., & Ward, P.S. (2019). Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of Development Economics*, 136(2019), pp. 1 – 17.

Hinton, D.P. & Platt, T. (2019). Measurement Theory and Psychological Scaling. In: P.M.W. Hackett (Ed.). *Quantitative Research Methods in Consumer Psychology: Contemporary and Data-Driven Approaches*. New York, NY: Routledge.

Hohl, R.M. (2019). *Agricultural risk transfer: from insurance to reinsurance to capital markets*. Hoboken, NJ: John Wiley & Sons.

Hornby, D. & Cousins, B. (2016). *Rethinking agriculture in South Africa: Constraints and opportunities: key lessons for policy makers*. Conference: Cape Town, 11-13 October, 2016.

Hosu, S.Y., Cishe, E.N. & Luswazi, P.N. (2016). Vulnerability to climate change in the Eastern Cape Province of South Africa: What Does the future holds for smallholder crop farmers? *Agrekon*, 55(1-2), pp. 133 – 167.

Hountondji, L.R., Tovignan, S.D., Kokoye, S.E. & Chabi, E. (2019). Maize Farmer perception and participation in crop and rainfall index-based insurance program in Benin. *International Journal of Food and Agricultural Economics*, 7(4), pp. 313 – 327.

Hox, J.J. & Bechger, T.M. (1998). An introduction to Structural Equation Modeling. *Family Science Review*, 11, pp. 354 – 373.

Hoyos, D. & Mariel, P. (2010). Contingent Valuation: Past, Present and Future. *Prague Economic Paper, University of Economics, Prague*, 2010(4), pp. 329 - 343.

IAIS. (2017). *Scaling up agricultural index insurance in Africa: Building disaster resilience of smallholder farmers*. In: 10th Consultative Forum on microinsurance regulation for insurance supervisory authorities, insurance practitioners and policymakers. 24 and 25 May 2017, Common Wealth Speke Resort, Kampala, Uganda: International Association of Insurance Supervisors.

Ibrahim, R.M., Nunung, N., Bustanul, A. & Toni, B. (2020). factors influencing farmers' intention to participate in crop insurance. *RJOAS*, 9(105), pp. 46 – 52.

Idang, G.E. (2015) African culture and values. *Phronimon*, 16(2), pp. 97–111.

Impact Insurance. (2018) Retrieved 01/10/2019 from http://www.impactinsurance.org/practitioner-lessons/giif/planetguarantee.

In'nami, Y. & Koizumi, R. (2013). Structural Equation Modeling in educational research: A primer. In: M.S. Khine (Ed.). *Application of Structural Equation Modeling in Educational Research and Practice. Contemporary Approaches to Research in Learning Innovations.* Rotterdam: Sense Publishers.

Institute for Poverty, Land and Agrarian Studies. (2016). *Diagnostic Report on Land Reform in South Africa*. Commissioned report for High Level Panel on the assessment of key legislation and the acceleration of fundamental change, an initiative of the Parliament of South Africa. Western Cape: University of Western Cape.

Insurance Regulatory Authority. (2015). *The Kenya index-based insurance policy paper*. Nairobi: Insurance Regulatory Authority

Isaboke, H.N., Qiao, Z., & Nyarindo, W.N. (2016). The effect of weather index based micro-insurance on food security status of smallholders. *International Journal of Food and Agricultural Economics*, 2(3), pp. 5 – 21.

Isaboke, H.N., Qiao, Z., Nyarindo, W.N. & Ke, W. (2016). Explaining the perception of smallholders towards weather index micro-insurance alongside risks and coping strategies. *International Journal of Food and Agricultural Economics*, 4(4), pp. 59 – 77.

Islam, T.U. (2019). Ranking of normality tests: An appraisal through skewed alternative space. *Symmetry*, 11(7), pp. 1 – 14.

Jalili, Y.A, Ghaleh S. (2019). Knowledge sharing and the theory of planned behavior: a meta-analysis review. *VINE Journal of Information and Knowledge Management Systems*.

Jansson-Boyd, C.V. (2019). Quantitative research: Its place in consumer psychology. In: P.M.W. Hackett (Eds.). *Quantitative Research Methods in Consumer Psychology: Contemporary and Data-Driven Approaches*. New York, NY: Routledge.

Janzen, S.A. & Carter, M.R. (2019). After the drought: The impact of microinsurance on consumption smoothing and asset protection. *American Journal of Agricultural Economics*, 101(3), pp. 651 - 671.

Jarzabkowski, P., Chalkias, K., Clarke, D., Iyahen, E., Stadtmueller, D. & Zwick, A. (2019). *Insurance for climate adaptation: Opportunities and limitations*. Rotterdam and Washington D.C.: Global Commission on Adaptation.

Jensen, N.D. & Barrett, C.B. (2016). Agricultural index insurance for development. *Applied Economic Perspectives and Policy*, 39(2), pp. 199-219.

Jensen, N.D., Barrett, C.B. & Mude, A.G. (2016). Index insurance quality and basis risk: Evidence from Northern Kenya. *American Journal of Agricultural Economics*, 98(5), pp. 1450–1469.

Jin, J., Wang, W. & Wang, X. (2016). Farmers' risk preferences and agricultural weather index insurance uptake in rural China. *International Journal of Disaster Risk Science*, 7(4), pp. 366 -373.

Johnson, L. (2013). Index insurance and the articulation of risk-bearing subjects. *Environment and Planning A: Economy and Space*, 45(11), pp. 2663 - 2681.

Jokonya, O. (2017). *Critical literature review of Theory of Planned Behavior in the Information Systems research*. 2nd international conference on Advances in Management Engineering and Information Technology.

Joshi, P. (2019). Research Design. In: V. Bairagi. & M.V. Munot (Eds.). *Research Methodology: a practical and scientific approach.* New York, NY: CRC Press.

Judge, M., Warren-Myers, G. & Paladino, A. (2019). Using the Theory of Planned Behaviour to predict intentions to purchase sustainable housing. *Journal of Cleaner Production*, 215(2019), pp. 259 – 267.

Jumare, H., Visser, M. & Brick, K. (2018). *Risk preferences and the poverty trap: A look at technology uptake amongst smallholder farmers in the Matzikama Municipality*. Cape Town: Economic Research Southern Africa.

Jurkovicova, M. (2016). Behavioral aspects affecting the purchase of insurance - Different behavior of men and women. *Economic Review,* 45(2), pp. 181 - 196.

Jusufovic, K. (2016). On the significance of risk preference for insurance demand. Retrived 02/05/2020 from https://www.researchgate.net/profile/Kenan_Jusufovic/publication/329702153_On_the_Significance_of_Risk_Preference_for_Insurance_Demand/links/5c168c12a6fdcc494ffa162e/On-the-Significance-of-Risk-Preference-for-Insurance-Demand.pdf.

Kahan, D. (2013). Farm management extension guide: Managing risk in farming. Rome: Food and Agriculture Organization of the United Nations.

Karekezi, C. (2017). *Driving Africa's insurance penetration through innovative insurance solutions*. Johannesburg: Africa Reinsurance Pulse 2017.

Karlan, D., Osei, R., Osei-akoto, I. & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2), pp. 597 – 652.

Kempson, E., Collard, S. & Moore, N. (2005). *Measuring financial capability: an exploratory study*. Prepared for the Financial Services Authority by Personal Finance Research Centre, University of Bristol. Consumer Research 37.

Kempton, E., Perotti, V. & Scott, K. (2013). *Measuring financial capability: questionnaires and implementation guidance for low- and middle-income countries*. Washington D.C.: The World Bank.

Kepe, T. & Hall, R. (2016). *Land Redistribution in South Africa*. Commissioned report for High Level Panel on the assessment of key legislation and the acceleration of fundamental change, an initiative of the Parliament of South Africa. Pretoria: Government Printers.

Ketley, R., Mela, M., Thomas, J., Nixon, D & Van Rensburg, C. (2015). *Bancassurance, vertical integration and customer outcomes: An independent review of the Bancassurance model in South Africa*. Johannesburg: Genesis Analytics (Pty) Ltd.

Kim, H. Y. (2013). Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restorative dentistry & endodontics*, 38(1), pp. 52–54.

King, M., Singh, A.P. (2018). *Understanding farmers' valuation of agricultural insurance: Evidence from Viet Nam*. WIDER Working Paper, No. 2018/93, ISBN978-92-9256-535-0. Helsinki: The United Nations University World Institute for Development Economics.

Kiriti, T.W. & Tisdell, C. (2004). Commercial agriculture, marital status and other influences on food availability: A Kenyan case study. *Journal of Food, Agriculture & Environment*, 2(3&4), pp. 141 - 148.

Klingaman, N. & Keat, W. (2018). *El Niño 2018-19: Historical impact analysis*. Reading: University of Reading.

Koçaslan, G. (2019). Rational economic decision making: The relevance among the axioms of the Theory of Expected Utility. *Gaziantep University Journal of Social Sciences*, 18(1), pp. 535-548.

Kokot, Ž, Marković, T. & Pajić, N. (2017). Risk management in crop production based on the regional index. *Ratarstvo i povrtarstvo,* 54(1), pp. 13 - 18.

Koloma, Y. (2015). Crop microinsurance for maize farmers in Burkina Faso: Access and agriculture performance in the Dandé Village. *Strategic Change: Briefings in Entrepreneurial Finance*, 24(1), pp. 115 - 129.

Krychevska, L., Shynkarenko, I. & Shynkarenko, R. (2017). *Agricultural insurance in China: History, development and success factors*. Kiev: Agroinsurance International LLC.

Kumari, M., Singh, K.M., Mishra, R.R., Sinha, D.K. & Ahmad, N. (2017). Role of socio-economic variables in adoption of crop insurance: A discriminant function approach. *Economic Affairs*, 62(3), pp. 361 – 365.

Kumar, R. (2011). *Research methodology: a step-by-step guide for beginners*. 3rd Edition. London: Sage Publication Ltd.

Kunreuther, H. & Pauly, M. (2014). *Behavioral economics and insurance: Principles and solutions*. Working Paper - 2014-01. Philadelphia, PA: University of Pennsylvania.

Kusuma, A., Noy, I. & Jackson, B. (2017). *A viable and cost-effective weather index insurance for rice in Indonesia*. CESifo Working Paper, No. 6530. Munich: Center for Economic Studies and Ifo Institute (CESifo).

Lakhraj-Govender, R. & Grab, S.W. (2019). Assessing the impact of El Niño–Southern Oscillation on South African temperatures during austral summer. *International Journal of Climatology*, 39(1), pp.143 - 156.

Lalani, B., Dorward, P., Holloway, G. & Wauters, E. (2016). *Smallholder farmers' motivations for using Conservation Agriculture and the roles of yield, labour and soil fertility in decision making*. Reading: University of Reading.

Lampe, I. & Würtenberger, D. (2019). Loss aversion and the demand for index insurance. *Journal of Economic Behavior and Organization*. DOI:10.2139/ssrn.3406641.

Land Bank. (2019). *Integrated annual report – 2019*. Retrieved 22/05/2020 from https://landbank.co.za/Shared%20Documents/Annual-Report-2018-2019.pdf.

Land Bank. (2020). Land Bank presentation to the standing committee on appropriations. Retrieved 01/11/2020 from https://landbank.co.za/Investor%20Presentations/20200515%20_%20LB%20and%20NT%20Presentation%20to%20SCoA%20_%20Final.pdf.

Land Bank Insurance. (2018). *Land Bank Insurance Company (SOC) Limited annual financial statement 2019*. Centurion: Land Bank Insurance.

Langat, W.P., Naibei, I. & Getare. C.M. (2017). Determinants of insurance uptake in developing countries: Evidence from CIC insurance, Kericho Branch, Kenya. *International Journal of Scientific and Research Publications*, 7(12), pp. 703 – 715.

Lansigan, F.P. (2015). *Implementation issues in weather index-based insurance for agricultural production: A Philippine case study*. Kanagawa: Institute of Global Environmental Strategies.
Lee. D. (2019). The convergent, discriminant, and nomological validity of the Depression Anxiety Stress Scales-21 (DASS-21). *Journal of Affective Disorders*, 259(2019), pp. 136 – 142.

Lence, S. (2015). *Agricultural insurance in Ghana*. A report under contract No. 641-C-14-00001. Ghana feed the future agriculture policy support project (APSP). Retrieved 02/02/2020 from https://ghanalinks.org/documents/20181/0/Agricultural+Insurance+in+Ghana/b89d6bf5-ab1f-4b35-aeb7-1be44e2ca90e?version=1.0

Li, X. (2014). *The development of agricultural insurance in China*. Beijing: China Property & Casualty Reinsurance Company Ltd.

Li, Y., Guan, K., Schnitkey, G.D., De Lucia, E. & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, 2019(25), pp. 2325 – 2337.

Lin, J., Boyd, M., Pai, J., Porth, L., Zhang, Q. & Wang, K. (2015). Factors affecting farmers willingness to purchase weather index insurance in the Hainan Province of China. *Agricultural Finance Review*, 75(1), pp. 103 – 113.

Liu, X., Tang, Y., Ge, J. & Miranda, M.J. (2018). Does experience with natural disasters affect willingness-to-pay for weather index insurance? Evidence from China. *International Journal of Disaster Risk Reduction*, 33(2019), pp. 33 – 43.

Loki, O., Mudhara, M. & Pakela-Jezile, Y. (2020). Factors influencing farmers' use of different extension services in the Eastern Cape and Kwazulu-Natal provinces of South Africa. *South African Journal of Agricultural Extension*, 48(1), pp. 84 - 98.

Longbottom, D. & Lawson, A. (2019). Alternative Research Methods: Introducing Market Sensing—A Qualitative and Interpretive Perspective on Research. In: P.M.W. Hackett (Ed.). *Quantitative Research Methods in Consumer Psychology: Contemporary and Data-Driven Approaches.* New York, NY: Routledge.

López-Mosquera, N., García, T. & Barrena, R. (2014). An extension of the Theory of Planned Behavior to predict willingness to pay for the conservation of an urban park. *Journal of Environmental Management*, 135(2014), pp. 91 - 99.

Lybbert, T.J. & Carter, M.R. (2014). *Bundling Drought Tolerance and Index Insurance to Reduce Rural Household Vulnerability to Drought*. In: Sustainable Economic Development. Cambridge, MA: Academic Press.

Lyu, K. & Barré, T.J. (2017). Risk aversion in crop insurance program purchase decisions: Evidence from maize production areas in China. *China Agricultural Economic Review,* 9(1), pp. 62 – 80.

Madlala, L. & Luyaba, V. (2019). Non-life industry experience 2018. South African Reserve Bank: Prudential Authority. Retrieved 24/09/2020 from https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/8964/PA%20Non-Life%20Industry%20Experience%20Dec%202019.pdf.

Maestas, N., Mullen, K.J. & Powell, D. (2016). *The effect of population aging on economic growth, the Labor force and productivity*. NBER Working Paper No. 22452. Cambridge, MA: National Bureau of Economic Research.

Mahato, S. & Saha, A. (2019). Weather index insurance: An alternative approach towards protecting farmer's income in the face of weather aberration. *International Journal of Chemical Studies,* 7(3), pp. 551 – 560.

Mahlati, V., Hall, R., Karaan, M., Kriek, D., Mabasa, B., Moagi, T., Ngcobo, T., Ngcukaitobi, T., Serfontein, N. & Sihlobo, W. (2019). *Final report of the Presidential Advisory Panel on land reform and agriculture*. Presidential Advisory Panel on Land Reform and Agriculture: Pretoria: South Africa. Government Printers.

Mahul, O. & Stutley, C.J. (2010). *Government Support to Agricultural Insurance: Challenges and Options for Developing Countries*. Washington D.C.: The World Bank.

Mai, T.H., Nguyen, T.C., Vu, L.L., Bui, V.H., Nguyen, T.T. & Do, D.T. (2020). A study on behaviors of purchasing life insurance in Vietnam. *Management Science Letters*, 10(8), pp. 1693 – 1700.

Manda, J., Khonje, M.G., Alene, A.D., Tufa, A.H., Abdoulaye, T., Mutenje, M., Setimela, P. & Manyong. (2020). Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. Technological Forecasting and Social Change, 158(2020), pp. 1 – 12.

Manderson, A., Kubayi, N. & Drimie, S. (2016). The impact of the South African drought as experienced by smallholder farmers over the June 2015-February 2016 Period. In: *The Mopani District of Limpopo, South Africa*. Pretoria: Southern Africa Food Lab.

Mapfumo, S. (2007). *Weather index insurance: The case for South Africa*. Micro-Insurance Agency. Retrieved 11/01/2019 from https://www.findevgateway.org/sites/default/files/publications/files/mfg-en-case-study-weather-index-insurance-the-case-for-south-africa-feb-2007.pdf.

Mapfumo, S., Groenendaal, H & Dugger, C. (2017). *Risk modeling for appraising named peril index insurance products: A guide for practitioners*. Washington D.C.: World Bank Group.

Martinez-Lòpez, F. J., Gázquez-Abad, J. C. & Sousa, C. M. (2013). Structural equation modelling in marketing and business research: critical issues and practical recommendations. *European Journal of Marketing,* 47(1/2), pp. 115 - 152.

Matlou, R.C. & Bahta, Y.T. (2019). Resilience of smallholder livestock farmers in South Africa. *FarmBiz*, 5(8), pp.40 - 41.

Matsuda, A. and Kurosaki, T. (2019). Demand for temperature and rainfall index insurance in India. *Agricultural Economics*, (20190319), pp. 1 – 28.

Maziya, M., Mudhara, M. & Chitja, J. (2017). What factors determine household food security among smallholder farmers? Insights from Msinga, KwaZulu-Natal, South Africa. *Agrekon*, 56(1), pp. 40 – 52.

Mbonane, N.D. & Makhura, M.N. (2018). *Factors influencing maize farmers' interest in crop insurance in Swaziland*. Pretoria: Southern Africa – Towards Inclusive Economic Development.

Mbugua, M., Nzuma, J. & Muange, E. (2019). Social networks and ex-post risk management among smallholder farmers in Kenya. *Development Studies Research*, 6(1), pp. 30-39. DOI: 10.1080/21665095.2019.1573149

McIntosh, C., Sarris, A. & Papadopoulos. (2013). Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture In Ethiopia. *Agricultural Economics*, 44(2013), pp. 399 – 417.

Meyer, J. (2002). Expected utility as a paradigm for decision making in agriculture. In: R.E. Just. & R.D. Pope. *A comprehensive assessment of the role of risk in US Agriculture* (pp. 3 – 19) Boston, MA: Springer Science & Business Media.

Meyer, R, Hazell, P & Varangis, P (2017). *Unlocking smallholder credit: does credit-linked agricultural insurance work*? Geneva: International Labour Organization and International Finance Corporation.

Microinsurance Network. (2017). The state of microinsurance: The insider's guide to understanding the sector. *Microinsurance Network Annual Journal*, 3(2017), pp. 1 – 68.

Ministry for Agriculture and Land Affairs. (1998). *Agricultural policy in South Africa – A discussion document.* Pretoria: Ministry for Agriculture and Land Affairs.

Miranda, M.J. & Mulangu, F.M. (2016). *Index Insurance for agricultural transformation in Africa*. Accra: African Centre for Economic Transformation and Japan International Cooperation Agency Research institute.

Mishra, P., Pandey, C.M., Singh, U., Gupta, A., Sahu, C. & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia*, 22(1), pp. 67-72.

Mobarak, A. & Rosenzweig, M. (2012). *Selling formal insurance to the informally insured*. Center Discussion Paper, No. 1007. New Haven, Connecticut: Yale University, Economic Growth Center.

Mohajan, H.K. (2017). Two criteria for good measurements in research: Validity and reliability. Annals of Spiru Haret University. *Economic Series*, 17(3), pp.1 - 31.

Mohajan, H.K. (2018). Qualitative research methodology in social sciences and related subjects. *Journal of Economic Development, Environment and People*, 7(1), pp. 23 – 48.

Mokhaukhau, J. P., Hlongwane, J. J., Chaminuka, P., Mayekiso, A., & Cholo, M. S. (2020). Risk management strategies adopted by small-scale vegetable farmers in Thaba Chweu Local Municipality, Mpumalanga Province in South Africa. *Journal of Agribusiness and Rural Development*, 1(55), pp. 45–51.

MoneyMarketing. (2019). *Tailor-made insurance for local grain farmers*. *MoneyMarketing,* 2019(7), pp. 27 – 27.

Montmasson-Clair, G., Mudombi, S. & Patel, M. (2019). *Small business development in the climate change adaptation space in South Africa*. Pretoria: Trade & Industrial Policy Strategies.

Mookerjee, A., Clarke, D., Grenham, D., Sharpe, J. & Stein, D. (2014) Crop microinsurance: tackling poverty, one insurance policy at a time. *Annals of Actuarial Science,* 8(2), pp. 253 – 280.

Mookerjee, A. (2016). *Support agencies promoting weather based insurance schemes for smallholder farmers" in Uganda and Zambia*. Pretoria: Food Agriculture and Natural Resources Policy Analysis Network (FANRPAN).

Mookerjee, A. & Nyoni, B. (2016). *Operational & Regulatory Strategies for Weather-based Index Insurance*. Policy brief 02/2016. Pretoria: Food Agriculture and Natural Resources Policy Analysis Network (FANRPAN).

Moore, D., Niazi, Z., Rouse, R. & Kramer, B. (2019). Building resilience through financial inclusion: A review of existing evidence and knowledge gaps. Innovations for Poverty Action. Retrieved 13/05/2020 from https://www.poverty-action.org/publication/building-resilience-through-financial-inclusion-review-existing-evidence-and-knowledge.

Morsink, K., Clarke, D.J. & Mapfumo, S. (2016). *How to measure whether index insurance provides reliable protection*. Policy Research Working Paper 7744. Washington D.C.: World Bank Group.

Mubhoff, O., Hirschauer, N., Gruner, S. & Pielsticker, S. (2018). Bounded rationality and the adaptation of weather index insurance: evidence from an extra-laboratory experiment with farmers in Germany. *Agricultural Finance Review*, 78(1), pp. 116 – 134.

Mude, A. & Carter, M.R. (2016). Evidence on the impact of index insurance on small farm investment and social protection. Retrieved 29/07/2020 from https://basis.ucdavis.edu/publication/spotlight-evidence-impact-index-insurance-small-farm-investment-and-social-protection.

Mukasa, A.N. & Salami, A.O. (2015). *Gender productivity differentials among smallholder farmers in Africa: A cross-country comparison*. Working paper series no 231. Abidjan: African Development Bank.

Mukherjee, P., Pandey, M. & Prashad, P. (2017). *Bundling to make agriculture insurance Work*. Paper No. 47. Geneva: International Labour Office Impact Insurance Facility.

Munyoro, G. & Moyo, B.A. (2019). The significance of agricultural insurance in the development of the agricultural sector in Zimbabwe: A case study of Mashonaland Central Province. *International Journal of Research in Business, Economics and Management*, 3(1), pp. 15 – 33.

Musya, M & Muttai, M (2020). *Formative evaluation on increasing the uptake of ACRE Hakika in Kenya*. 3ie Formative Evaluation Report. New Delhi: International Initiative for Impact Evaluation (3ie).

Mutaqin, D.J. (2019). Determinants of farmers' decisions on risk coping strategies in rural West Java. *Climate*, 7(1), pp. 1 – 23.

Muthelo, D., Owusu-Sekyere, E. & Ogundeji, A.A. (2019). Smallholder farmers' adaptation to drought: Identifying effective adaptive strategies and measures. *Water*, 11(10), pp. 1 – 18.

Mutyasira, V., Hoag, D. & Pendel, D. (2018). The adoption of sustainable agricultural practices by smallholder farmers in Ethiopian highlands: An integrative approach. *Cogent Food & Agriculture*, 4(1), pp. 1 – 17.

Myeni, L.M., Moeletsi, M., Thavhana, M, Randela, M. & Mokoena, L. (2019). Barriers affecting sustainable agricultural productivity of smallholder farmers in the Eastern Free State of South Africa. *Sustainability*, 11(3003), pp. 1 – 18.

NAMC. (2016). *Measuring and tracking smallholder market access in South Africa*. Working Paper (NAMC/WP/2016/03). Pretoria: National Agricultural Marketing Council.

NAMC. (2018). *South Africa's agriculture and food system*. A Scenarios Analysis. Report On The Gcrf-Africap Participatory Scenarios Workshop. Pretoria: National Agricultural Marketing Council.

Nanziri, E.L. & Leibbrandt, M. (2018). Measuring and profiling financial literacy in South Africa. *South African Journal of Economic and Management Sciences*, 21(1), pp. 1 – 17.

Nardi, P.M. (2016). *Doing survey research: A guide to quantitative methods*. 3rd Edition. New York, NY: Routledge.

National Planning Commission. (2012). *National Development Plan 2030: Our future – make it work*. Pretoria: Department of the Presidency - Republic of South Africa. Government Printers.

National Treasury. (2015). *Provincial budgets and expenditure review: 2010/11 – 2016/17*. . Pretoria: Department: National Treasury – Republic of South Africa. Government Printers.

National Treasury. (2018). 2018 Budget: Estimation of National expenditure. Vote 4: Cooperative Governance and Traditional Affairs. Retrieved 12/01/2020 from http://www.treasury.gov.za/documents/national%20budget/2018/enebooklets/Vote%2004%20Cooperative%20Governance%20and%20Traditional%20Affairs.pdf.

National Treasury. (2019). *Economic transformation, inclusive growth, and competitiveness: towards an Economic Strategy for South Africa*. Pretoria: Department: National Treasury – Republic of South Africa. Government Printers.

National Treasury. (2020). *Financing a sustainable economy: Technical paper 2020*. Pretoria: Department: National Treasury – Republic of South Africa. Government Printers.

Ncube, B. (2018). Constraints to smallholder agricultural production in the Western Cape, South Africa. *Physics and Chemistry of the Earth*, 106(2018), pp. 89 – 96.

Ncube, B. & Shikwambana, S. (2016). *Coping and adaptation strategies for agricultural water use during drought periods. Review of drought coping and adaptation strategies in dryland cropping systems, irrigation, livestock and mixed systems*. Pretoria, Water Research Commission.

Ndegwa, M.K., Shee, A., Turvey, C.G. & You, L. (2020). Uptake of insurance-embedded credit in presence of credit rationing: Evidence from a randomized controlled trial in Kenya. *Agricultural Finance Review*, 80(5), pp. 745 – 766.

Netshipale, A.J., Oosting, S.J., Mashiloane, M.L., van Reenen, C.G., de Boer, I.J. & Raidimi, E.N. (2020). Agriculture in land reform farms: Impact on livelihoods of beneficiaries in the Waterberg district, South Africa. *Land Use Policy*, 97(2020), pp. 1 – 10.

Neuman, W.L. (2014). *Social Research Methods: qualitative and quantitative approaches*. 7th Edition. Essex: Pearson Education Limited.

NGPF. (2002). *South Africa's National Policy framework for women's empowerment and gender equality*. Pretoria: National Gender Policy Framework .Government printer.

Niemelä-Nyrhinen, J. & Leskinen, E. (2014). Multicollinearity in marketing models: Notes on the application of ridge trace estimation in Structural Equation Modelling. *The Electronic Journal of Business Research Methods*, 12(1), pp. 3 - 15.

Njobe, B. (2015). *Women and agriculture: The untapped opportunity in the wave of transformation*. Abidjan: African Development Bank.

Njue, E., Kirimi, L. & Mathenge, M. (2018). Uptake of crop insurance among smallholder farmers: Insights from maize producers in Kenya. In: *30th International conference of Agricultural Economists*. Vancouver, 28 July – 2 August, 2018.

Norton, M., Boucher, S. & Chiu, L.V. (2015). Geostatistics, basis risk, and weather index insurance. In: *Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting*. San Francisco, Ca. 26 – 28 July, 2015.

Norton, M., Osgood, D., Madajewicz, M., Holthaus, E., Peterson, N., Diro, R. & Gebremichael, M. (2014). Evidence of demand for index insurance: experimental games and commercial transactions in Ethiopia. *Journal of Development Studies*, 50(5), pp. 630 - 648.

Ntukamazina, N., Onwonga, R.N., Sommer, R., Rubyogo, J.C., Mukankusi, C.M., Mburi, J. & Kariuki, R. (2017). Index-based agricultural insurance products: challenges, opportunities and prospects for uptake in sub-Sahara Africa. *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, 118(2), pp. 171 – 185.

Nyaaba, J.A., Nkrumah-Ennin, K & Anang, B.T. (2019). Willingness to pay for crop insurance in Tolon District of Ghana: Application of an endogenous treatment effect model. *AIMS Agriculture and Food,* 4(2), pp. 362 – 375.

Nyasimi, M., Amwata, D., Hove, L., Kinyangi, J. & Wamukoya G. (2014). *Evidence of Impact: Climate-Smart Agriculture in Africa*. CCAFS Working Paper no. 86. Wageningen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Obasoro A.S., Obisesan O.O. & Onabajo O.J. (2016). Rice farmers' willingness to pay for agricultural insurance in Ogun state, Nigeria. *Bioscience Methods*, 7(2), pp, 1 - 11.

Obi, A. & Ayodeji, B.T. (2020). Determinants of Economic farm-size–efficiency relationship in smallholder maize farms in the Eastern Cape Province of South Africa. *Agriculture*, 10(98), pp. 1 – 18.

OECD. (2018). The contribution of reinsurance markets to managing catastrophe risk. Retrieved on 14/04/2020 from http://www.oecd.org/finance/the-contribution-of-reinsurance-markets-to-managing-catastrophe-risk.pdf.

Ofori, E., Sampson, G.S. & Vipham, J. (2019). The effects of agricultural cooperatives on smallholder livelihoods and agricultural performance in Cambodia. *Natural Resources Forum*, 43(2019), pp. 218 – 229.

Ogunmefun, S.O. & Achike, A.I. (2015). Informal insurance practices in low income farmer communities: Odogbolu case study (Ogun State, Nigeria). *International Journal of Agricultural Policy and Research*, 3(12), pp. 412 – 418.

Okoffo, E.D., Denkyirah, E.K., Adu, D.T., & Fosu-Mensah, B.Y. (2016). A double-hurdle model estimation of cocoa farmers' willingness to pay for crop insurance in Ghana. *Springer Plus*, 5(873), pp. 1 – 19.

Okunlola, A., Ngubane, M., Cousins, B. & du Toit, A. (2016). *Challenging the stereotypes: Small-scale black farmers and private sector support programmes in South Africa: A national scan*. Research report 53. Institute for Poverty, Land and Agrarian Studies.

Olum, S., Gellynck, X., Juvinal, J., Ongeng, D. & De Steur, H. (2020). Farmers' adoption of agricultural innovations: A systematic review on willingness to pay studies. *Outlook on Agriculture*, 0030727019879453.

Omair, A. (2014). Sample size estimation and sampling techniques for selecting a representative sample. *Journal of Health Specialties*, 2(4), pp. 142 – 147.

Omolo, N. & Mafongoya, P.L. (2019). Gender, social capital and adaptive capacity to climate variability: A case of pastoralists in arid and semi-arid regions in Kenya. *International Journal of Climate Change Strategies and Management*, 11(5), pp. 744 – 758.

Omoregbe, F.E., Ighoro, A. & Ejembi, S.A. (2013). Analysis of the effects of farmers characteristics on poverty status in Delta State. *International Journal of Humanities and Social Science Invention*, 2(5), pp. 11 - 16.

Orduño Torres, M. A., Kallas, Z. & Ornelas Herrera, S. I. (2019). Analysis of farmers' stated risk using lotteries and their perceptions of climate change in the northwest of Mexico. *Agronomy*, 9(4), pp. 1 – 18.

Outreville, J. F. (2013). Risk aversion, risk behavior, and demand for insurance: A survey. Working Paper No. 11/2013. Torino: International Centre for Economic Research.

Pacheco, J.M., Santos, F.C. & Levin, S.A. (2015). Evolutionary dynamics of collective index insurance. *Mathematical Biology*, 2016(72), pp. 997 - 1010.

Park, H. (2013). An introduction to logistic regression: From basic concepts to interpretation with particular attention to nursing domain. *Journal of Korean Academy of Nursing*, 43(2), pp. 154-164.

Park, J.H. & MacLachlan, D.L. (2008). Estimating willingness to pay with exaggeration bias-corrected contingent valuation method. *Marketing Science*, 27(4), pp. 691 – 698.

Park, S. & Lemaire, J. (2012). The impact of culture on the demand for non-life insurance. ASTIN Bulletin: *The Journal of the IAA*, 42 (2), pp. 501-527.

Partridge, A.G. & Wagner, N.J. (2016). Risky Business: Agricultural insurance in the face of climate change. *Elsenburg Journal*, 13(3), pp. 49-53.

Pearson, G., Stoop, P.N. & Kelly-Louw, M. (2017). Balancing responsibilities – financial literacy. *PER: Potchefstroomse Elektroniese Regsblad*, 20(1), pp. 1 – 55.

Platteau, J. P., De Bock, O. & Gelade, W. (2017). The demand for microinsurance: a literature review. *World Development*, 94(C), 139–156.

Pradhan, K.C. & Mukherjee, S. (2018). Covariate and idiosyncratic shocks and coping strategies for poor and non-poor rural households in India. *Journal of Quantitative Economics*, 16(1), pp. 101 – 127.

Pu, C., Chen, Y. & Pan, X. (2018). Weather indexes, index insurance and weather index futures. *Insurance Markets and Companies*, 9(1), pp. 33 – 40.

PWC. (2018). *Ready and Willing: African insurance industry poised for growth*. Retrieved 15/09/2019 from https://www.pwc.co.za/en/assets/pdf/south-african-insurance-2018.pdf.

Qing-song, W. (2010). The Farmers behavior in agricultural insurance under the Von·Neuman-Morgenstern Utility Model. *Agriculture and Agricultural Science Procedia*, 1(2010), pp. 226–229.

Rahman, M.M., Ghosh, B.C., & Chowdhury, M.K. (2014). Problems and prospects of weather index based crop insurance in developing countries: A case for rural farmers in Bangladesh. *IOSR Journal of Humanities and Social Science*, 19(9), pp. 44-53.

Rahman, W., Shah, F.A. & Rasli, A. (2015). Use of Structural Equation Modeling in social science research. *Canadian Center of Science and Education*, 11(4), pp. 371 – 377.

Raju, K.V. Naik, G., Ramseshan, R., Pandey, T., Joshi, P., Anantha, K.H., Kesava Rao, A.V.R, Moses, S.D. & Kumara, C.D. (2016). *Transforming weather index-based crop insurance in India: Protecting small farmers from distress. Status and a way forward*. Research Report IDC-8. Patancheru: ICRISAT Development Center.

Ramasubramanian, J.A. (2012). *Willingness to pay for index based crop microinsurance in India*. NEUDC 2012, Darmouth College, USA.

Ramasubramanian, J.A. (2014). Demand and Impact of Crop Microinsurance in India. Doctoral thesis in Philosophy. University of Sussex.

Ranganathan P, Pramesh C.S. and Aggarwal, R. (2017). Common pitfalls in statistical analysis: Logistic regression. *Perspect Clin Res*, 8(3), pp. 148-151.

Rankin, J. & Robinson, A. (2018). *Accounting for protest zeros in contingent valuation studies: A review of literature*. HEG Working Paper, No. 18-01. Norwich: University of East Anglia, Health Economics Group (HEG).

Refera, M.K., Dhaliwal, N.K. & Kaur, J. (2016). Financial literacy for developing countries in Africa: A review of concept, significance and research opportunities. *Journal of African Studies and Development*, 8(1), pp. 1 – 12.

Reyes, C.M., Agbon, A.D., Mina, C.D. & Gloria, R.A. (2017). *Agricultural insurance program: Lessons from different country experiences*. Discussion Paper Series, No. 2017-02, Quezon City: Philippine Institute for Development Studies.

Reyes, C.M., Mina, C.D., Gloria, R.A., & Mercado, S.J. (2015). *Review of design and implementation of the agricultural insurance programs of the Philippine Crop Insurance Corporation (PCIC).* Makati City: Philippine Institute for Development Studies.

Robert, M., Thomas, A. & Bergez, J. (2016). Processes of adaptation in farm decision-making models. A review. *Agronomy for Sustainable Development*, 36(64), pp. 1 – 15.

Romero, H.G. & Molina, A. (2015). *Agriculture and adaptation to climate change: The role of insurance in risk management: The case of Colombia*. Washington, D.C: Inter-American Development Bank.

Roopa, S. & Rani, MS. (2012). Questionnaire designing for a survey. *The Journal of Indian Orthodontic Society*, 46(4), pp. 273 – 277.

Roshani. P. & Bagrecha, C. (2017). A Structural Equation Model for work-life balance of women nursing professionals of government and private hospitals in Bangalore. *Amity Journal of Healthcare Management*, 2(2), pp. 1 – 12.

Roznik, M., Porth, C.B., Porth, L., Boyd, M. & Roznik, K. (2019). Improving agricultural microinsurance by applying universal kriging and generalised additive models for interpolation of mean daily temperature. *The Geneva Papers on Risk and Insurance - Issues and Practice,* 44(3), pp. 446 – 480.

Sadik-Rozsnyai, O. (2016). Willingness to pay for innovations: An emerging European innovation adoption behaviour. *European Journal of Innovation Management,* 19(4), pp. 568 -588.

Safiih, L.M. & Azreen, N. (2016). Confirmatory factor analysis approach: A case study of mathematics students' achievement in TIMSS. *Malaysian Journal of Mathematical Sciences*, 10(2016), pp.41 - 51.

SAIA. (2019). Annual review – 2019. Retrieve15/11/2019 from https://www.saia.co.za/info-center/saia-documents/publications/annual-reviews/.

Santam. (2019). Santam 2019 Integrated Report. Retrieved 24/09/2020 from https://www.santam.co.za/media/2685862/2019-integrated-report.pdf.

Sandmark, T., Debar, J. & Tatin-Jaleran, C. (2013). *The emergence and development of agriculture microinsurance - A discussion paper*. Luxembourg: Microinsurance Network.

Sasria. (2018). *Corporate plan & budget 2018 -2019*. Illovo: South African Special Risk Insurance Association.

Saunders, M.N.K, Lewis, P. & Thornhill, A. (2019). *Research methods for business students*. 8th Edition. New York, NY: Pearson.

Schäfer, L., Warner, K., & Kreft, S. (2019). Exploring and managing adaptation frontiers with climate risk insurance. In: R. Mechler, L. Bouwer, T. Schinko, S. Surminski. & J. Linnerooth-Bayer (Eds.). *Loss and Damage from Climate Change. Climate Risk Management, Policy and Governance.* Cham: Springer.

Schlesinger, Harris. (2013). The theory of insurance demand. In *Handbook of Insurance*, 2nd ed. Edited by Georges Dionne. New York, NY: Springer, pp. 167–84.

Schmidt, J. & Bijmolt, T.H., (2020). Accurately measuring willingness to pay for consumer goods: a meta-analysis of the hypothetical bias. *Journal of the Academy of Marketing Science*, 48(3), pp.499-518.

Schober, P., Boer, C. & Schwarte, L.A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analgesia*. 126(5), pp. 1763 – 1768.

Schrum, M.L., Johnson, M., Ghuy, M & Gombolay, M.C. (2020). Four Years in Review: statistical practices of Likert Scales in human-robot interaction studies. In: *ACM/IEEE International Conference on Human-Robot Interaction (HRI '20)*. Cambridge, 23 – 26 March, 2020.

Schulze, R.E. (Ed.) (2016). *Handbook for Farmers, Officials and Other Stakeholders on Adaptation to Climate Change in the Agriculture Sector within South Africa*. Pretoria: Department of Agriculture Forestry and Fisheries.

Schulze, R.E. & Durand, W. (2016). *Maize production in South Africa and climate change*. In: Schulze, R.E. (Ed.) Handbook for Farmers, Officials and Other Stakeholders on Adaptation to Climate Change in the Agriculture Sector within South Africa. Section C: Crops in South Africa and Climate Change, Chapter C1.

Schumacker, R.E. & Lomax, R.G. (2010). *A Beginner's Guide to Structural Equation Modeling*. 3rd Edition. New York, NY: Routledge.

Schwan, S. & Yu, X. (2018). Social protection as a strategy to address climate-induced migration. *International Journal of Climate Change Strategies and Management*, 10(1), pp. 43 – 64.

Sebola, M.P. (2018). Financing emerging black farmers for agricultural development in South Africa: A wasteful and unworkable model for creating black farmers. *The Journal for Transdisciplinary Research in Southern Africa*, 14(1), pp. 1 – 7.

Senapati, A.K. (2019). Insuring against climatic shocks: Evidence on farm households' willingness to pay for rainfall insurance product in rural India. *International Journal of Disaster Risk Reduction*, 101351, pp. 1 – 10.

Senger, I., Borges, J.A.R. & Machado, J.A.D., (2017). Using the theory of planned behavior to understand the intention of small farmers in diversifying their agricultural production. *Journal of Rural Studies*. 49, 32–40.

Senthilnathan, S. (2019). Usefulness of Correlation Analysis. Available at SSRN 3416918.

Senyolo, M.P., Long, T.B., Blok, V. & Omta, O. (2017). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, 172, pp. 3825 - 3840.

Shah, H., Siderius, C. & Hellegers, P. (2020). Cost and effectiveness of in-season strategies for coping with weather variability in Pakistan's agriculture. *Agricultural Systems*, 178(2020), pp. 1 - 23.

Shakhovskoy, M. & Mehta, R. (2018). *Protecting growing prosperity: agricultural insurance in the developing world*. Basel: Syngenta Foundation for Sustainable Agriculture.

Sheahan, M. and Barrett, C.B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy*, 67(2017), pp.12-25.

Shee, A., Turvey, C.G. & You, L. (2018). Design and rating of risk-contingent credit for balancing business and financial risks for Kenyan farmers. In: *30th International Conference of Agricultural Economists*. July 28 – 02 August, 2018. Vancouver.

Sherraden, M. (2013). Building blocks of financial capability. In: J. Birkenmaier., M. Sherraden. & J., Curley (Eds.). *Financial education and capability: Research, education, policy, and practice*. New York, NY: Oxford University Press.

Shields, D.A. (2015). Federal crop insurance: Background. In: T.E. Bonner (Ed.) *Government procedures and operations: Federal crop insurance - Farm bill provisions, Trends, and premium reduction considerations*. New York, NY: Nova Science Publishers.

Shirsath, P., Vyas S., Aggarwal P. & Rao K.N. (2019). Designing weather index insurance of crops for the increased satisfaction of farmers, industry and the government. *Climate Risk Management*, 25(100189).

Shkoler, O. (2019). Using contemporary quantitative techniques. In: P.M.W. Hackett (Ed.) *Quantitative Research Methods in Consumer Psychology: Contemporary and Data-Driven Approaches*. New York, NY: Routledge.

Sibiko, K.W. & Qaim, M. (2017). *Weather index insurance, agricultural input use, and crop productivity in Kenya*. Global Food Discussion Paper 94. Göttingen: University of Göttingen.

Sibiko, K.W., Veettil, P.C. & Qaim, M. (2018). Small Farmer's Preferences for Weather Index Insurance: Insights from Kenya. *Agriculture & Food Security*, 7(53), pp. 1 – 14.

Sihem, E. (2019). Economic and socio-cultural determinants of agricultural insurance demand across countries. *Journal of the Saudi Society of Agricultural Sciences,* 18(2019), pp. 177 – 187.

Sikwela, M.M., Fuyane, N. & Mushunje, A. (2016). The role of cooperatives in empowering smallholder farmers to access markets: A case study of Eastern Cape and KwaZulu Natal cooperatives in South Africa. *International Journal of Development and Sustainability*, 5(11), pp. 536 – 552.

Singh, A.S. & Masuku, M.B. (2014). Sampling techniques & determination of sample size in applied statistics research: an overview. *International Journal of Economics, Commerce and Management*, 2(11), pp. 1 – 22.

Singh, P. &Agrawal, G. (2020). Development, present status and performance analysis of agriculture insurance schemes in India: Review of evidence. *International Journal of Social Economics*, 47(4), pp. 461 – 481.

Sinha, S. & Tripathi, N.K. (2016). Assessing the Challenges in Successful Implementation and Adoption of Crop Insurance in Thailand. *Sustainability*, 8(1306), pp. 1 – 20.

Sitko, N.J., Chamberlin, J., Cunguara, B., Muyanga, M. & Mangisoni, J. (2017). A comparative political economic analysis of maize sector policies in eastern and southern Africa. *Food Policy*, 69(2017), pp. 243 - 255.

Skees, J.R. (2016). *Financial disaster risk management to facilitate recovery lending*. Lexington: GlobalAgRisk.

Skees, J.R. & Barnett, B.J. (1999). Conceptual and practical considerations for sharing catastrophic/systemic risks. *Review of Agricultural Economics*, 21(2), pp. 424 - 441.

Smit, H., Denoon-Stevens, C. & Esser, A. (2017). InsurTech for development: A review of insurance technologies and applications in Africa, Asia and Latin America. Retrieved

02/06/2020 from https://cenfri.org/wp-content/uploads/2017/11/InsurTech-Research-Study March-2017.pdf.

Smith, J. & Noble, H. (2014). Bias in research. *Evidence-based nursing*, 17(4), pp. 1 – 5.

Smith, V. (2016). Producer insurance and risk management options for smallholder farmers. *The World Bank Research Observer*, 31(2), pp. 271 – 289.

South African Government. (2020). *Determination of alert level*. Government notices no. 43620. Retrieved 28/08/2020 from https://www.gov.za/sites/default/files/gcis_document/202008/43620gon891s_0.pdf.

South African Government. (2019). *Land Reform*. Retrieved 01/10/2019 from https://www.gov.za/issues/land-reform.

Spear, D. & Chappel, A. (2018). Livelihoods on the edge without a safety net: The case of smallholder crop farming in North-Central Namibia. *Land*, 7(79), pp. 1 – 11.

Stats SA. (2016). *Community survey 2016 agricultural households*. Pretoria: Statistics South Africa.

Stats SA. (2019). *Towards measuring food security in South Africa: An examination of hunger and food inadequacy.* Pretoria: Statistics South Africa.

Stats SA. (2020a). *Gross Domestic Product. First Quarter 2020*. Pretoria: Statistics South Africa.

Stats SA. (2020b). *Quarterly labour force survey - Quarter 1: 2020*. Pretoria: Statistics South Africa.

Stein, D. & Tobacman, J. (2015). *Weather insurance savings accounts*. Policy Research Working Paper 7235. Washington D.C.: World Bank Group.

Steinmetz, H., Knappstein, M., Ajzen, I., Schmidt, P. & Kabst, R. (2016). How effective are behavior change interventions based on the theory of planned behavior?. *Zeitschrift für Psychologie*, 224(3), pp. 216 – 233.

Still, L. & Stokes, G. (2016). Short term insurance in South Africa 2016/17. Retrieved 02/03/2019 from https://aon.co.za/Assets/docs/publications/Short_Term_Insurance_in_South_Africa_2016-17_Condensed_Version.pdf.

Stoeffler, Q., Carter, M., Guirkinger, C. & Gelade, W. (2020). *The spillover impact of index insurance on agricultural investment by cotton farmers in Burkina Faso*. Working Paper 27564. Cambridge, MA: National Bureau of Economic Research.

Stojanović, Z., Rakonjac-Antić, T. & Koprivica, M. (2019). Farmers' willingness to purchase crop insurance: evidence from wheat and raspberry sectors in Serbia. *Economics of Agriculture*, 66(4), pp. 1107-1125.

Stoppa, A. & Dick, W. (2018). *Agricultural insurance in Burkina Faso: Challenges and perspectives*. Oxford: Oxfam International.

Stoppa, A. & Manuamorn, O.P. (2017). *Weather index insurance for maize production in Eastern Indonesia: a feasibility study*. Washington, D.C.: World Bank Group.
Subia, M.P. & Martinez, N. (2014). *Mobile money services: "A bank in your pocket": Overview and opportunities.* Background Note: ACPOBS/2014/BN14. Pretoria: International Organization for Migration: ACP Observatory on Mitigation.

Suhr, D. (2008). Step your way through Path Analysis. In*: Western users of SAS software conference proceedings* (pp. 1-10). November 5-7, 2008, Universal City, California, 98 papers.

Sulewski, P. & Kłoczko-Gajewska, A. (2014). Farmers' risk perception, risk aversion and strategies to cope with production risk: an empirical study from Poland. *Studies in Agricultural Economics*, 116(2014), pp. 140 – 147.

Sulewski, P., Wąs, A., Kobus, P., Pogodzińska, K., Szymańska, M. & Sosulski, T. (2020). Farmers' attitudes towards risk—an empirical study from Poland. *Agronomy*, 10(1555), pp. 1 – 21.

Sullivan, G. M. & Artino Jr, A. R. (2013). Analyzing and interpreting data from Likert-type scales. *Journal of Graduate Medical Education*, 5(4), pp. 541 - 542.

Suresh, K.P. & Chandrashekara, S. (2012). Sample Size estimation and Power analysis for Clinical research studies. *Journal of Human Reproductive Sciences*, 5(1), pp. 7 – 13.

Syroka, J. & Reinecke, E.B. (2015). Weather index insurance and transforming agriculture in Africa: Challenges and Opportunities. Retrieved 06/03/2020 from https://www.afdb.org/fileadmin/uploads/afdb/Documents/Events/DakAgri2015/Weather_Index_Insurance_and_Transforming_Agriculture_in_Africa.pdf.

Tadesse, M.A., Shiferaw, B.A. & Erenstein, O. (2015). Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for sub-Saharan Africa. *Agricultural and Food Economics*, 3(1), pp. 1 - 26.

Taherdoost, H. (2016). Validity and reliability of the research instrument; how to test the validation of a questionnaire/survey in a research. *International Journal of Academic Research in Management*, 5(3), pp. 28 – 36.

Taherdoost, H. (2017). Determining sample size; how to calculate survey sample size. *International Journal of Economics and Management Systems*, 2(1), pp. 237 – 239.

Tang, Y., Yang, Y., Ge, J. & Chen, J. (2019). The impact of weather index insurance on agricultural technology adoption evidence from field economic experiment in china. *China Agricultural Economic Review*, 11(4), pp. 622 – 641.

Teo T., Tsai L.T. &Yang C.C. (2013). Applying Structural Equation Modeling (SEM) in educational research. In: M.S. Khine (Eds). *Application of Structural Equation Modeling in Educational Research and Practice. Contemporary Approaches to Research in Learning Innovations.* Rotterdam: Sense Publishers.

Thamaga-Chitja, J.M. & Morojele, P. (2014). The context of smallholder farming in South Africa: towards a livelihood asset building framework. *Journal of Human Ecology*, 45(2), pp. 147 – 155.

Thinda, K.T., Ogundeji, A.A., Belle, J.A. & Ojo, T.O. (2020). Understanding the adoption of climate change adaptation strategies among smallholder farmers: Evidence from land reform beneficiaries in South Africa. *Land Use Policy,* 99(2020), pp. 1 – 10.

Timu, A.G., Gustafson, C.R., Ikegami, M. & Jensen, N. (2018). Indemnity payouts, learning from others and index insurance uptake. In*: Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting,* Washington, D.C., 5 -7 August, 2018.

Tobacman, J., Stein, D., Shah, V., Litvine, L., Cole, S. & Chattopadhayay, R. (2017). *Insuring against weather shocks: Evidence from India*. 3ie Impact Evaluation Report 29. New Delhi: International Initiative for Impact Evaluation (3ie).

Tobi, H. & Kampen, J.K. (2018). Research design: the methodology for interdisciplinary research framework. *Quality & quantity,* 52(3), pp.1209-1225.

Tolno, E., Kobayashi, H., Ichizen, M., Esham, M. & Balde, B.S. (2015). Economic analysis of the role of farmer organizations in enhancing smallholder potato farmers' income in middle Guinea. *Journal of Agricultural Science,* 7(3), pp. 123 – 137.

Tsikirayi, C.M.R., Makoni, E. & Matiza, J. (2013). Analysis of the uptake of agricultural insurance services by the agricultural sector in Zimbabwe. *Journal of International Business and Cultural Studies,* 7, pp.1 - 14.

Ulbinaite, A., Kucinskiene, M. & Le Moullec, Y. (2014). The complexity of the insurance purchase decision making process. *Transformations in Business and Economics,* 13(3), pp. 1 - 20.

UNCTAD. (2020) World investment report 2020. United Nations Conference on Trade and Development. Retrieved 24/09/2020 from https://unctad.org/en/PublicationsLibrary/wir2020_en.pdf.

van Asseldonk, M., Porgo, I., Hamusimbi, C., Mumba, G., Banda, J., Maitre d'Hotel, E., le Cotty, T., Burger, K., & Onumah, G. (2015). Is there evidence of linking crop insurance and rural credit and its potential benefits? Policy Brief No 1, 2015. The Farm Risk Management for Africa (FARMAF).

van Asseldonk, M., van der Woerd, J. & Vakaki, E. (2018). Growing credit-linked and stand-alone index-based drought insurance in Uganda. *The State of Microinsurance,* 2018(4), pp. 23 – 26. Luxembourg: Microinsurance Network.

van Niekerk, D., Wentink, G.J. & Shoroma, B. (2018). *Natural Hazards Governance in South Africa*. Oxford Research Encyclopedia of Natural Hazard. https://doi.org/10.1093/acrefore/9780199389407.013.246.

van Wyk, R.B. & Dlamini, C.S. (2018). The impact of food prices on the welfare of households in South Africa. *South African Journal of Economic and Management Sciences*, 21(1), pp. 1 – 9.

Vasilaky, K., Diro, R., Norton, M., McCarney, G. & Osgood, D. (2019). Can education unlock scale? the demand impact of educational games on a large-scale unsubsidised index insurance programme in Ethiopia, *The Journal of Development Studies*, 56(2), pp. 361 – 383.

Vasilaky, K., Sáenz, S.M., Stanimirova, R. & Osgood, D. (2020). Perceptions of farm size heterogeneity and demand for group index insurance. *Games*, 11(15), pp. 1 – 21.

Vishwakarma, G. (2017). Sample size and power calculation. In: *Research Methodology*, Chapter: Sample Size and Power Calculation, (pp.1 - 21).

von Loeper, W.J., Drimie, S. & Blignaut, J. (2018). The struggles of smallholder farmers: A cause of modern agricultural value chains in South Africa. In: G. Egilmez (Eds). *Agricultural Value Chain*. London: IntechOpen.

von Loeper, W.J, Musango, J., Brent, A. & Drimie, S. (2016). Analysing challenges facing smallholder farmers and conservation agriculture in South Africa: A system dynamics approach. *South African Journal of Economic and Management Sciences*, 19(5), pp. 747-773.

Voster, N. (2019). Land and identity in South Africa: An immanent moral critique of dominant discourses in the debate on expropriation without compensation. *HTS Theological Studies*, 75(4), pp.1 – 9.

Wairimu, E., Obare, G. & Odendo, M. (2016). Factors affecting weather index-based crop insurance in Laikipia County, Kenya. *Journal of Agricultural Extension and Rural Development*, 8(7), pp. 111 – 121.

Walliman, N. (2011). *Research Methods: the basics*. Abingdon: Routledge.

Wan, J., Li, R., Wang, W., Liu, Z. & Chen, B. (2016). Income diversification: A strategy for rural region risk management. *Sustainability*, 8(1064), pp. 1 – 12.

Wang, H.H., Karuaihe, R.N., Young, D.L. & Zhang, Y. (2013). Farmers' demand for weather-based crop insurance contracts: the case of maize in South Africa. *Agrekon*, 52(1), pp. 87-110. DOI: 10.1080/03031853.2013.778468

Wang, J. & Wang, X. (2020). *Structural Equation Modeling: Application using Mplus*. 2nd Edition. Oxford: John Wiley & Sons.

Ward, P. (2017). *Index insurance as an instrument for managing risk and modernizing agricultural production*. Washington, D.C.: International Food Policy Research Institute.

Ward, P. & Makhija, S. (2018). New modalities for managing drought risk in rainfed agriculture: Evidence from a discrete choice experiment in Odisha, India. *World Development*, 107(2018) pp. 163 – 175.

Ward, P., Makhija, S. & Spielman, D.J. (2019). Drought-tolerant rice, weather index insurance and comprehensive risk management for smallholders: evidence from a multi-year field experiment in India. *Australian Journal of Agricultural and Resource Economics,* 59(1), pp. 1 – 34.

Weber, E.J. (2019). *Weather index insurance in Sub-Saharan Africa*. Discussion Paper 19.03. Crawley: The University of Western Australia.

Weber, R., Fecke, W., Moeller, I. & Musshoff, O. (2015). Meso-level weather index insurance: Overcoming low risk reduction potential of micro-level approaches. *Agricultural Finance Review*, 75(1), pp. 31 – 46.

Weedige, S.S, Ouyang, H, Gao, Y. & Liu Y. (2019). Decision making in personal insurance: Impact of insurance literacy. *Sustainability*, 11(23), pp. 1 - 24.

Weingartner, L., Simonet, C. and Caravani, A. (2017). *Disaster risk insurance and the triple dividend of resilience*. Working paper 515. London: Overseas Development Institute.

Westland, J.C. (2015). *Structural Equation Models: From path to networks*. Studies in Systems, Decision and Control, 22. New York, NY: Springer.

WFP. (2017). *R4 Rural Resilience Initiative – Annual report – January – December 2017*. Rome: World Food Programme.

WFP. (2019). *R4 Rural Resilience Initiative - Quarterly report - January - March 2019*. Rome: World Food Programme.

Wilk, J., Andersson, L. & Warburton, M. (2012). *Adaptation to climate change and other stressors among commercial and small-scale South African farmers*. Berlin: Springer Verlag.

Wiese, A. (2019). *Current trends in agriculture insurance - risk management*. Farmers Weekly, 2019(19007), p. 30.

World Bank. (2011). *Weather index insurance for agriculture: Guidance for development practitioners. Agriculture and Rural Development – Discussion Paper 50*. Washington D.C.: World Bank Group.

World Bank. (2014). *Financial protection against natural disasters: an operational framework for disaster risk financing and insurance*. Washington, DC.: World Bank Group.

World Bank. (2015). *Kenya: Towards a national crop and livestock insurance program – background report.* Washington D.C.: World Bank Group.

World Bank. (2016). *South Africa: Towards a national agricultural insurance program – initial diagnostic study*. Washington D.C.: World Bank Group.

World Bank. (2017). *Agriculture and climate risk enterprise: Kilimo Salama - Kenya, Rwanda, Tanzania (English). Global Index Insurance Facility (GIIF) partner profile*. Washington, D.C. : World Bank Group.

World Bank. (2018). *Overcoming poverty and inequality in South Africa: An assessment of drivers, constraints and opportunities.* Washington, D.C.: World Bank Group.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A. & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, 54(2017), pp. 223 - 233.

Wrede, P. & Phily, C. (2015). *Pricing for Microinsurance: a technical guide*. Geneva: International Labour Organization.

Wuensch, K.L. (2020). Binary Logistic Regression with SPSS. Retrieved 02/08/2020 from http://core.ecu.edu/psyc/wuenschk/MV/Multreg/Logistic-SPSS.PDF

Würtenberger, D. (2019). *Index based insurance in developing countries: Rational neglect*? Hamburg: ZBW – Leibniz Information Centre for Economics.

Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q.P. & Lillard Jr. J.W. (2014). A study of effects of multicollinearity in the multivariable analysis. *International Journal of Applied Science and Technology*, 4(5), pp. 9 – 19.

Yore, R. & Walker, J.F. (2019). Microinsurance for disaster recovery: Business venture or humanitarian intervention? An analysis of potential success and failure factors of microinsurance case studies. *International Journal of Disaster Risk Reduction*, 33(2019), pp. 16 – 32.

Zantsi, S., Greyling, J.C. & Vink, N. (2019). Towards a common understanding of 'emerging farmer' in a South African context using data from a survey of three district municipalities in the Eastern Cape Province. *South African Journal of Agricultural Extension*, 47(2), pp. 81 – 93.

Žarković, N., Miloradić, J. & Samardžić, S. (2016). The risk of drought in crop production insurance. *Economics of Agriculture*, 63(4), pp.1297 - 1308.

Zhang, J., Brown, C. & Waldron, S. (2017). *Case study analysis on household attitudes towards weather index crop insurance in rural China*. Brisbane: University of Queensland.

Zhang, Y., Ju, G. & Zhan, J. (2019). Farmers using insurance and cooperatives to manage agricultural risks: A case study of the swine industry in China. *Journal of Integrative Agriculture*, 18(12), pp. 2910 – 2918.

Zhong, M., Sun, Z., Lai, G. &Yu, T. (2015). Cultural influence on insurance consumption: Insights from the Chinese insurance market. *China Journal of Accounting Studies*, 3(1), pp. 24 – 48.

Ziegler, M. & Hagemann, D. (2015). Testing the unidimensionality of items: pitfalls and loopholes. *European Journal of Psychological Assessment*, 31(4), pp. 231 – 237.

Zikmund, W.G., Babin, B.J., Carr, J.C. &Griffin, M. (2009). Business Research Methods. 8th Edition. New Castle: South-Western College Pub.

Zollmann, J. (2015). *Two steps back: how low income Kenyans think about and experience risk in their pursuit of prosperity*. Geneva: The International Labour Organisation's Impact Insurance Facility.

Zwane, M. & Montmasson-Clair, G. (2016). *Climate change adaptation and agriculture in South Africa: a policy assessment*. Newlands: WWF-SA.

APPENDICES

Appendix A: Informed Consent Form

UNIVERSITY OF KWAZULU-NATAL
GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

Dear Respondent,

DBA Research Project

Researcher: Mr Mpho Steve Mathithibane C: [redacted] E: mphomathithibane@gmail.com
Supervisor: Dr Bibi Zaheenah Chummun T: 031-260-8943 E: ChummunB@ukzn.ac.za
Research Office: Ms M Snyman T: 031-260-8350 E: HssrecLms@ukzn.ac.za

My name is Mpho Steve Mathithibane a Doctor of Business Administration (DBA) student (student no. 219074152), at the Graduate School of Business and Leadership, of the University of KwaZulu Natal. You are invited to participate in a research project entitled: A conceptual framework for factors that influence willingness of low-income farmers to pay for weather index insurance in South Africa. The aim of this study is to: provide market insight into low-income farmers' preferences and willingness to pay for innovative insurance products in order to reduce agricultural production risk.

Through your participation I hope to understand low-income farmers' willingness to pay for weather index insurance, the price range and the factors that influence the decision to pay or not to pay. The results of the survey are intended to contribute to the creation an initial framework for the pricing and acceptance of weather index insurance contracts in South Africa.

The information that you provide will be used for scholarly research only. Your participation in this project is voluntary. You may refuse to participate or withdraw from the project at any time with no negative consequence. There will be no monetary gain from participating in this survey. Confidentiality and anonymity of records identifying you as a participant will be maintained by the Graduate School of Business and Leadership, UKZN.

If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor at the numbers listed above.

The survey should take you about 15 minutes to complete. I hope you will take the time to complete this survey.

Sincerely

Mpho Steve Mathithibane

[redacted]

UNIVERSITY OF KWAZULU-NATAL
GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

DBA Research Project

Researcher: Mr Mpho Mathithibane C: [redacted] E: mphomathithibane@gmail.com
Supervisor: Dr Bibi Zaheenah Chummun T: 031-260-8943 E: ChummunB@ukzn.ac.za
Research Office: Ms M Snyman T: 031-260-8350 E: HssrecLms@ukzn.ac.za

<u>CONSENT</u>

I……………………………………………………………………… (full names of participant) hereby confirm that I understand the contents of this document and the nature of the research project, and I consent to participating in the research project. I understand that I am at liberty to withdraw from the project at any time, should I so desire.

Signature of participant   Date

……………………………   ………………………

Appendix B: Questionnaire

The following questionnaire deals with your views on crop insurance. Kindly mark responses to section A – E. with an X where appropriate.

Section A: Demographic information

1. What is your gender?

1	Male	2	Female		3	Prefer not to say	

2. What is your age?

1	18 – 35	
2	35 – 44	
3	45 – 54	
4	55 - 64	
5	65 or older	

3. What is your ethnic group?

1	Black African	
2	Coloured	
3	Indian/Asian	
4	White	
5	Prefer not to say	

4. What is your marital status?

1	Married	
2	Single	
3	Divorced	
4	Widowed	
5	Prefer not to say	

5. What is the size of your household?

1	1 – 5 people	
2	6 – 10 people	
3	11 or more	

6. What is your highest level of education?

1	No formal education	
2	Primary education	
3	Secondary education	
4	Tertiary education	

7. Do you have any form of insurance? E.g. funeral cover, car insurance etc. **Yes/ No**

Section B: Farm Characteristics

8. How many years have you been involved in maize crop farming?

1	Less than 5 year	
2	5 years – 10 years	
3	11 years –15 years	
4	16 years – 20 years	
5	More than 20 years	

9. How many hectares (ha) of agricultural land do you plant?

1	Less than 20 ha	
2	21 ha - 50 ha	
3	51 and 100 ha	
4	101 and 150 ha	
5	More than 150 ha	

10. What is your annual income/revenue from crop activities?

1	Less than R250 000	
2	R250 001 – R500 000	
3	R500 001 – R1 000 000	
4	R1 000 001 – R2 000 000	
5	More than R2 000 000	

11. Have you received a production loan/credit in the last 5 years? **Yes / No**

12. Are you part of a farming group or association? **Yes / No**

Section C: Farm Risk Analysis

13. What is the **single** biggest source of weather risk affecting your crops?

1	Drought	
2	Low rainfall	
3	High rainfall	
4	Hail Storm	
5	Other – please specify	

14. How much of your crops do you lose following the identified weather event?

1	Less than 25%	
2	Between 26% and 50%	
3	Between 51% and 75%	
4	More than 75%	

15. What is your level of preparedness in dealing with crop loss due to adverse weather?

1	Prepared	
2	Somewhat prepared	
3	Neutral/Cannot judge	
4	Not prepared	
5	Somewhat unprepared	

16. How do you manage the risk of crop failure due to weather risk? Please select your **single** most trusted strategy.

1	I plant less in times of uncertainty	
2	I diversify my crops	
3	I shift crop planting dates	
4	I focus on off-farm income	
5	I rely on irrigation	
6	I utilize my savings	
7	I apply for loans/credit	
8	I use crop insurance	
I	I rely on government support	

Section D: Risk Preference

17. Please indicate to what extent you agree or disagree with the following statements:

	Strongly agree	Agree	Neutral	disagree	Strongly disagree
17.1 - **Insurance culture**					
I have a good understanding of how crop insurance works.					
I have considered using crop insurance to protect my assets and livelihood.					
I understand that paying for crop insurance does not guarantee a claim payout.					
17.2 - **Financial capability**					
I have access to emergency savings for farm operations.					
I have sufficient funds to carry on my farming operations for the next year.					
I manage farm income and expenditure according to a planned budget.					
17.3 - **Risk perception**					
I am careful when planning for the next crop planting cycle.					
I make planting decisions based on available weather reports.					
I am more cautious because of previous crop loss experience.					
Compared to other farmers I would say I take more risks.					

Section E: Weather Index Insurance

Weather Index insurance is crop cover that uses a measure of rainfall to estimate crop damage. For example, if rainfall is below a determined level over the crop planting season, then insurance payouts will be made to farmers without on-field farm verifications. It should be noted though, that there is a possibility that farm level crops can be damaged as a result of a lack of rainfall, however the insurance payout will not be made if the overall rainfall index in the region has not fallen below the pre-set level.

18. Are you willing to pay **5%** of your annual income for Index Insurance? **Yes / No**

19. Are you willing to pay **10%** of your annual income for Index Insurance? **Yes / No**

20. [**If No** to question 18] Would you pay 2.5%? **Yes / No**

21. If you are not willing to pay any amount, to what extent to you agree or disagree with the below statements:

		Strongly agree	Agree	Neutral	disagree	Strongly disagree
21.1	Premiums are expensive					
21.2	I have other priorities					
21.3	I don't trust insurance					
21.4	No one in my community uses agricultural insurance					
21.5	My crop management plan is working well					

Thank you

Appendix C: Gatekeeper Letter

Confidential

The Land and Agricultural Development Bank of South Africa
P O Box 375 Pretoria 0001
Block D Eco Glades 2 Office Park, 420 Witch Hazel Avenue Eco Park
CENTURION

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18 June 2019

University of KwaZulu-Natal
Graduate School of Business Leadership
University Road, Westville, 3630

Dear Sir/Madam

Permission to access development/smallholder farmer contact details

I am writing to formally indicate our awareness of the research proposed by Mpho Mathithibane, an employee of the Land and Agricultural Bank of South Africa (Land Bank) and a DBA student at UKZN Graduate School of Business Leadership, under the research title:

A conceptual framework for factors that influence willingness of low-income farmers to pay for weather index insurance in South Africa

We are aware that Mpho intends to conduct his research by administering a survey based on a sample of development/smallholder farmers taken from the Land Bank Loan Book.

This letter hereby grants permission to conduct the research based on data obtained from the Land Bank database.

Sincerely,

[redacted]

Ms KM Gugushe

Acting Chief Executive Officer

Appendix D: Ethical Clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

15 February 2021

Mr Mpho Steve Mathithibane (219074152)
Grad School Of Bus & Leadership
Westville Campus

Dear Mr Mathithibane,

Protocol reference number: HSSREC/00002388/2021
Project title: A conceptual framework for factors that influence willingness of low-income farmers to pay for weather index insurance in South Africa
Degree: PhD

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 02 February 2021 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid until 15 February 2022.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
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