

The application of geographical information systems to infectious diseases and health systems in Africa

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Submitted in fulfilment of the requirements for the degree of Doctor of Philosophy to the
Faculty of Medicine, University of Natal.

DURBAN
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For my wife Leonie.

Declaration

I declare that this thesis is my own, unaided work unless specifically acknowledged in the text. It is being submitted for the Degree of Doctor of Philosophy in the faculty of Medicine, University of Natal. It has not been submitted before for any degree at any other University.

A handwritten signature in black ink, appearing to be 'H. M. ...', is written above a horizontal line.

10th November 2000

Preface

I believe geographical information systems (GIS) have considerable application for health research and planning in Africa. My overall goal for this thesis was to demonstrate some of this potential by applying GIS to the most pressing health issues in Africa using a range of different GIS techniques. I accomplished this through a series of six papers that have been submitted to international journals for publication. Except for stylistic standardisation and references to appendices, the papers remained unchanged to those submitted. Taken together, they are intended to form a coherent, significant instalment to the potential applications of GIS to infectious diseases and health systems in Africa. In line with recent scientific writing trends (Brown, 1997), I have written the papers that make up the thesis using the first person. If the reader bears in mind that some of the papers were submitted by multiple authors then it will be clear why I have left the corresponding chapters in the first person plural. There is some repetition of the descriptions of the study area and methods of data collection between chapters. This was to maintain the integrity of the publications.

Hlabisa district was selected for the location for a demographic surveillance system (DSS). The primary objective of the system is to collect detailed vital event data for a typical rural South African population of 100, 000 people and to monitor the demographic impact of the HIV epidemic. The mapping of the facilities and homesteads in the district provided the foundation on which to build the DSS and was therefore part of a more detailed research agenda. It also presented an excellent opportunity to conduct district-level GIS research by

linking the spatial data with existing facility-based infectious disease data. Detailed demographic data was not collected during the homestead mapping and interview exercise because the DSS will collect this type of data.

Chapter one commences with a brief introduction to the history of medical geography and an introduction to GIS. This is followed by an overview of the current major health priorities in Africa. The chapter then examines previous GIS research that has been undertaken in Africa and, in light of the existing research deficits and Africa's disease burden, concludes with a summary of the objectives of the research.

Chapter two deals with the setting up of the GIS platform and methods of data collection. This chapter is included because I wasn't able to go into sufficient detail in the papers regarding the data collection process. The chapter describes the rationale behind differential global positioning systems (GPS) and the mapping of homesteads and facilities throughout the district. Quality control measures and the hardware, software and additional datasets used are described.

The third chapter is intended to demonstrate the utility of GIS in health systems research. This chapter fulfils two main purposes: Firstly, it provides an overview of primary health care in Hlabisa. Secondly, it demonstrates the application of distance calculations, kernel filtering, distance (theissen) polygons, contouring, buffering and thematic maps to the analysis of mode clinic utilisation patterns. These techniques are then brought together to produce spatial indices that quantify clinic usage in the district.

Chapters four and five use homestead positions obtained partly from differential GPS and partly from geo-corrected aerial photography. This was because the mapping of homesteads had not yet been completed for the whole district. Chapter four comprises two papers that investigate the spatial implications of the tuberculosis directly observed treatment (DOT) strategy using GIS. Raster surfaces are used to calculate the distance of every homestead in the district to nearest supervision point. The study presents quantitative spatial evidence for the shift in strategy from hospital to community-based.

Chapter five uses GIS to explore one of the possible reasons for heterogeneity in HIV prevalence in Hlabisa. Raster surfaces are used to measure the mean distance between nearest road and homesteads in each of the 11 clinics operating in the district in 1997. The results are then compared against HIV prevalence in pregnant women attending each of the clinics.

Chapter six focuses on a heterogeneous subsection of the district where the demographic DSS is being set up. The DSS uses a large number of fieldworkers on foot to interview homestead residents. Significant problems exist in the estimation and equitable distribution of fieldworker workload in the area. A number of physical factors are brought together in the GIS to estimate inter-homestead walking time. Techniques used include surface interpolation, fuzzy logic and kernel filtering. The physical factors are then married to social factors and workload is equitably distributed among fieldworkers. The study is important for three reasons: Firstly, it is an example of a practical application of GIS to health research. Secondly, the study makes use of a variety of novel modelling techniques (most notably fuzzy logic) and uses a large number of datasets (including satellite

imagery). Thirdly, and importantly, the study has a large number of potential applications to improving the effectiveness of health systems in rural Africa.

Chapter seven focuses on the application of GIS to model malaria seasonality across Africa. The study uses long term raster surfaces of rainfall and temperature to identify malaria transmission ‘windows’. Advanced Boolean logic in association with temporal smoothing is used to produce the seasonality images. The model is compared against historical maps and existing case data. The model is also compared against malaria surveys conducted across Africa to establish the relationship between predicted length of malaria season and transmission intensity. The impact of simple climatic change scenarios on malaria seasonality are evaluated.

The final chapter reviews the major research findings and their implications for health policy and directions for future research. This is followed by general conclusions regarding the application of GIS to health in Africa.

Acknowledgements

Many people contributed either directly or indirectly to the birth of this thesis. A particularly big thank you must go to David le Sueur and David Wilkinson who contributed significantly to the overall conceptualisation of the research. Together they have taught me what science is all about. The outline and content of the thesis were the fruit of many discussions with both of them. David Wilkinson taught me how to write a scientific paper and gave expert input into the HIV and tuberculosis sections of this research. For much of the time of my writing this thesis, David le Sueur was sailing around the world on his yacht. Despite this, he found a way of sending me detailed replies to any of my queries and for this I am particularly grateful. I wish to thank my supervisor and co-supervisor Brian Sharp and Geoff Solarsh respectively for their input and allowing me significant latitude to develop my own ideas. Thanks also to Geoff who in conjunction with Vicky Hosegood provided input into the mapping of homesteads methodology. A large amount of work went into preparing the Hlabisa community for the study and the majority of this was orchestrated by Geoff. Brian provided excellent feedback on the relationship of numerous permutations of the malaria seasonality model to 'reality'. I would also like to thank David le Sueur, David Wilkinson, Wim Stuurm, Rob Brooks, Brian Sharp, Salim Karim and Tony Palmer for convincing me to write up my research as a series of publications and using these as chapters within the thesis.

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The malaria seasonality component of this thesis is an output of the ‘mapping malaria risk in Africa’ (MARA) collaboration. I would like to thank the members of the MARA collaboration, in particular Bob Snow for their guidance and feedback on the malaria seasonality component of this thesis. It has been a privilege to work with some of the highest calibre malaria scientists in Africa. Thanks to Colleen Fraser and Karun Naidoo for database support. I am grateful to Don de Savigny, Tom Smith, Marlies Craig, Justus Benzler, Vicky Hosegood and Mike Bennish for their comments on various aspects of the thesis.

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I gratefully acknowledge financial support from the Wellcome Trust through the Africa Centre for Population Studies and Reproductive Health. Additional support was also received from the South African MRC and the IDRC.

Publications arising from the research

I wish to thank all of my co-authors for their contributions to the following papers that have arisen from this research and have been submitted to international journals for publication:

1. **Tanser FC** (2000) A model to equitably distribute fieldworker workload in a large, rural South African health survey. *submitted for publication*.
2. **Tanser FC, Hosegood V, Benzler J and Solarsh G** (2000) New approaches to spatially analyse primary health care usage patterns in rural South Africa. *submitted for publication*.
3. **Tanser FC, Le Sueur D, Solarsh G and Wilkinson D** (2000) HIV heterogeneity and proximity of homestead to roads in rural South Africa: an exploration using a geographical information system. *Trop Med Int Health* (5) **1**, 40-46.
4. **Tanser FC, Sharp B and Le Sueur D** (2000) Malaria seasonality and population exposure in Africa: a high resolution climatic model. *submitted for publication*.
5. **Tanser FC and Wilkinson D** (1999) Spatial implications of the tuberculosis DOTS strategy in rural South Africa: a novel application of geographical information system and global positioning system technologies. *Trop Med Int Health* (4) **10**, 634-8.
6. **Wilkinson D and Tanser FC** (1999) GIS/GPS to document increased access to community-based treatment for tuberculosis in Africa. *Lancet* (354) **9176**, 394-5.

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Abstract

The health sector has not yet begun to explore the full potential of geographical information system (GIS) technology for health research and planning. The goal of this thesis is to demonstrate this potential in Africa through the application of GIS to the most important health issues in the continent.

In excess of 23,000 homesteads are mapped and interviewed throughout Hlabisa district, Kwa-Zulu Natal using differential global positioning systems (GPS). I use the GIS to analyse mode health care usage patterns. 87% of homesteads use the nearest clinic and travel an average distance of 4.72 km to do so. There is a significant logarithmic relationship between distance from clinic and usage by the homesteads ($r^2 = 0.774$, $p < 0.0001$). I propose the distance usage index (DUI) as a composite spatial measure of clinic usage. The index is the sum of the distances from clinic to all actual client homesteads divided by the sum of the distances from clinic to all homesteads within its distance-defined catchment. The index encompasses inclusion, exclusion and strength of patient attraction for each clinic. The DUI highlights significant disparities in clinic usage patterns across the district (mean = 110%, SD = 43.7). The results of the study have important implications for health planning in Africa.

I use GIS/GPS technology to quantify the spatial implications of a shift towards community-based treatment of tuberculosis using the DOTs strategy in Hlabisa. The mean distance from each homestead in the district to nearest supervision point is measured using a GIS. The shift in treatment strategy from hospital to community-based between 1991-1996 reduces the mean distance to treatment point from 29.6 km (94% of the population > 5km) to 1.5km (entire population < 5km). GIS effectively documents and quantifies the impact of community-based tuberculosis treatment on access to treatment.

I produce the first quantifiable evidence of a relationship between distance to roads and HIV prevalence using a GIS. HIV prevalence was measured through anonymous surveillance among pregnant women in Hlabisa and stratified by clinic attended. Assuming women attend the nearest clinic, the mean distance from homesteads to a primary or secondary road for each clinic catchment is strongly correlated with HIV prevalence ($r = 0.66$; $p = 0.002$). Further research is needed to better understand this relationship both at ecological and individual levels.

I develop a methodology that has numerous applications to health systems provision in developing countries where limited physical access to primary health care is a major factor contributing to the poor health of populations. I use an accessibility model within a GIS to subdivide an area into units of equal workload using a range of physical and social variables. The methodology could be used to ergonomically design programmes for home-based care and tuberculosis directly observed treatment. It could also be used as a basis for more efficient distribution of community health workers.

I use high-resolution long-term rainfall and temperature data to produce the first malaria seasonality (length, start and end of transmission season(s)) maps for Africa. I relate the model to population data and estimate the population exposure in a variety of transmission settings. I investigate the relationship between predicted length of transmission season and parasite ratio from 2335 geo-referenced studies of children < 10 years across Africa. The research is the first to correlate actual malaria survey data with model predictions at a continental scale. The seasonality model corresponds well with historical expert opinion maps and case data. A significant logarithmic relationship is detected between predicted length of transmission season and parasite ratio ($r^2=0.712$, $p=0.001$). I recompute the changes in the disease likely to occur as a result of global warming. The seasonality model constitutes an important first step towards an estimate of continental intensity of transmission.

Chapter One:

Introduction

“The spatial distribution of diseases remains one of the oldest of puzzles and yet one of the most contemporary.....” (Cliff and Haggett, 1988).

Health and ill-health have always had a spatial dimension. The idea that place and location can influence health is a very old and familiar concept. As far back as the time of Hippocrates, physicians have observed that certain diseases seem to occur in certain places and not in others (Smith, 1994). Hippocrates himself (commenting on what was later to be known as malaria) made reference to the relationship between proximity to marshes and enlargement of the spleen (Bruce-Chwatt, 1999). People have also been aware of the process of disease diffusion across geographic regions for centuries (during the black death, for example), even during times when the aetiology of the disease was not understood (Marks, 1971).

More than a century ago, physicians began to explore the potential of maps for understanding the spatial dynamics of disease. One of the most famous examples is that of the English physician John Snow in 1854. Snow hypothesised that cholera might be spread by contaminated water. Using maps showing the geographical distribution of cholera deaths in the Soho area of London, Snow was able to demonstrate a striking geographical distribution of cholera deaths around contaminated water supplies (Snow, 1855).

1.1 GEOGRAPHICAL INFORMATION SYSTEMS (GIS)

Despite the realisation (dating back to historic times) that diseases and space are intimately related, the tools to understand, analyse and predict these relationships have not been available. GIS are an innovative, new technology that may have considerable potential in analysing the spatial dimensions of disease and in health research in general. A number of definitions of GIS have been proposed with variations that depend on the perspective of the author, the specific application, the software available at a given time and the level of complexity appropriate for the intended audience (Richards *et al.*, 1999) GIS is thought of as both a technology and a science (Reader, 1994). In the former case GIS is viewed as a technological tool that helps the analyst to use his/her knowledge and insight to study substantive issues. In the latter case GIS is viewed as the science of geographic or spatial information that possesses its own set of research questions (Rhind *et al.*, 1991).

Alternatively, GIS has been termed the technological component of geographic information science (Goodchild, 1992). From a technological perspective, geographical information systems are “automated systems for the capture, storage, retrieval, analysis and display of spatial data” (Clarke, 1995).

GIS data types

Data can be stored and analysed in a GIS in two ways: in raster format and in vector format. The raster format stores geographic data or graphic images as a matrix of evenly divided grid cells. The position of the cell in the matrix provides information about location. Additional information about attributes is stored within each grid cell. Raster data can be scanned from maps or obtained from photographs or remotely sensed data (e.g. from satellites). At their most simplistic raster data allows point disease phenomena (e.g.

distribution or incidence) to be interpolated into a single continuous surface without gaps. They also provide a basis whereby spatially continuous models of disease phenomena can be verified against data which consist of spatially heterogeneous point events. Raster data facilitate easy image overlay modelling procedures.

Vector data consist of strings of coordinates and are represented in a GIS by three types of features: points, lines, or polygons (areas). A point is represented by a single x, y coordinate in a Cartesian coordinate system that is geographically referenced. Lines are represented by the x,y coordinates of their beginning and ending points, with intermediate points or vertices defining the shape of the line. Areas are represented as a boundary made up of a series of connecting line segments. Vector data is suited to the displaying of thematic maps of disease distributions and to accurate distance and area measuring operations. It is also suited to aggregating, and subsequently displaying and analysing disease data using various areal units e.g. district, province and nation.

Spatial Analysis using a GIS

The term spatial analysis encompasses a wide range of techniques for analysing, computing, visualising and theorising about geographic data. Spatial analysis refers to the “ability to manipulate spatial data into different forms and extract additional meaning as a result” (Bailey, 1994). Methods of spatial analysis can be as simple as taking measurements from a map or as sophisticated as complex geocomputational procedures based on numerical analysis. Gattrell and Bailey (1995) describe three general types of spatial analysis tasks: visualisation, exploratory data analysis and model building.

Visualisation includes the production of thematic maps, basic map overlay operations,

animation and exploring the results of traditional statistical analysis. Exploratory spatial analysis allows the analyst to sift meaningfully through spatial data, identify ‘unusual’ spatial patterns and formulate hypotheses to guide future research. Modelling includes procedures for testing hypotheses about the causes of disease and the nature and processes of disease transmission.

1.2 HEALTH PRIORITIES IN AFRICA

The physical and ecological structure of Africa is as varied as its social, political and demographic characteristics (Kalipeni, 2000). Major biomes in the continent include tropical rainforest, montane forest, moist and dry savanna, semi-desert and desert and temperate grasslands (Stock, 1995). The political environment, poverty and generally low levels of well-being for the majority of the people in the region combine with the varied climatic conditions, vegetation and biogeography to explain the prevalence of disease-causing organisms, or pathogens such as bacteria, viruses and worms (Kloos and Zein, 1993).

If the potential for GIS to contribute to health research and planning in Africa is to be properly evaluated then the technology must be applicable to the most pressing health problems in the continent. HIV, malaria and tuberculosis are among the major public health threats in Africa. The diseases all rank in the top six infectious diseases in the continent (WHO, 2000) defined on the basis of disease burden using disability adjusted life years (Murray and Lopez, 1997). I therefore sought to apply GIS to various components of these diseases as well as the analysis and improvement of health systems that must assist in the attenuation and control of Africa’s diseases.

HIV/AIDS

HIV/AIDS is the leading cause of mortality and morbidity in Africa (WHO, 2000). Since its appearance 15-20 years ago human immunodeficiency virus (HIV) has spread to almost every country in the world affecting an estimated 34 million people (World Bank 2000a). Nearly 24 million people in Africa currently live with HIV/AIDS and the epidemic continues to ravage the development prospects for millions of Africans throughout the continent. In 1999, about 3.8 million Africans were infected with HIV during that year, and a total of 10.7 million children were estimated to be orphaned by it (World Bank, 2000b). The 21 countries with the highest HIV prevalence are in Africa. In South Africa, Botswana and Zimbabwe, one in four adults is infected. A child born in Zambia or Zimbabwe today is more likely than not to die of AIDS. In many other African countries, the lifetime risk of dying of AIDS is greater than one in three (World Bank, 2000b). While prevalence in many west and central African countries has remained relatively low and stable, eastern and southern Africa have experienced explosive epidemics with HIV prevalence exceeding 40% among pregnant women in some regions. Around 5 million new infections are currently occurring annually worldwide, over 90% in developing countries (World Bank, 2000a).

One of the reasons for the severity of Africa's HIV/AIDS epidemic is the high prevalence of other sexually transmitted infections (STIs) and the inadequacy of STI services. Another reason for the recent rise in HIV in Africa is the gradual adaptation to new environments, for example, as people migrate from rural to urban areas in search of work. However, the spread of sexually transmitted diseases can also be sharply intensified by crises such as natural disasters, social disintegration, armed conflict and mass population movements

(UNAIDS, 1998). HIV is especially burdensome as the infection and resultant disease primarily affects young and mature adults in their most productive years (15-25) when older and younger family members are dependent on them. The global HIV pandemic is composed of a series of several smaller epidemics. Even within Africa, where levels of infection are the highest in the world, there is substantial heterogeneity of levels of infection.

Tuberculosis

Tuberculosis is the leading infectious cause of death worldwide, killing more people aged over 5 years of age than AIDS, malaria, diarrhoea and all other tropical diseases combined. The World Bank estimate that the disease accounts for 26% of all avoidable adult deaths in less-developed countries (World Bank, 1993). So serious is the threat of tuberculosis that in 1993, the World Health Organisation took the unprecedented step of declaring this disease a global emergency (WHO, 1994). HIV infection renders a person infected by *Mycobacterium tuberculosis* much more likely to develop overt tuberculosis, and the evolution of the disease is considerably accelerated. About 20% of tuberculosis cases in Africa are believed to be related to HIV infection (Raviglione *et al.*, 1997). WHO has calculated that, unless urgent action is taken the annual global number of deaths could rise from 3 million to 4 million by the year 2004. The need for effective intervention is compelling because tuberculosis treatment is one of the most cost-effective of all health interventions. In response to this re-emerging epidemic, the World Health Organisation is promoting the DOTS control strategy (directly observed therapy, short course) with community based treatment at its core (WHO, 1997).

Malaria

In the last decade, in Africa, the incidence of malaria has been escalating at an alarming rate. Cases in Africa account for 90% of malaria cases in the world (WHO, 1996). Until recently, malaria was ranked as the leading disease in terms of disease burden (World Bank, 1993). It is now estimated that only HIV has a larger impact on the health of the African population than that of malaria (WHO, 2000). Malaria is estimated to cause disease in 400 million individuals in Africa and is responsible for 20-50% of all hospital admissions. Mortality associated with cerebral malaria has not improved in the past 30 years (Anderson *et al.*, 1996) and severe malaria anaemia is on the increase (Marsh and Snow, 1999). Snow *et al.* (1999b) used the first truly empirical approach to estimating malaria mortality. The researchers estimated that during 1995, 0.75 to 1.3 million deaths resulted from malaria in Africa and that approximately 80% of these occurred in children < 5 years of age.

The development of drug-resistant strains of the malaria parasite *Plasmodium falciparum* has been one of the greatest obstacles to controlling the disease (Trape *et al.*, 1998). Drugs such as chloroquine, which were once highly effective, are now almost useless for treating malaria in many parts of the world (Krishna, 1997). Frequent armed conflicts, migration of non-immune populations, changing climatic patterns, adverse socioeconomic patterns (e.g. gross inadequacies of funds for drugs), high birth rates and changes in the behaviour of the vectors are also responsible for the upsurge (Nchinda, 1998). The upsurge has also been attributed in part to the declining nutritional status of individuals in both urban and rural areas (Stock, 1995). Malaria and underdevelopment are closely intertwined. The disease causes widespread premature death and suffering, imposes financial hardship on poor

households, and holds back economic growth and improvements in living standards.

Malaria flourishes in situations of social and environmental crisis, weak health systems and disadvantaged communities (WHO, 2000).

Health Systems

Health systems in Africa face increasingly diverse and complex health problems, rapidly growing populations, and severe resource constraints. Improving the performance of health systems has been identified as a major global health priority (WHO, 2000). Health systems' performance makes a profound difference to the quality, as well as the length of the lives of the billions of people they serve. If health systems are poorly constituted and managed, life-enhancing interventions cannot be delivered effectively to those in need. Malaria and tuberculosis are examples of diseases that thrive in the absence of well constituted, effective health systems. This is particularly pertinent for Africa where health systems often perform poorly and are unreliable.

1.3 GIS IN HEALTH

Despite the rapid and productive adoption of GIS by sectors such as agriculture, natural resources, demography and urban planning, the health sector has not begun to explore the full potential of GIS for health research and planning (de Savigny *et al.*, 1994). GIS technology is a tool of great potential for health researchers. As health is largely determined by environmental factors (including the sociocultural and physical environment, which vary greatly in space), it always has an important environmental and spatial dimension. The spatial modelling capacity offered by GIS is directly applicable to understanding the spatial variation of disease, and its relationship to environmental factors

and the health care system (Loslier, 1994). Public health practice needs timely information on the course of disease and other health events to implement appropriate actions. GIS are an innovative technology for generating this type of information.

Unfortunately, the importance of the spatial distribution of the disease has been too often overlooked (Scholten and de Lepper, 1991). Kabel (1990) uses the example of AIDS; in order to be of use to resource planners, predictions of AIDS should include a spatial component. Kabel's argument is that modelling the geographical distribution of AIDS can contribute to both educational intervention and the planning of health care delivery systems. Studies incorporating GIS technology (and the potential applications of GIS) have been critiqued by numerous authors (Mayer, 1983; Gesler, 1986; Twigg, 1990; Marshal, 1991; Scholden and de Lepper, 1991; Walter, 1993; Briggs and Elliot, 1995; Clarke *et al.*, 1996; Vine, 1998; Moore and Carpenter, 1999). The authors all agree that GIS has significant potential for health but that its full potential is far from realised. Despite the fact that the database constraints of the early 90s have lessened considerably, the primary bottleneck in the implementation of a GIS is the development of GIS databases. This can account for as much as 70% of the time and resources necessary to conduct spatial research (Briggs and Elliot, 1995).

Current applications of GIS to Africa's health priorities

There is little known about the relationship between space and disease. The spatial dynamics of tuberculosis, HIV and malaria are different because of the different modes of transmission and differing relationships to the environment. For example, tuberculosis (transmitted by respiratory droplets) and HIV (transmitted largely through sexual contact)

rely on close human contact for transmission. Malaria however is transmitted by mosquito and the flight distance of mosquitos in one vector species has been measured at a maximum distance of 1.8km (Charlwood and Bryan, 1987). Other spatial factors such as human density are also important (Bruce-Chwatt, 1999). Climatic factors play a large part in determining the distribution of malaria, whereas HIV and tuberculosis are affected more by the social environment. These differences will necessarily affect the types of GIS methodologies used to understand the various spatial components of these diseases.

GIS research undertaken in Africa, specifically in malaria, HIV, tuberculosis and health systems is summarised (Table 1.1). Whereas in the West a large number of GIS studies have concentrated on cluster analyses of rare cancers (e.g. Openshaw *et al.*, 1988), in Africa diseases affecting the lives of millions of people have not been spatially analysed to any great degree (Table 1.1).

Table 1.1: Published studies that have applied GIS to malaria, HIV, tuberculosis and health systems in Africa.

Application	Number	References
Malaria	20	Martens <i>et al.</i> , 1995; Smith <i>et al.</i> , 1995; Ribeiro <i>et al.</i> , 1996; Thomson <i>et al.</i> , 1996a; Thomson <i>et al.</i> , 1996b; Hay <i>et al.</i> , 1998; Hightower <i>et al.</i> , 1998; Lindsay <i>et al.</i> , 1998; Omumbo <i>et al.</i> , 1998; Schellenberg <i>et al.</i> , 1998; Snow <i>et al.</i> , 1998; Chadee and Kitron, 1999; Craig <i>et al.</i> , 1999; Snow <i>et al.</i> , 1999a,b; Thomson <i>et al.</i> , 1999; Coetzee <i>et al.</i> , 2000; Kleinschmidt <i>et al.</i> , 2000; Hay <i>et al.</i> , 2000a; Thomas and Lindsay, 2000
Tuberculosis	2	Beyers <i>et al.</i> , 1996; van Rie <i>et al.</i> , 1999
HIV	-	
Health Systems	1	Zwarenstein <i>et al.</i> , 1991

The literature search only located two studies that applied GIS to tuberculosis and one study that applied GIS to health systems in Africa. Although several studies analysing geographic variations in HIV in Africa have been conducted (Amat-Roze, 1993; Remy, 1993a,b; Sokal et al., 1993; Killewo *et al.*, 1994), no published studies could be located that applied GIS to the analysis of HIV. Only one additional GIS study conducted outside Africa, in each of tuberculosis (Bishai *et al.*, 1998) and HIV (Latkin *et al.*, 1998) was found. A number of studies have applied GIS to health systems in the West (e.g. McLafferty, 1988; Walsh *et al.*, 1997; Parker and Campbell, 1998). Several studies have applied GIS to malaria in Africa. However, diseases which operate within ill-defined environmental parameters (such as tuberculosis and HIV) also have an important spatial dimension.

1.4 OBJECTIVES

Goal

To demonstrate the potential of GIS to be an effective, relevant and powerful tool for health research and development in Africa.

General objectives

To demonstrate this potential through specific innovations in the application of GIS to the most important health issues in Africa; namely malaria, tuberculosis, HIV and the improvement of health systems.

Specific objectives

Tuberculosis

- Quantify and display the spatial implications of the shift towards the tuberculosis DOT strategy through a community-based programme in Hlabisa district, Kwa-Zulu Natal, South Africa.

HIV

- Investigate possible reasons for the spatial heterogeneity in HIV prevalence among pregnant women in Hlabisa.

Malaria

- Produce a continental model of malaria seasonality in Africa (this includes start, end and length of transmission season).
- Estimate the population exposed to malaria in Africa in a variety of transmission settings.
- Explore the relationship between length of malaria transmission season and parasite ratio data from geo-referenced surveys across Africa.
- Evaluate the impact of simple climatic change scenarios on the temporal, spatial and population exposure aspects of malaria.

Health Systems

- Develop new indices to spatially analyse and quantify clinic usage patterns in Hlabisa.

- Evaluate and quantify the relationship between distance from clinic and usage in Hlabisa.
- Develop a methodology for equitably distributing fieldworker workload across a heterogeneous landscape in a large rural health survey and suggest potential uses for the methodology in improving health systems in Africa.

Chapter Two:

Creation of GIS Platforms and Data Collection

The research in this thesis includes studies at both a district and a continental level. The HIV, tuberculosis and health systems components of the research are conducted at a district level using homestead and clinical data from the district of Hlabisa, South Africa. The malaria component of the research is conducted at a continental level using climatic and parasitological data from across the continent of Africa. The primary purpose of this chapter is to describe the data collection and setting up of the district-level GIS platform since it involved a large amount of primary data collection. Existing spatial data sets used at both the district and continental levels are also described. The chapter concludes with a description of the hardware and software used in the research.

2.1 CREATION OF A DISTRICT-LEVEL GIS PLATFORM

Study area

Hlabisa district is located in the North East of South Africa in the province of KwaZulu-Natal (Figure 2.1), is 1430 km² in size and has a resident population of 210, 000 people. The district is located between the geographical coordinates of 31° 47'E; 27° 55'S and 32°24'E; 28° 28'S. The most salient characteristics of the area are that it is Zulu-speaking and predominantly rural (although there are pockets of urban and peri-urban populations in the southern part of the district near the market town of Mtubatuba). The population, with an annual per capita income of US\$ 1730, relies mainly on migrant labour

remittances, subsistence farming, and pensions for its support and livelihood (Department of National Health, 1996). The rural population is scattered throughout the district and is not concentrated into villages or compounds as is the case in many other parts of Africa.

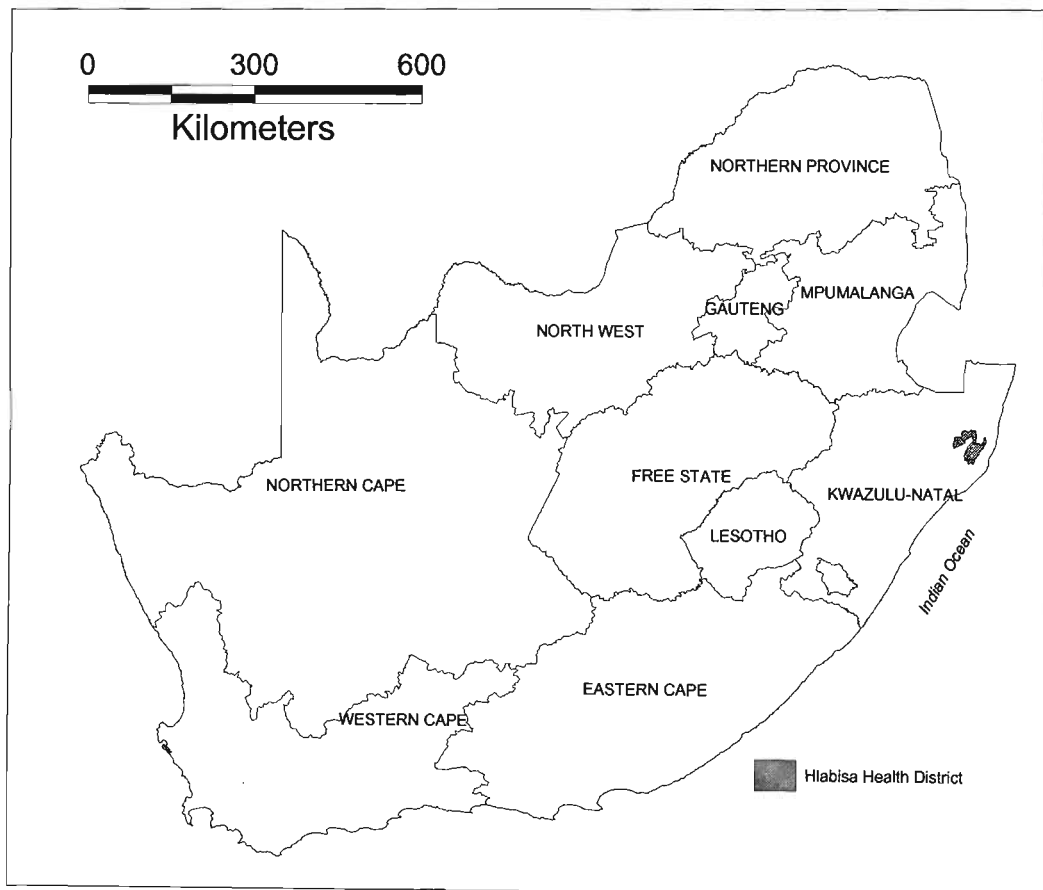


Figure 2.1: The location of the Hlabisa district in South Africa

Mapping Methodology

Global Positioning Systems (GPS)

All mapping and data collection were achieved using hand-held GPS units. The GPS system owned by the United States Department of Defence, comprises a constellation of 24 satellites that orbit the Earth every 12 hours. A GPS establishes the coordinates of the user on the ground by calculating the distance from a minimum of three satellites. Each satellite transmits two carrier signals termed L1 and L2 respectively. Modulated onto the L1 signal are two pseudo-random binary code sequences known as the coarse acquisition (C/A) code and the precise (P) code. The use of pseudo-random binary code sequences enable all satellites to transmit on the same frequency without creating a garbled mess of radio interference. The C/A code is intended to assist with the acquisition of the P code for approximate position measurements and civilian use¹, whereas the P code is intended for the military and is more precise by an order of magnitude (Koh and Edwards, 1996). The intentional error introduced in the C/A code is known as selective availability.

GPS accuracy

Ardö and Pilesjö (1992) demonstrated that the maximum error encountered was 44m from a known fixed point using a single GPS. This error is unacceptable in the study area where homesteads are sometimes < 10m apart. I therefore used a technique known as differential correction to overcome this error. By plotting the errors over time of a fixed GPS (base-station) of known location, it is possible to subtract these errors from a roving GPS in the field. Differential correction can occur in real time (by means of a radio link between the

¹ C/A code was abolished by the United States government on the 1st May 2000.

stationary and roving GPS) or subsequent to data collection (post-processing). I used the post-processing method of differential correction using data from base-stations in Durban and Dundee (both approximately 200km away). This involves computing corrections to the range of each satellite. The base-station computes the correct range (based on the satellite’s ephemeris and knowledge of the precise geodetic location) and rate-of-change to each satellite being tracked. These data are then used in the differential correction process. To ensure that the base-station GPS units use the same satellites as the roving GPS units I set the elevation mask to 15° (i.e. the roving GPS units will not use satellites below an azimuth of 15°). I compared the differential GPS coordinates against 10 trigonometric beacons found in the study area whose precise coordinates are known. In all cases errors were < 2m and in 90% of cases errors were <1m. Other important settings on the GPS are given in Table 2.1. Position dilution of precision (PDOP) is a measure of the accuracy of the GPS reading (that takes into account the spread and azimuths of available satellites). The higher the PDOP the lower the accuracy of the reading. Once the PDOP > 6.0, the GPS units will not record coordinates and the fieldworker will have to wait (typically about 20 minutes) until the PDOP falls below 6.0 again (Table 2.1). There are a maximum of two such occurrences every day in the southern hemisphere at different times and approximately 20 minutes in duration.

Table 2.1: Important GPS settings.

Setting	Value
Datum	Cape
Elevation Mask	15°
Signal to Noise Ratio (SNR) Mask	5.0
PDOP Mask	6.0
Feature logging (points, lines/area)	5, 1 seconds
Minimum number of positions recorded	10

Data collection using a GPS

GPS also have the capacity to capture other descriptive information pertaining to the feature, through the use of a data dictionary. A GPS data dictionary is a GPS-resident data storage facility that enables attribute data, to control the capture of features (objects) and attributes (information about those objects). A data dictionary includes a list of features that are captured in the field and, for each feature, a list of attributes that describe that feature.

Mapping of facilities and key homesteads

My first objective was to map all facilities and key homesteads in Hlabisa and to collect selected attribute data pertaining to each. I trained three fieldworkers in the use of differential GPS for both mapping and data collection. All mapped facilities and key homesteads (e.g. community health workers) and associated attribute data are given (Table 2.2). A complete list of all data collected (some of which was not used directly in this research) for each facility/key homestead are given in Appendix 1.

Table 2.2: Data collected for all facilities and key homesteads mapped in Hlabisa district

Facility/Key homestead	Attribute data	Number
Fixed clinic or hospital	Name, location	12
Mobile clinic point	Name, location	31
Community health worker (CHW)	Name, location	131
Shop	Name, location, Tuberculosis supervision point (Y/N)	162
School	Name, location, TB supervision point (Y/N)	178
Church	Name, location, TB supervision point (Y/N)	62
Induna ²	Name, location	55
Traditional Healer	Name, location	348

Mapping of homesteads across the district

Homestead definition

Prior to the start of homestead mapping an extensive piloting exercise was undertaken to determine what constituted a mapable definition of homestead. The definition had to be consistent spatially as well as socially. In rural areas the boundaries of a homestead are easy to identify; however, in the peri-urban informal settlement around KwaMsane in the South East of the study area, it becomes more difficult. In rural KwaZulu-Natal land is allocated to an individual by an Induna. Homesteads are thus defined on the basis of ownership by one person.

² A tribal chief

A homestead is a discrete set of structures, bounded or otherwise which must have residential function and fall under the ownership of one person.

The term homestead (the location of the buildings in which the family resides) should not be confused with the term household (family group(s) within a homestead).

Constitution of mapping teams and data collection in the field

Prior to commencing the mapping of homesteads, ethical clearance was obtained from the University of Natal Ethics Committee. In addition, meetings were conducted with traditional leaders and civic associations in the area to obtain community consent.

I trained an additional 14 fieldworkers in the use of differential GPS. I then divided the fieldworkers into four teams (three 'mapping teams' of four members and one 'backup team' of two members). Each mapping team was assigned a supervisor (previously fieldworkers from the mapping of facilities), given a portion of the district to map and a set of maps covering the district. The maps contained approximate positions of all homesteads occurring in the district (obtained from aerial photographs). The supervisors were responsible for coordinating the movements of the fieldworkers. A number of homestead categories were defined and a list of questions generated (Table 2.3). A complete list of all data collected some of which are not directly relevant to this study are given in Appendix 2.

Each member of a mapping team was assigned one GPS and a unique block of 5000 numbers to identify homesteads. Unique data dictionaries (only allowing entry of the unique block of 5000 numbers) were uploaded to each fieldworker's GPS (Appendix 3).

Table 2.3: Homestead type (defined for mapping purposes), number mapped and associated data collected by fieldworkers.

Homestead Type	Definition	Associated Data	Number mapped
Ordinary	A homestead where a senior resident of the homestead is present who can give the fieldworker authority to map the homestead	ID, location, owner name, number of residents, tenants (Y/N), fixed clinic preference, mobile clinic preference, CHW name, tag affixed (Y/N), fieldworker name, date, time	23202
Absent	A homestead where residents are not present at the time of mapping OR the residents present are not able to give authority for mapping	ID, location, fieldworker name, date, time	948
Refusal	A homestead where residents of the homestead refuse the fieldworker permission to map and interview the homestead	ID, location ³ , fieldworker name, date, time	86
Under-construction	A homestead which is in the process of being built for residential purposes but does not serve any residential function at present	ID, location, fieldworker name, date, time	552
Abandoned ⁴	A homestead where none of the buildings are used for residential or any other purpose.	location, fieldworker name, date, time	1811

³ The GPS reading was taken immediately outside the homestead perimeter

⁴ The purpose of mapping abandoned homesteads is to reconcile them with homesteads obtained from aerial photographic data.

The data dictionaries allowed the fieldworkers to perform collection of all attribute data using the GPS units. Supervisors were issued with the PDOP graph (Appendix 4) for the current day so that breaks in work could be planned to correspond to high PDOP times. Fieldworkers only affixed identification tags and collected information about the homestead if there was a senior resident present who could give the fieldworker permission to map (an ordinary homestead). The reading was taken in the middle of the homestead.

The ‘backup team’ were responsible for visiting absentee homesteads and collecting the associated attribute data and affixing tags. Residents of some homesteads were not present after numerous visits by the ‘backup team’ and were therefore never converted to ordinary homesteads. Once the fieldworkers returned from the field the data were downloaded to computers. Differential correction occurred the subsequent day. The entire mapping exercise took approximately 1 year to complete at an average of 8 homesteads per fieldworker per working day. A map showing all homesteads and facilities mapped in Hlabisa is given (Figure 2.2).

Quality control

I applied the following measures to ensure a good quality of data collection and comprehensive coverage of the district:

- Supervisors were responsible for accompanying each member of the team to several homesteads during the field operation to ensure that proper data collection procedures were followed.
- Supervisors were responsible for checking through data collected at each homestead once the files had been downloaded to the computer at the end of the

day. Erroneous data was either corrected by the supervisor in consultation with the fieldworker or the fieldworker visited the homestead on the subsequent day to recollect the information.

- Random standard deviation of position checks were conducted to confirm that fieldworkers were not moving around whilst positioning a homestead.
- A 'quality control team' composed of senior Zulu-speaking staff performed random visits to homesteads to compare the information obtained against information collected by the fieldworker. Exact data matches were obtained in excess of 90% cases. Most of the differences observed were due to the questions being obtained from different informants or were due to temporal changes in the data (e.g. number of residents per homestead).
- Daily reports and checks (e.g. duplicate IDs) were generated by the database. Fieldworkers were sent to rectify these errors the subsequent day.
- Once areas had been completed, mapped homesteads were compared against homesteads obtained from aerial photographs to confirm that sections of the area had not been missed. If such areas were identified, a mapping team was deployed to complete the area.

The above measures ensured a good quality of data collection as well as comprehensive coverage of the district. Nevertheless, despite these measures a small number of homesteads were inadvertently not mapped. In a subsequent intensive questionnaire exercise covering approximately 11 000 homesteads in a contiguous geographic area, 1.7% of randomly distributed homesteads were found to have not been mapped. This small number is unlikely to affect any of the results in this thesis.

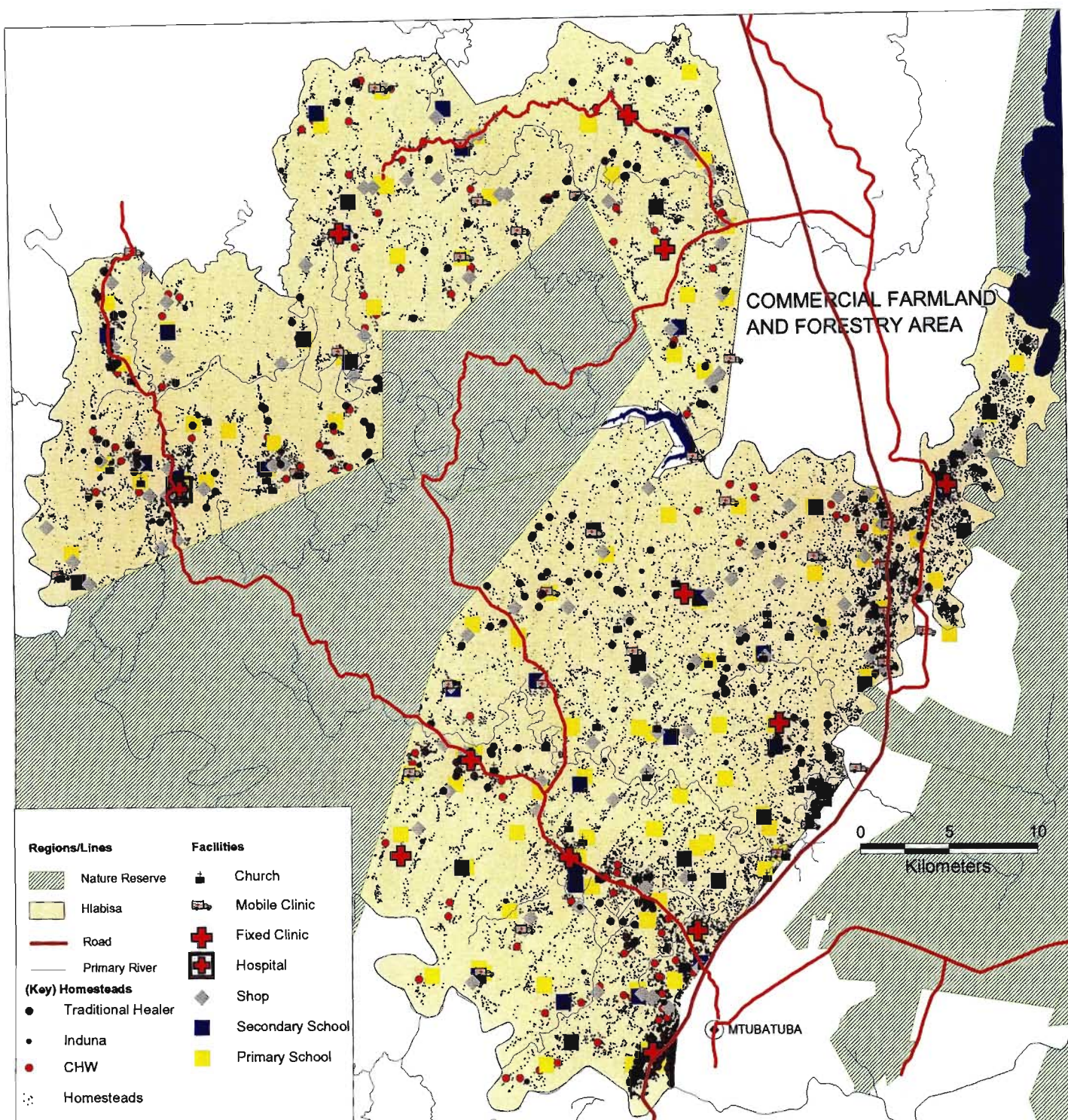


Figure 2.2: Map of all facilities and homesteads mapped in Hlabisa

Additional data used

GIS data

The additional GIS data sets used in the district-level GIS are given (Table 2.4).

Table 2.4: Additional GIS data sets used at a district level.

Data	Scale/Resolution	Source
Magisterial boundaries, tribal boundaries, nature reserve boundaries, rivers, lakes, roads	1: 50 000	Digitised from topographical maps.
Elevation contours	20m	Purchased from the director of survey and mapping
Normalised difference vegetation index (NDVI)	1.1 km (1999)	Advanced very high resolution radiometer (AVHRR) satellite imagery
Homesteads (approximate positions)	1: 30 000 (1996)	Digitised from aerial photographs and subsequently geometrically corrected

Clinical data

The clinical data sets used in Hlabisa comprise HIV seroprevalence data for pregnant women in Hlabisa and tuberculosis treatment data from Hlabisa hospital registers. These data are described in the relevant chapters and do not warrant repeating here.

2.2 A CONTINENTAL GIS PLATFORM

One of the objectives of the research was to generate a continental model of malaria seasonality. The data used in this component of the thesis are listed here.

GIS data

The continental GIS data sets used in the research are given (Table 2.5).

Table 2.5: Continental GIS data sets used in the research.

Data	Scale/Resolution	Source
long-term (1920 - 1980) monthly mean, minimum, maximum temperature and rainfall raster data	3 minutes	Hutchinson <i>et al.</i> , 1995
Raster population data, 1995	2.5 minutes	Deichmann, 1996
Cities, towns and villages in Africa	1: 250 000	WRI, 1995

Parasitological data

The parasitological data used in the continental component of the research comprise malaria surveys conducted across Africa. These data are described in chapter seven.

2.3 HARDWARE AND SOFTWARE USED

12 Trimble Geo-explorer II differential GPS units were used for mapping and data collection in Hlabisa. I used Pathfinder Office 2.11 to create and upload all data dictionaries onto the GPS units. On completion of data collection in the field, the GPS data were downloaded directly from the GPS into Pathfinder Office and all positions differentially corrected using the post-processing method. The data were then exported to MapInfo 5.5 where the data were stored, manipulated and analysed in a vector GIS environment. I used Idrisi 2.0 and 32 to analyse the GPS data in conjunction with various raster surfaces (e.g. aerial photographs, satellite data and elevation data) in a raster environment. The GPS data were archived in Microsoft Access 2000.

I conducted all image overlay procedures to produce the continental model of malaria seasonality in Idrisi. I also used Vertical Mapper 2.5 in the vector to raster conversion and in the interrogation of the raster data. I used SPSS 9.0 and BMDP 7.0 to statistically analyse the data. All data processing and analysis took place on a desktop computer (Pentium II 300 MHz, 128 Mb Ram) within a Windows environment.

Chapter Three:

New approaches to spatially analyse primary health care usage patterns

Tanser *et al.* (2000a) *Submitted for publication*

3.1 ABSTRACT

Introduction Knowledge and understanding of health care usage and population distribution is vital for health resource allocation and planning. There is a need for indices that enable the large-scale spatial usage patterns of health facilities to be quantitatively assessed.

Methodology We map and interview in excess of 23,000 homesteads (approximately 200,000 people) in the Hlabisa district, South Africa and spatially analyse their modal primary health usage patterns using a geographical information system. We generate contour maps of health service usage. We quantify the relationship between actual clinic catchments and distance-defined catchments using inclusion and exclusion error. We propose the distance usage index (DUI) as an overall spatial measure of clinic usage. The index is the sum of the distances from clinic to all actual client homesteads divided by the sum of the distances from clinic to all homesteads within its distance-defined catchment. The index encompasses inclusion, exclusion, and strength of patient attraction for each clinic.

Results 87% of homesteads use the nearest clinic. Residents of homesteads travel an average Euclidean distance of 4.72 km to attend clinics. There is a significant logarithmic

relationship between distance from clinic and usage by the homesteads ($r^2 = 0.774$, $p < 0.0001$). The DUI values range between 31 and 198% (mean = 110%, SD = 43.7) for 12 clinics and successfully highlight clinic usage patterns across the district.

Conclusions The DUI proves to be a powerful and informative composite measure of clinic usage. The results of the study have important implications for health care provision in developing countries.

3.2 INTRODUCTION

Proximity to primary health care has long been considered a major factor contributing to the health of populations (Perry and Gesler, 2000). Knowledge and understanding of health service usage and population distribution are therefore vital for health resource allocation and planning (Joseph and Phillips, 1984). Good health system management depends on informed decisions regarding resource allocation. Unfortunately, these decisions often occur in the absence of data that allow the pattern of resource allocation to be assessed.

Physical accessibility of health services is determined by the geographical location of client homesteads in relation to available facilities, by physical and topographical barriers and by the modes of transport that are available to reach these destinations. The effect of distance on patient travel to health care facilities and the estimation of critical distance thresholds for different levels of health care have been subjects of extensive study (Morrill and Earickson, 1968; Morrill and Earickson, 1970; Shannon and Dever, 1974). There is ample evidence to suggest that physical accessibility of services is a major factor influencing patient choice of health care facility (Shannon *et al.*, 1969) and that attendance rates at

health facilities decline markedly with distance (Rahaman *et al.*, 1982; Stock, 1983; Kloos, 1990; Müller *et al.*, 1998). In developing countries where health facilities are relatively sparse and access often achieved on foot (Stock, 1985) it has been assumed that patients will preferentially use nearest health facilities and that there is a finite limit to the distance that patients will travel for health care. These assumptions may not hold in countries like South Africa in which well resourced facilities of reasonable quality are available and where public transport may increase access to facilities some distance away from home.

Accessibility is also influenced by social and cultural factors such as knowledge and information, and by economic factors since the use of different forms of transport and access to channels of communication are usually associated with some monetary cost (Deichmann, 1997). Various social factors affecting choice and usage of health services in developing countries have been studied (Habib and Vaughan, 1986; Egunjobi, 1983; Van der Stuyft *et al.*, 1996). These factors include quality of care, perceived level of sickness, income, transport availability, religion, occupational status, relationships to health facility staff and proximity of relatives to health facility. Although social factors are important determinants of health service usage, these factors will vary from household to household and are difficult to measure. They are therefore less readily available to health planners than physical space, which has provided the traditional basis for macro planning of health services and for which there are increasingly sophisticated spatial analytical tools. It is also held that improvements in health care usage can be quickly realised by the simple expedient of relocating health centres or improving the road network (Airey, 1992).

To the best of our knowledge, large-scale usage patterns of multiple primary health care

services across an integrated health unit have never been spatially investigated. Health care systems in the developing world face increasingly diverse and complex health problems. There is a need for methods that enable the large-scale spatial usage patterns of health facilities to be quantitatively assessed (Joseph and Phillips, 1984). These data are needed to inform resource allocation methodologies in developing countries. We interviewed in excess of 23,000 geo-referenced homesteads (approximately 200,000 people) and analyse their modal usage patterns using a geographical information system (GIS). We map facility usage across the district, analyse the effect of distance on facility usage and develop indices that quantify the relative patient attraction and repulsion by the different health facilities. We develop a new index as an overall spatial measure of facility usage in relation to the size of the facility's distance-defined catchment.

3.3 METHODS

Study area

Hlabisa district is located in northern KwaZulu-Natal, South Africa and is 1430 km² in size. The resident population of 210, 000 people is Zulu-speaking and predominantly rural (although there are pockets of urban and peri-urban populations in the southern part of the district near the market town of Mtubatuba). This population, with an annual per capita income of US\$ 1730, relies mainly on migrant labour remittances, subsistence farming and pensions for its support and livelihood (Department of Health, 1996). The rural population is scattered throughout the district and is not concentrated into villages or compounds as is the case in many other parts of Africa.

The district is transected by a nature reserve and bounded by hard boundaries in the form of

large perennial rivers, nature reserves, forestry areas and commercial farmland (Figure 2.2). This makes Hlabisa district a geographically discrete unit with minimal cross boundary population flow, and is therefore ideal for a study of this nature. KwaZulu-Natal has the highest HIV prevalence in South Africa (Department of Health, 1996). HIV infection has spread rapidly in Hlabisa, and HIV prevalence among pregnant women increased from 4.2% in 1992 to 14% in 1995 (Coleman and Wilkinson, 1997) and to 41.2% in 1998 (Wilkinson *et al.*, 1999).

Primary health care in Hlabisa district

A community hospital and 11 satellite fixed clinics provide primary health care in the Hlabisa district. The hospital and one of the fixed clinics (KwaMsane) provide 24 hour clinical cover, the remainder only function during the day. This district with its health infrastructure is typical of many similar rural health systems in South Africa and functions as a semi-autonomous unit at the third tier of a national health system. In addition to providing emergency and curative care for the entire district, Hlabisa hospital also serves as a clinic for the surrounding population and is therefore equivalent, for the purposes of this study, to the other fixed clinics in the district. The clinics handle minor ailments, family planning, antenatal and postnatal care, deliveries, treatment of sexually transmitted diseases, child immunization, tuberculosis directly observed therapy (DOTs), chronic illnesses (such as diabetes and hypertension) and emergencies. The clinics are staffed by nurses, some of whom have advanced training in midwifery and primary health care, and are visited monthly by medical officers from the hospital. In comparison with the rest of Africa, clinics are well resourced; most have telephones, running water and are relatively accessible to the local population.

In addition to the fixed clinics, there are 31 mobile clinic points throughout the district, that are visited twice monthly. The mobile clinics offer family planning, child immunization, treatment of chronic illness and antenatal care. The district is also serviced by 131 community health workers (CHW), each of whom is expected to regularly visit a group of assigned homesteads. The CHWs are responsible for health education, nutritional support, first aid and, in selected cases for HIV home-based care. They are also responsible for the dispensing of tuberculosis DOTs and for directing obviously ill patients to the clinics or district hospital. The CHWs work 16 days a month and on average should visit each of their allotted homesteads once a month but frequency varies between CHWs. In addition to the community health workers there are approximately 90 community volunteers disseminating tuberculosis DOTs. The spatial configuration of the tuberculosis DOTs programme has been described (Tanser and Wilkinson, 1999, this thesis).

Location of homesteads

All 24,236 homesteads in the study area were positioned using global positioning systems (GPS) (Trimble Geoexplorer II) between June 1998 and June 1999. The GPS system, owned by the United States Department of Defence, introduces an intentional error to the system, typically around 50-100m. This error is unacceptable in the study area where some homesteads are only 10m apart. We differentially corrected for this and other errors against a local base station. By plotting the errors over time, it is possible to subtract these errors from a roving GPS in the field. Differential correction occurred subsequent to positioning in the field. Comparison with trigonometric beacons in the district revealed all positions to be accurate within 2m.

Creating the primary health care GIS

We obtained GPS coordinates for the hospital, fixed clinics, mobile clinic points and for all CHW homesteads. All homesteads in the district were uniquely numbered and a dataset collected about the usage of health and educational services. Our objective was to perform a geographical analysis of modal primary health care usage patterns across the entire district at a homestead level. At each homestead we therefore asked a single informant ‘which fixed clinic/mobile clinic most people in the homestead normally use’. Informants were also asked whether the homestead was visited by a CHW. All data were collected in the field using the GPS data dictionary facility. We could not obtain information in some homesteads due to the residents being absent (3.9%) or refusing to answer questions (0.4%). These point locations were superimposed on a base map consisting of a series of geographical layers of the district (including magisterial and tribal areas, nature reserve boundaries, roads and rivers) digitised from 1:50 000 topographical maps using MapInfo (MapInfo Corporation, New York).

Analysing clinic and community health worker usage across the district

We produced contour usage maps for fixed clinics, mobile clinics and CHWs. All homesteads were superimposed onto a 20m raster grid in Idrisi 32 (the Idrisi project, Clark University, Worcester, MA, USA). We then passed a moving 1km x 1km filter across the image which calculated the percentage of homesteads that made use of clinics and CHWs in the filter window. In the resulting images the value of each pixel is the percentage of homesteads that make use of primary health care facilities in the surrounding 1km x 1km neighbourhood. The images were then converted into vector format and exported to MapInfo (Figure 3.2).

Spatial indices to quantify clinic usage

We plotted all homesteads occurring in the study area on the GIS and colour coded them by actual clinic used. We constructed distance (theissen) polygons for each of the fixed clinics in MapInfo and superimposed them onto the homesteads. Distance polygons divide space such that any particular home is allocated to its geographically nearest clinic.

Cross-tabulations of predicted clinic usage (on the basis of distance) and actual clinic usage were used to generate an error matrix. We defined the terms exclusion error (the proportion of homesteads from a particular distance clinic catchment who use other clinics) and inclusion error (the proportion of homesteads from other distance clinic catchments who use a particular clinic) to assess discrepancies. In epidemiological terms (using distance as the predictor of actual clinic catchments) exclusion and inclusion error are equal to *1 - the positive predictive value* and *1 - sensitivity* respectively. A clinic with a strong attraction of patients from within other distance clinic catchments will have a high inclusion error, whilst those with a high proportion of homesteads within their distance catchments who use other clinics will have a high exclusion error. There is some interaction between the indices for neighbouring clinics. Patients not using their closest clinics will increase exclusion errors in their origin distance catchment and increase inclusion errors in their destination clinic. Variation in exclusion and inclusion errors does not necessarily indicate discrepancies in standard of service delivery. The differences may be a function of the relative accessibility (e.g. by public transport) of the health facilities.

We calculated the average Euclidean distance that patients will travel to use each clinic as another measure of the strength attraction of a clinic. However, clinics with large distance clinic catchments will be predisposed to having patients travel longer distances to seek

primary health care and it is because of necessity and not relative attraction of a particular clinic that patients will travel longer distances. We therefore propose a new measure which we have termed the distance usage index (DUI) as an overall measure of inclusion, exclusion and the strength of patient attraction (using distance travelled). The denominator of the index is the sum of the distances between all homesteads within a distance clinic catchment and the clinic. The numerator of the DUI is the sum of the distances between all homesteads actually using a particular clinic and the clinic itself. The index is expressed as a percentage. Thus a clinic which attracts a large number of patients from great distances (from outside its own distance clinic catchment) and has a good attendance within its own distance catchment, will have a DUI of greater than 100%. Conversely a clinic which only attracts patients from short distances and has a poor attendance within its own distance clinic catchment will have a DUI value of less than 100%. The concepts are illustrated using a simple map (Figure 3.1). We also applied the above methodology to mobile clinic points and compared the values obtained with the fixed clinic results.

The effect of distance on clinic usage

We wanted to establish the effect of distance from clinics on usage. We therefore constructed 500m buffers around each of the fixed and mobile clinics and calculated usage within each of the buffers. We then plotted the relationship between distance from clinic and usage within each distance clinic catchment.

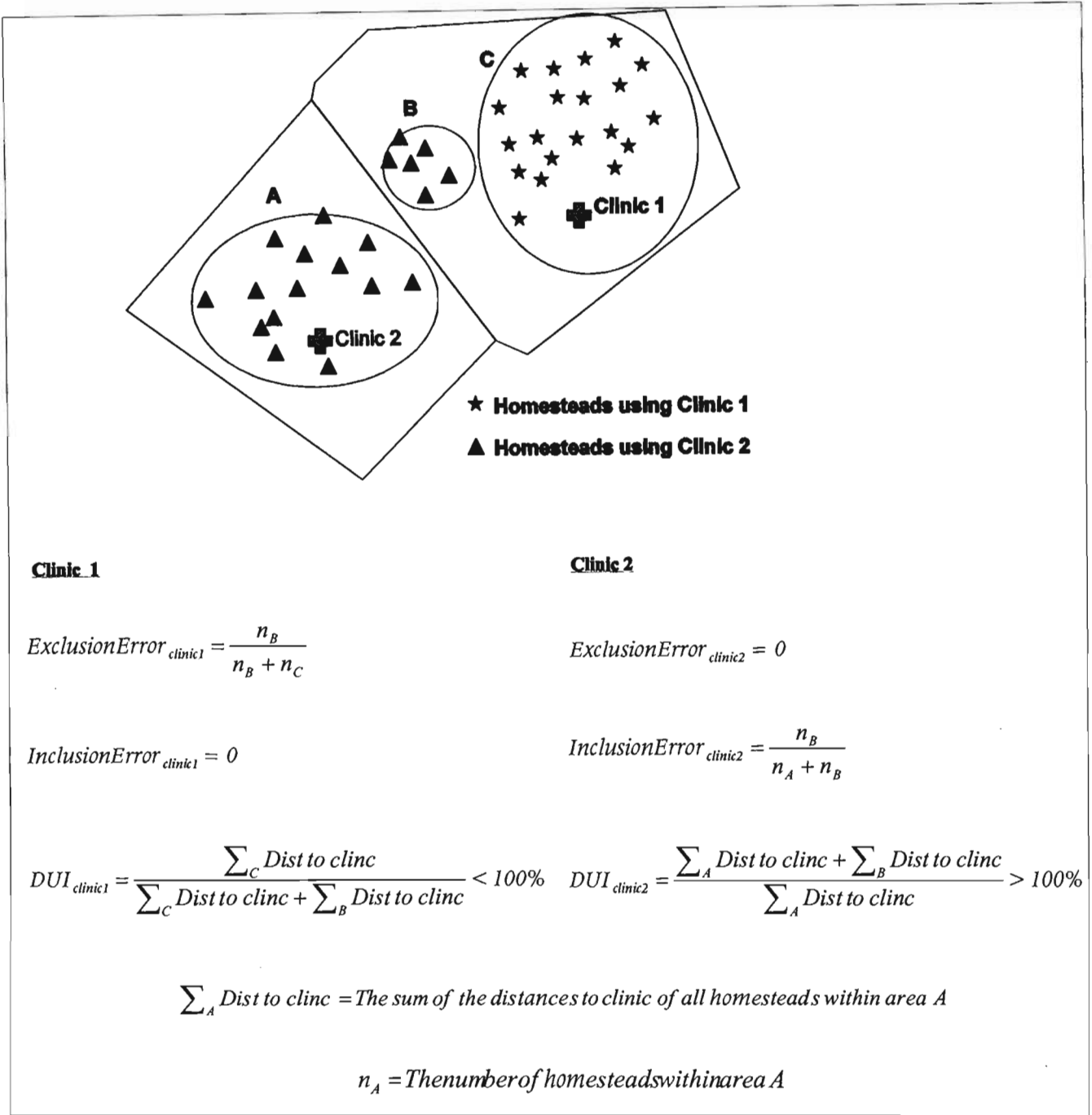


Figure 3.1: Illustrative map and associated equations to demonstrate the concepts of inclusion error, exclusion error and distance usage index. The outer polygons define the respective distance catchments for clinics 1 and 2.

3.4 RESULTS

Contour usage maps for fixed clinics, mobile clinics and CHWs are shown (Figure 3.2). 93 % of homesteads use fixed clinics (64% use fixed clinics only); 34% use mobile clinics (5.0% use mobile clinics only); 29% use both fixed and mobile clinics and 1.7% used neither. From a spatial perspective, the proposed location (obtained by independent means) by the Provincial Department of Health (Figure 3.2a) of a new clinic is optimal, given the low clinic usage and population of the surrounding area. It is striking that the mobile clinics service all of the areas of low fixed clinic usage. In addition, they service those areas with high homestead densities that are a significant distance from the fixed clinics (Figure 3.2b,d). 36% of homesteads reported regular visits by CHWs. The community health worker distribution reveals a large gap in service in the middle of the largest of the four tribal areas (Figure 3.2c).

There is a large amount of congruence between actual clinic usage and those predicted by distance (Figure 3.3). In some cases (e.g. Nkundusi) major public transport routes appear to have had a 'distorting' effect on the shape of a clinic catchment providing greater accessibility to patients living in close proximity to these routes.

The error matrix and associated spatial indices of actual versus distance-predicted fixed clinic usage are given (Table 3.1). The horizontal axis shows actual clinic usage whilst the vertical axis shows the nearest clinic on the basis of Euclidean distance. For example, 261 of the 269 homesteads that actually used Esiyembeni clinic came from within its distance catchment and only 8 homesteads came from the neighbouring catchment of Machibini (inclusion error = 3%).

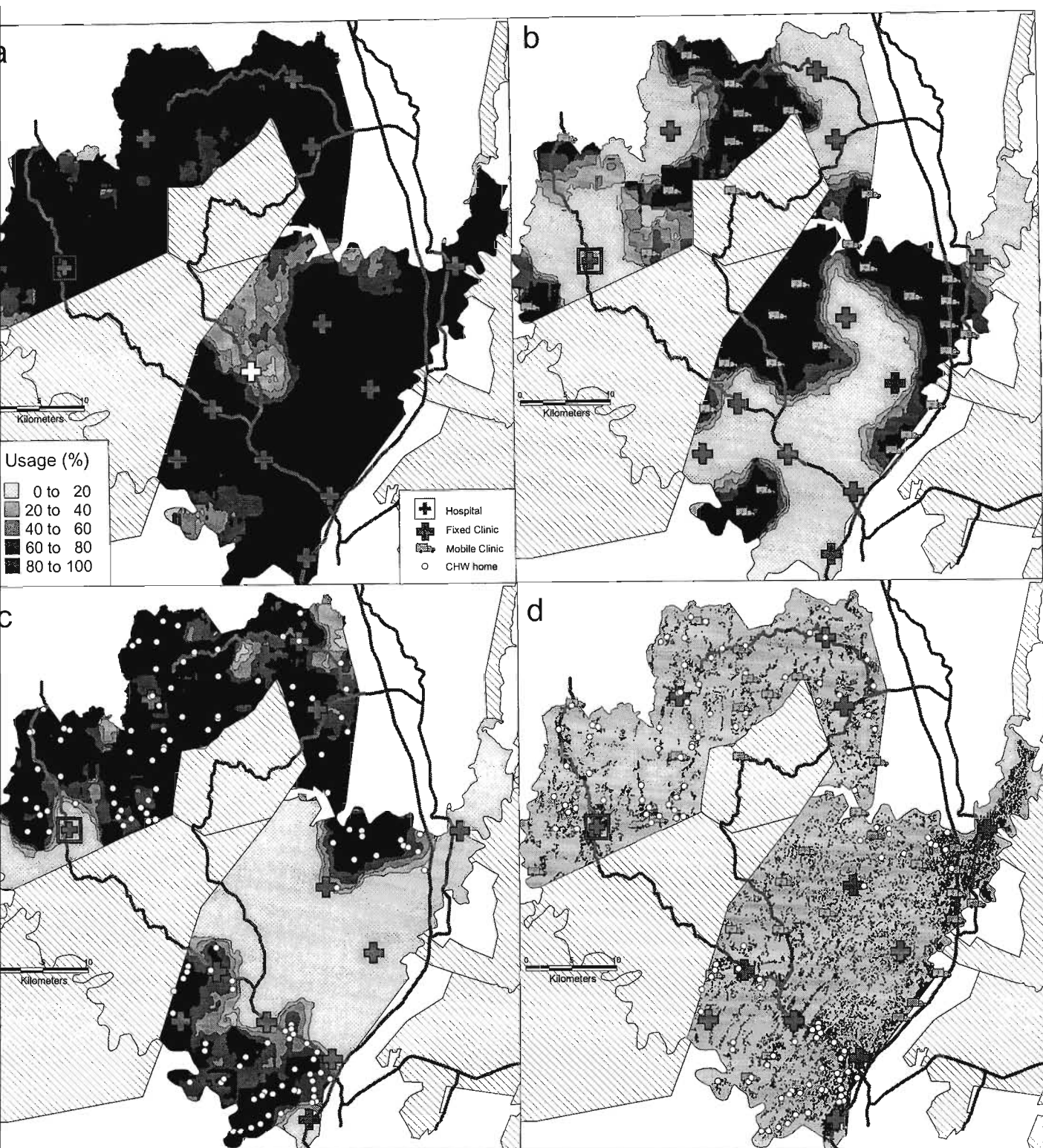


Figure 3.2: Fixed clinic (a), mobile clinic (b) and community health worker (c) mode usage (%) and homesteads (d) in Hlabisa district. The proposed location of a new fixed clinic is shown as a white cross.

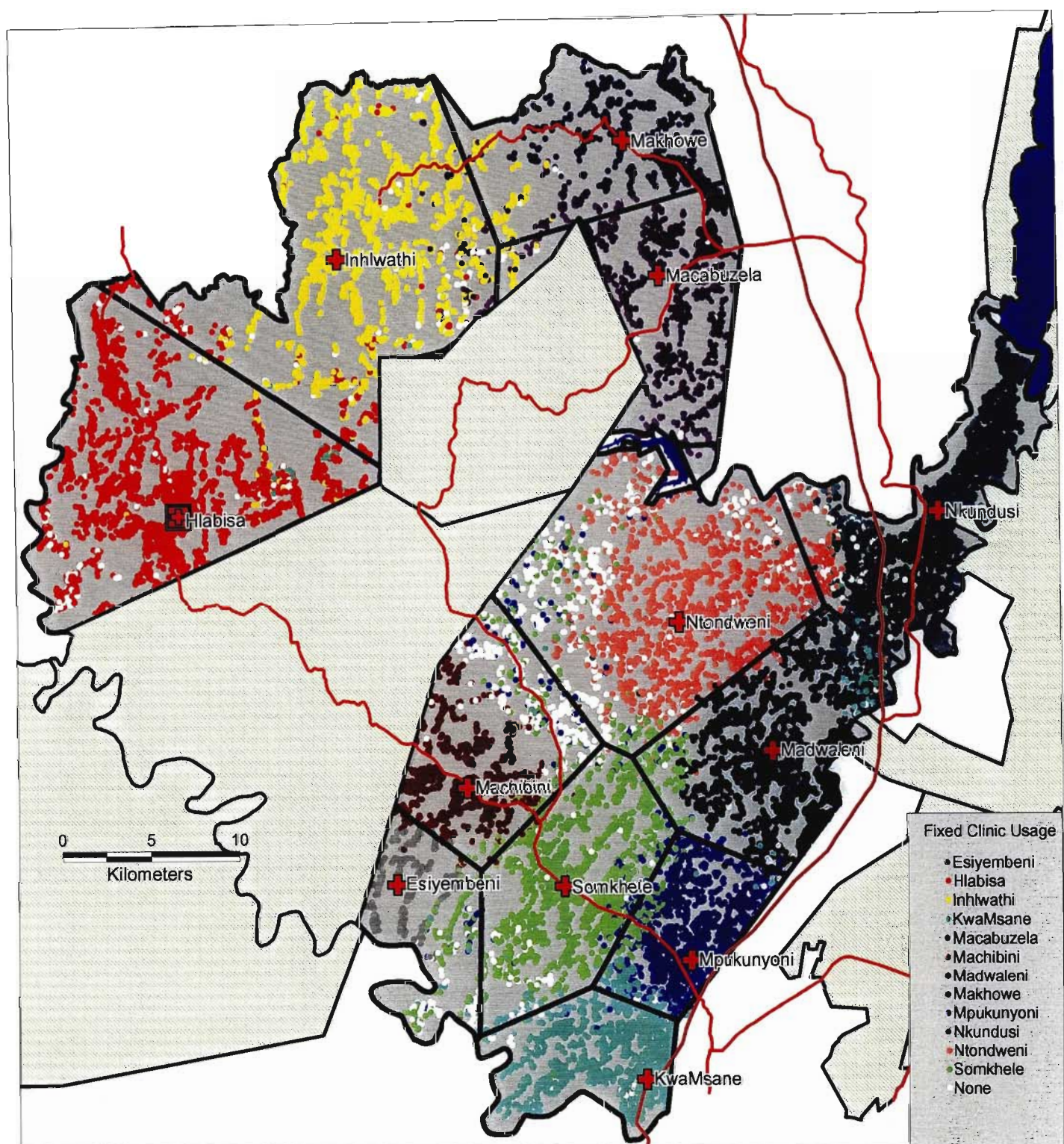


Figure 3.3: Comparison between actual fixed clinic usage and nearest clinic in Hlabisa district. The solid black boundaries represent distance polygons and the dots represent all homesteads in the district colour-coded by actual fixed clinic usage

Table 3.1: Error matrix of the relationship between actual fixed clinic usage and nearest clinic. Exclusion error, inclusion error, mean Euclidean distance travelled by residents of homesteads to attend clinic and the distance usage index (DUI) are displayed for each clinic

		A C T U A L C L I N I C U S A G E															Exclusion error (%)	Mean Distance (km)	DUI (%)
NAME		None	Esiyembeni	Hlabisa	Inhlwathi	KwaMsane	Macabuzela	Machibini	Madwaleni	Makhowe	Mpukunyoni	Nkundusi	Ntondweni	Somkhele	TOTAL	Unknown			
NEAREST CLINIC	Esiyembeni	79	261	0	0	22	0	45	0	0	15	0	0	109	531	8	50.8	2.4	30.9
	Hlabisa	146	0	2,818	61	43	0	0	0	0	0	0	0	0	3,068	46	8.1	5.7	109.5
	Inhlwathi	111	0	255	1,501	3	67	0	1	4	0	0	0	0	1,942	113	22.7	5.9	84.9
	KwaMsane	167	0	0	0	2,721	0	0	0	0	7	1	0	7	2,903	217	6.3	3.9	198.0
	Macabuzela	20	0	0	25	0	1,052	0	0	76	0	0	3	0	1,176	134	10.5	4.8	121.7
	Machibini	283	8	0	0	8	1	738	0	0	48	0	0	163	1,249	29	40.9	3.0	44.9
	Madwaleni	61	0	0	0	75	0	2	1,741	0	49	406	31	125	2,490	95	30.1	4.0	60.1
	Makhowe	7	0	0	106	0	117	0	0	573	0	0	0	0	803	97	28.6	3.6	72.1
	Mpukunyoni	36	0	0	0	246	1	0	11	0	1,669	0	0	142	2,105	69	20.7	4.1	121.9
	Nkundusi	119	0	0	0	20	0	0	12	0	1	3,032	124	1	3,309	129	8.4	5.4	113.6
	Ntondweni	430	0	0	0	8	20	1	11	0	53	7	1,180	132	1,842	60	35.9	4.9	66.8
	Somkhele	98	0	0	0	54	0	11	1	0	87	0	4	1,529	1,784	37	14.3	5.0	170.4
	TOTAL	1,557	269	3,073	1,693	3,200	1,258	797	1,777	653	1,929	3,446	1,342	2,208	23,202	1,034	18.9	4.7	110.3
	Inclusion error (%)	-	3.0	8.3	11.3	15.0	16.4	7.4	2.0	12.3	13.5	12.0	12.1	30.8	13.0				

However, a large proportion of homesteads whose nearest clinic is Esiyembeni used other clinics/didn't use clinics (exclusion error = 51%). Inclusion error can be used as a measure of attraction whilst exclusion error can be used as a measure of repulsion. There is an overall inclusion error of 13% (i.e. 87% of homesteads making use of clinics used the nearest clinic) across the district. The results show that distance to primary health care centre is a major factor influencing clinic choice.

Exclusion and inclusion error, average distance travelled and the DUI are displayed for all fixed clinic distance catchments in the form of thematic maps (Figure 3.4). There is substantial variation in these indices across the district. The largest proportion of homesteads not using the closest clinic/not using clinics, occur within Esiyembeni (exclusion error = 51%) and Machibini (exclusion error = 41%) distance catchments. Somkhele clinic (inclusion error = 31%) attracted the largest proportion of patients from outside its own distance catchment. The clinics with the largest exclusion and inclusion errors are adjacent, as a large number of patients from the distance clinic catchment of Esiyembeni use Somkhele clinic. Inclusion errors are similar for both mobile and fixed clinics (although there was more variation in mobile clinics). Exclusion error, DUI and average distance travelled differ markedly as would be expected (Table 3.2).

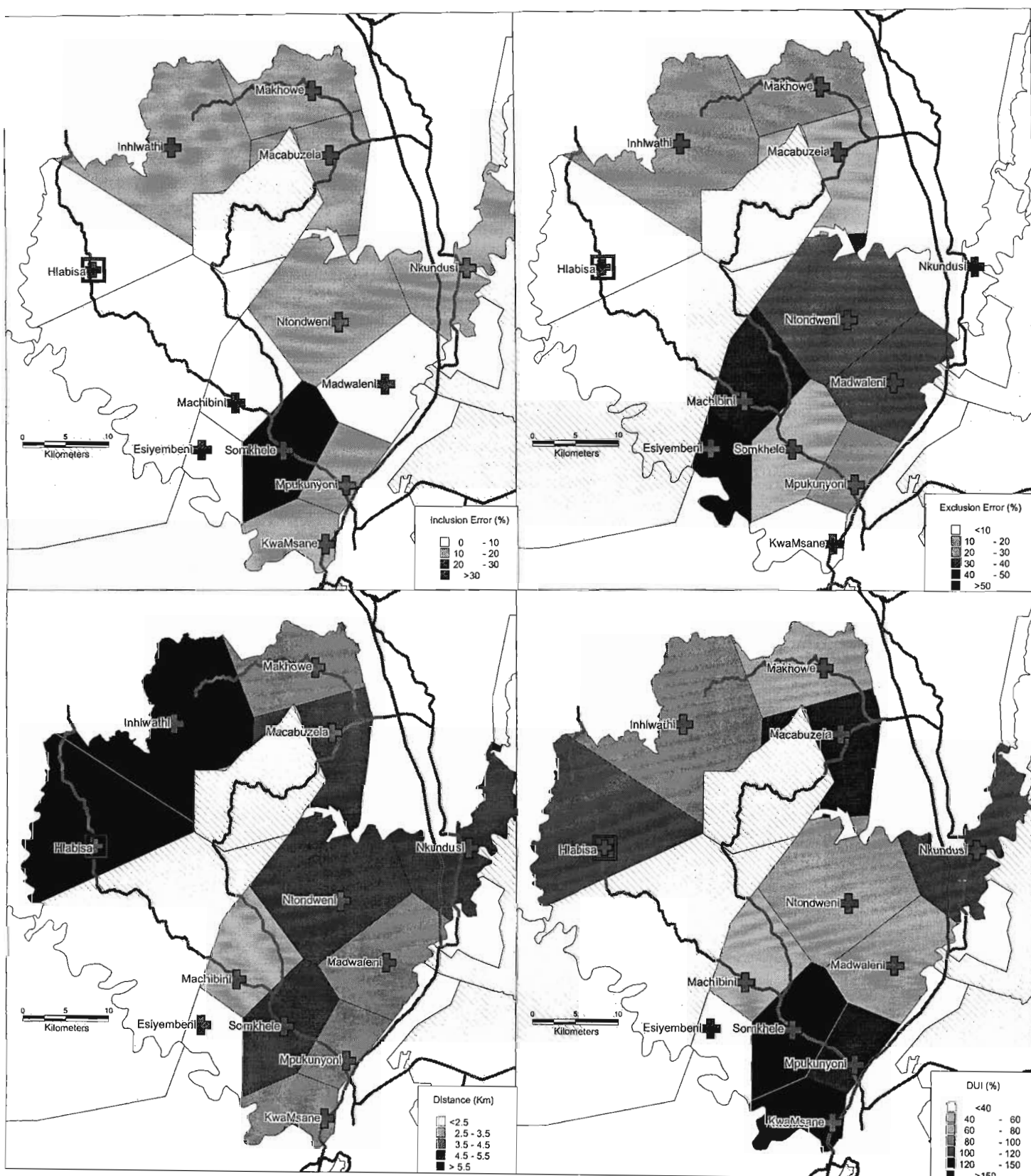


Figure 3.4: Inclusion error, exclusion error, average Euclidean distance travelled to clinic and distance usage index (DUI) for all fixed clinics in Hlabisa district.

Table 3.2: Weighted average (min - max; standard deviation) spatial indices and average Euclidean distance travelled to clinic for fixed and mobile clinics in Hlabisa.

Variable	Fixed Clinics		Mobile Clinics	
Usage (%)	93.3	(77 - 99; 6.7)	34.3	(7 - 96; 24.6)
Inclusion error (%)	13.0	(3 - 31; 6.9)	14.6	(1 - 34; 11.9)
Exclusion error (%)	18.9	(8 - 51; 12.1)	71.5	(19 - 95; 19.8)
Mean distance travelled (km)	4.72	(2.4 - 5.9; 0.85)	2.42	(0.8 - 3.9; 1.06)
Distance usage index (%)	110.3	(31 - 198; 43.7)	26.8	(2 - 157; 41.6)

Inhlwathi clinic (5.9 km) and Hlabisa hospital (5.7 km) recorded the largest average distance travelled by homesteads to attend clinics. The DUI indicated that the clinics with the strongest attraction, and least repulsion relative to catchment size are KwaMsane (198%) and Somkhele (170%). In other words, the sum of Euclidean distances between all client homesteads and KwaMsane clinic is approximately double that of all homesteads within its distance clinic catchment. KwaMsane (198%) and Nkundusi (113%) are characterised by similar inclusion and exclusion errors and therefore similar net influx of patients from other distance clinic catchments. The DUI shows however, that KwaMsane has a greater magnitude of attraction (attracts patients from a greater distances) relative to the size of its distance catchment.

The graph for the individual fixed clinics is given (Figure 3.5a). A large variation in decay curves is evident between the fixed clinics. For example, KwaMsane clinic shows almost no reduction in clinic usage 7 km from the clinic, whereas Esiyembeni clinic shows 0% usage 6 km from the clinic. Some clinics for example, Mpukunyoni show a decrease in usage until a point whereafter usage increases. This apparent paradox is explained by the fact that distance catchments are sometimes surrounded by clinics at differing distances and

differing strengths of attraction. For example, Somkhele and KwaMsane (which are the closest clinics to Mpukunyoni) attract large numbers of patients from the West and South of Mpukunyoni's distance catchment respectively. However, almost all patients in other parts of the distance catchment use Mpukunyoni, irrespective of distance (Figure 3.3). The combined graphs for fixed and mobile clinics are given (Figure 3.5b). The results reveal that mobile clinic usage decreases to 0% at approximately 8 km from mobile point, whilst at the same distance fixed clinic usage is still approximately 58%. The relationship between distance from clinic and usage was logarithmic and highly significant ($p < 0.0001$) in both fixed ($r^2 = 0.774$) and mobile ($r^2 = 0.874$) clinics. The logarithmic graph best represented the shape of the decay curve and has been described in other rural settings (Müller *et al.*, 1998). The relative increase in clinic usage after 8km from a fixed clinic (Figure 3.5b) is a function of the fact that only a small number of clinics have distance catchments exceeding 8km and within these clinic catchments, usage is good at these distances..

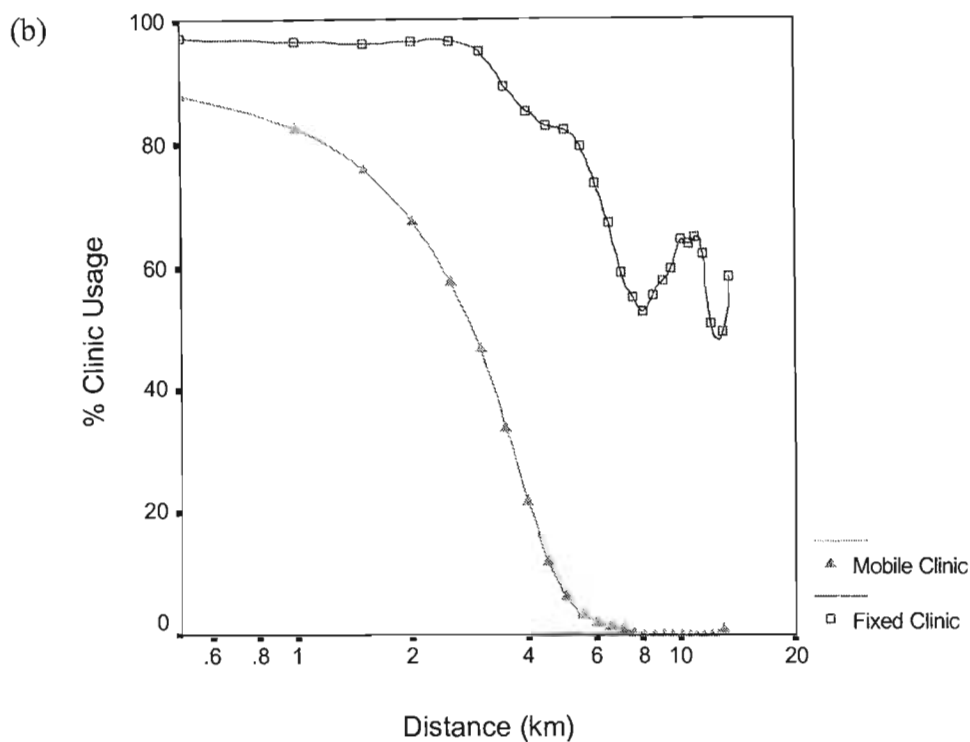
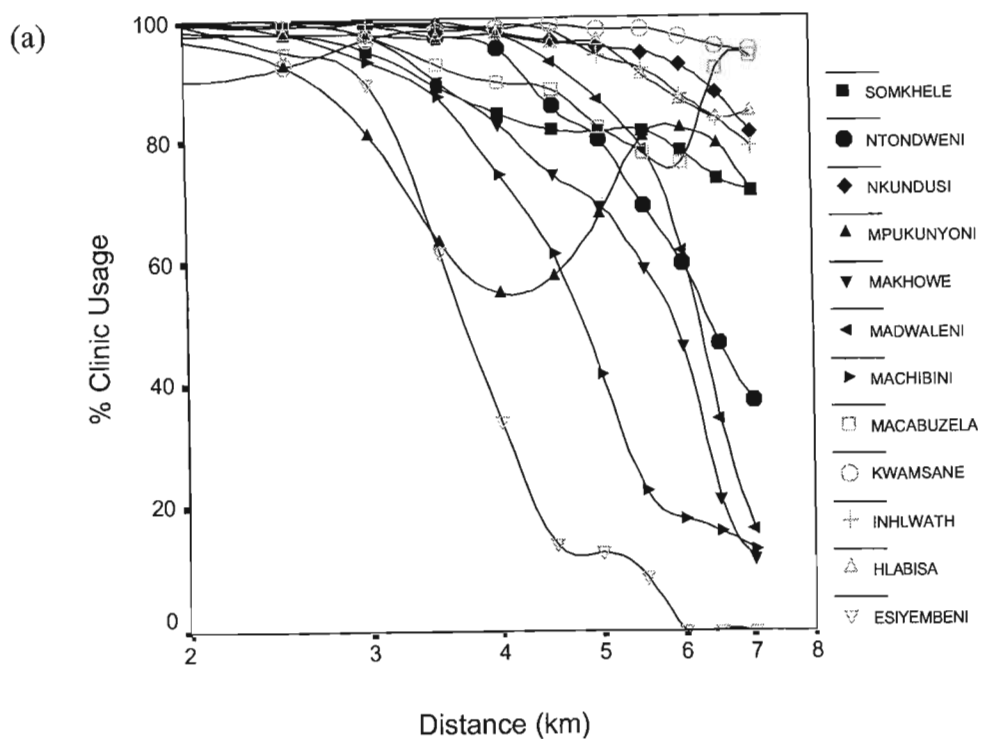


Figure 3.5: Graph showing the decay in usage with increasing distance from clinics for each of the fixed clinics (a) and for the combined fixed clinic (log relationship; $r^2 = 0.774$, $p < 0.0001$) and combined mobile clinic points (log relationship; $r^2 = 0.874$, $p < 0.0001$) in Hlabisa district (b). The usage figures have been subjected to a moving 1500m weighted average to spatially smooth the data.

3.5 DISCUSSION

We have used GIS/GPS technology to map the modal primary health care patterns of approximately 23, 000 homesteads. Our study has shown that there is a significant relationship between actual and distance clinic catchments in a typical rural South African setting. We propose the DUI as a composite spatial measure of inclusion error, exclusion error and strength of attraction.

The results show that coverage of the district by the health service is good. Only 1.7% of randomly distributed homesteads reported using neither fixed nor mobile clinics. A map showing how the mobile clinics close the gaps in health service coverage would thus be meaningless. 5% of homesteads used mobile clinics only and this figure is therefore unlikely to impact significantly on the fixed clinic DUI values. Disparities between actual and distance clinic catchments near the extremities of the distance polygons can probably be explained to a large degree by proximity to major public transport (in the form of minibus taxis) routes. Clinics sited on or at the intersection of major public transport routes attract large numbers of patients from other clinic catchments. For example, Somkhele clinic is sited at the intersection of two public transport routes and attracts 30% of its patients (inclusion error) from the neighbouring clinics of Esiyembeni, Madwaleni and Machibini. A detailed analysis of the reasons behind clinic choice went beyond the primary objectives of this research. However, we identified contiguous groupings of homesteads whose actual and distance-predicted clinic usage differed (near the extremities of distance polygons) and conducted informal interviews with residents of 20 homesteads in these areas. In all cases respondents reported that availability of public transport had determined their choice of clinic. This suggests that public transport access is an important

determinant of clinic choice at the margins of distance catchments. All clinics situated along major public transport routes had DUI values of >100%. Conversely, availability of public transport in the northern part of Machibini has deflected usage towards Somkhele along the secondary road (Figure 3.3). Future research will focus on increasing the accuracy of the indices by the construction of polygons obtained from cost surfaces. The cost surfaces should incorporate variables such as public transport access, rivers and terrain into their boundaries (Deichmann, 1997). We are unable to do this at present because public transport in the area is non-regulated, highly variable and unreliable and incorporating its effects would constitute a major data collection exercise in its own right. The situation is made even more complex by the fact that persons use walking as their primary mode of transport and the average threshold distance is at which public transport is utilised needs to be researched. KwaMsane is a 24 hour clinic as well as having good transport access via the national road and these factors may have contributed to its elevated DUI value. Somkhele clinic is the only clinic bordered on all sides by other clinic catchments. This centrality may have contributed to its increased DUI value. Some topographically complex areas (e.g. Macabuzela clinic) are characterised by large DUI values, whilst some areas with small variations in altitude (e.g. Esiyembeni, Machibini) are characterised by small DUI values (Appendix 5a & 5b), suggesting that topography is not an important or consistent barrier to usage in this topographical setting. Esiyembeni is the newest of the clinics but had been in operation for one year prior to the mapping exercise and this factor is therefore not likely to affect usage.

The DUI values indicate that Esiyembeni and Machibini clinic are not well used, for example. An analysis of health-seeking behaviour should be conducted within their

respective distance catchments to determine the reasons for this. There is additional complexity in the interpretation of mobile clinic spatial indices from a primary health care perspective because mobile clinics are likely to rank lower in the primary health care preference hierarchy because of the limited services offered and lower frequency of availability. A high exclusion error and low DUI in a fixed clinic indicates that the clinic is underutilised relative to its distance catchment. The same values for a mobile clinic may simply indicate that the mobile clinic point is effectively servicing those homesteads within its distance clinic catchment that are unable to attend fixed clinics. The results are still useful however, as they reveal mobile clinics that are used by their entire respective distance catchments (and beyond) and are thus indispensable. For example, three mobile clinic points have DUI values of approximately 150% and exclusion errors of only 20 - 30%. These mobile clinic points are further from the fixed clinics than their higher exclusion error/ lower DUI counterparts. Conversely, patients only utilising mobile clinics will necessarily lower their nearest fixed clinic DUI. Although the DUI is a single index expressing both inclusion error, exclusion error and strength of patient attraction, it cannot replace entirely its 'constituent' indices. This is because the spatial indices will need to be accessed independently to allow health planners to more fully understand the spatial dynamics of facility usage.

It was not possible to compare our distance decay data against previous studies in developing countries as these studies have incorporated a frequency component (i.e. number of clinic attendances per person per year) into their usage data. The results of these studies are worth mentioning however, as they were conducted in similar rural settings. The distance from health facility at which 50% of potential attendances are lost has been

measured at 3.5km (Müller *et al.*, 1998), 3.2 km (Jolly and King, 1966) and 3.4 km (Stock, 1983) in Papua New Guinea, Uganda and Nigeria respectively.

Distances travelled to clinics and clinic choice will differ by age, sex and diagnosis (Stock, 1983) and possibly season. We have examined modal usage patterns of homesteads and have therefore deliberately masked out deviant usage behaviour by individuals. This may take the form of different facility choice by an individual to that of the homestead or may be brought about by a change in an individual's health status. We did not obtain this information for this study because collection of this data for a population of 200,000 people would have been logistically impossible and fell outside the objectives of this research. We are currently conducting a study of 10, 000 homesteads (95,000 people) in five of the clinic catchments in the district and will use the indices to investigate health care usage patterns (including frequency and temporal variations) at an individual level. There is an argument that Euclidean distance is a sub-optimal measure of accessibility (Shannon *et al.*, 1973; Deichmann, 1997), since it ignores physical barriers such as hills, rivers, the transport system and social factors. Accessibility can be determined by a complex inter-linkage of both physical and human factors in addition to distance to clinics (Fiedler, 1981). The magnitude of the agreement between nearest clinic and actual clinic usage (87%) and the fact that a large number of people use walking as their primary mode of transport suggests that Euclidean distance is an adequate measure of accessibility for the purposes of this study and in this rural setting. Although the study area was selected on the strength of its geographic integrity, a limited amount of inter-district clinic usage will occur. This will increase attendances and average distance travelled to receive treatment. The spatial indices are unlikely to be affected significantly (as they are essentially ratios),

as the external clinic's distance catchments do not impinge on our existing catchments.

How can these results contribute to health provision and resource allocation in the developing world? Some may argue that the indices are of little use to district health services who are unlikely to have the resources to survey every homestead in a prescribed geographical area. However, geographically stratified sampling techniques of small populations can be successfully employed to facilitate calculation of the indices. Alternatively, patients using clinics over a specified time period could be geo-located. This method would ensure that the sample was weighted by frequency of clinic attendance as well as geographic distribution.

At a district level, health managers should strive towards low exclusion and inclusion errors and DUI values close to 100% at all health facilities. This indicates that the facilities are evenly distributed, patients are generally using their closest facility and attendance is good. Clinics exhibiting low DUI values should be further investigated to determine whether quality of service differs from other clinics or whether the differences are merely a function of physical accessibility. The fact that homesteads which commonly use a particular clinic can be predicted with a small margin of error in a rural South African setting is exceedingly useful for health care planning. There is more data required for successful health planning than the indices alone can provide. The indices need to be combined with demographic profiles and detailed health-seeking behaviour data to facilitate optimal positioning of the health services.

Research in a rural district approximately 200 km north of Hlabisa has shown that our results are not dissimilar to other rural populations in South Africa and that the percentage of people using the nearest clinic in our area may even be lower than the rural average. In a survey of 7,160 homesteads, it was found that 97.6% of homesteads attended the nearest clinic defined on the basis of Euclidean distance (J. Tsoka, *pers comm*). Both of these rural health districts make use of a similar integrated health system model.

It is not clear whether these results are transferable to other settings in the developing world outside Southern Africa. For example, in a study of 859 patients in Nigeria, it was found that although distance was the leading factor in determining hospital choice, it accounted for only 31.8% of the total responses (Egunjobi, 1983). Social factors accounted for the remaining 68.2%. The above comparison may not be strictly valid however, because hospitals offer a comprehensive range of services and are therefore more likely to be influenced by social factors than are clinics. Though it is better resourced than similar models elsewhere in sub-Saharan Africa the elements of many African health systems are similar and many of these spatial principles could well be applicable to other district health systems in scattered rural populations in the sub-continent. Future research should focus on the calculation of the DUI in different settings and stratified at an individual level, by age, sex and diagnosis. The indices should be weighted by frequency of clinic attendances. There is likely to be an increase in the indices with the shift from a homestead to an individual level as more deviant usage behaviour is revealed.

The world health report of 2000 (WHO, 2000) was dedicated to improving the performance of health systems. Health systems performance make a profound difference to the quality, as well as the length of the lives of the billions of people they serve. However, an important omission from the report was the spatial aspect of health systems research. The DUI provides a composite index of clinic usage and inter-clinic catchment interaction. Our study has shown how integrated health systems can be effectively spatially analysed and has highlighted the potential of GIS to play a key role in rational and more cost-effective health service planning and resource allocation in developing countries.

Chapter Four: Tuberculosis treatment and space

A. The spatial implications of the tuberculosis directly observed treatment (DOT) strategy

Tanser and Wilkinson, 1999 *Tropical Medicine and International Health* (4) 10, 634-8.

4.1 ABSTRACT

We used GIS/GPS technology to document and quantify improved access to tuberculosis treatment through a community-based programme in Hlabisa, South Africa. We plotted tuberculosis supervision points used by the district health system in 1991 (programme's first year) and 1996 (programme fully established), and quantified access by using GIS to measure mean distance from each homestead in the district to the hospital, clinics, community health workers (CHW), and volunteer supervisors. While tuberculosis caseload increased 3-fold, the number of community supervision points used increased from 37 in 1991 to 147 in 1996. Adding clinics and then CHWs to the hospital as treatment points reduced mean distance from homesteads to treatment point from 29.6km to 4.2km and to 1.9km respectively. Adding volunteers further reduced the distance to 800m. GIS/GPS effectively documents and quantifies the impact of community based tuberculosis treatment on access to treatment.

4.2 INTRODUCTION

GIS and GPS technology has a wide range of applications in health, many of which are only emerging now (Clarke *et al.*, 1996). GIS/GPS has been applied to environmental health, health system management, and a range of communicable diseases (Clarke *et al.*, 1996). In tuberculosis, the communicable disease that kills more adults each year than any other (World Bank, 1993), GIS/GPS has been linked to molecular epidemiological techniques in order to understand aspects of transmission dynamics (Bishai *et al.*, 1998).

Tuberculosis caseload is increasing rapidly in Africa, largely due to the HIV epidemic (De Cock *et al.*, 1992). Several countries report a 3-400% increase in the number of patients with tuberculosis and traditional treatment strategies based on hospitalisation (Graff, 1994) are no longer feasible or cost-effective (Floyd *et al.*, 1997). In response to this re-emerging epidemic, the World Health Organisation is promoting the DOTS control strategy (directly observed therapy, short course) with community based treatment at its core (WHO, 1997). Although community-based therapy has long been known to be safe and effective (Tuberculosis Chemotherapy Centre Madras, 1959), there is limited modern experience with it (Bayer and Wilkinson, 1995). In the Hlabisa district, South Africa, the tuberculosis control programme started using community-based treatment in 1991 (Wilkinson, 1994) and high levels of treatment adherence (Wilkinson *et al.*, 1996) and cure (Wilkinson *et al.*, 1998) have been achieved. In 1998 a district-wide GIS was established.

We have used this combination of experience to demonstrate and quantify how much access to tuberculosis treatment increases through a community based programme, and consider the further application of GIS/GPS technology to tuberculosis research, service

development and programme management in developing countries.

4.3 METHODS

Setting

Hlabisa district is situated in northern KwaZulu-Natal, South Africa and is home to 210,000 largely Zulu-speaking people who rely on subsistence farming, migrant labour and pension remittances. Annual per capita income is US\$1730, the literacy rate 69%, and life expectancy averages 63 years. HIV infection has spread rapidly in South Africa, and HIV prevalence among adults with tuberculosis in Hlabisa increased from 36% in 1993 (Wilkinson and Moore, 1996) to 66% in 1997 (Wilkinson, 1999). Consequent upon this, annual tuberculosis caseload has increased substantially (Wilkinson and Davies, 1997a).

Tuberculosis Control Programme

The control programme has been described before (Wilkinson, 1994). Briefly, all tuberculosis suspects are admitted to hospital for evaluation. Treatment starts in hospital with an average length of stay of 2-3 weeks, and approximately 90% of patients are then treated in the community, with treatment given twice weekly under direct observation. The remaining 10% are too sick for discharge. In 1991, when the programme first started, we initially used available health system resources as treatment points, with nurses in village clinics and community health workers (CHW) supervising treatment. It soon became apparent that the distance to clinics was too great for many patients, and that many parts of the district lacked CHWs, so we started recruiting volunteer supervisors. Most volunteers are storekeepers, though we have also used schools and churches (Wilkinson and Davies, 1997b). The programme maintains a computerised database that records all demographic,

clinical and programme management details, including type and location of supervisor.

The Hlabisa GIS

A series of geographical layers of the district (including magisterial and nature reserve boundaries) were digitised from 1:50 000 topographical maps using MapInfo (MapInfo Corporation, New York, 1998).

Locating homesteads

Two methods were used to obtain the geographical position of every homestead in the district. The 16 583 homesteads in the largest of the four tribal authorities that make up the Hlabisa district were positioned by GPS (Trimble Geoexplorer II). The GPS system owned by the United States Department of Defence introduces an intentional error to the system, typically around 50-100m (Ardö and Pilesjö, 1992). We differentially corrected for this and other errors against a local base station. By plotting the errors over time, it is possible to subtract these errors from a roving GPS in the field. Differential correction occurred subsequent to homestead positioning in the field. Comparison with trigonometric beacons in the district revealed all positions to be accurate within 2m.

The 7 741 homesteads occurring in the remainder of the district were digitised from 1:30 000 aerial photographs captured in 1996. The digitised points were corrected for geometric distortions. Comparison with differential GPS co-ordinates showed the average error to be 30m with a maximum error of 50m⁵.

⁵ Although the positional errors are on average 30m, the positions of the homesteads do not change significantly relative to each other.

Locating tuberculosis treatment points

We attempted to obtain differential GPS co-ordinates for all treatment points in the district. We omitted patients supervised outside the new district boundaries (defined in 1998) as the GIS does not extend to them. Patients supervised by employers in the main town (south-east corner of the district; Figure 4.1) were given one set of co-ordinates (centre of town). Some CHWs share identical surnames and we were unable to accurately locate 5% of patients. Such patients were allocated equally to the CHWs with identical surnames.

Creating the tuberculosis GIS

Tables generated from the programme database containing the geographical location of the supervision points and the number of patients supervised per year were converted into MapInfo version 5.0 format. Raster images of the supervision points in 1991, 1996 and potential supervision points (all clinics, community health workers' homes, shops, churches, schools and the hospital) were created (pixel resolution of 20m) in Idrisi version 2.0 (Clark Laboratories, Mass., 1998).

Analysis

The number of patients and the distribution of supervision points in 1991 (the first year) was compared against 1996 (programme fully established) in MapInfo. Euclidean distance images for each of the supervision point categories were computed in Idrisi. All 24,324 homesteads were overlaid onto the distance images and the distance of each homestead to the nearest supervision point in each category extracted. Average distances of homesteads to each of the supervision points in use in 1991 and 1996, as well as the potential supervision points available in 1998 were calculated. We were unable to calculate the

distance from individual patient's homes to actual supervision points as treatment had been completed before the district GIS was created in 1998.

4.4 RESULTS

Despite a substantial increase in caseload between 1991 and 1996, the proportion of patients treated in hospital (Figure 4.1) decreased from 19% (50/268) to 13% (100/773; $p=0.01$). The number of treatment points in the community increased from 37 in 1991 to 147 in 1996 (Figures 4.1 and 4.2). Whilst the number of cases have increased the apparent 'over-concentration' of treatment points in some areas is simply a function of the underlying population density.

Between 1991 and 1996, the proportion of patients supervised by volunteers increased from 16% to 41% ($p<0.0001$), and by CHWs from 9% to 24% ($p<0.0001$), while the proportion supervised at clinics fell from 56% to 24% ($p<0.0001$), (Figures 4.1 and 4.2).

The average distance from homesteads to supervisors used in the tuberculosis programme fell from 2.3km in 1991 (Figure 4.1) to 1.5km in 1996 (Figure 4.2). Table 4.1 shows the increase in access to treatment that occurs when all levels of the health system are included in the tuberculosis programme. Mean distance from hospital to homesteads was 29.7km. This fell to 5.5km in 1991 when clinics were included as treatment points, and fell further to 4.6km in 1996 due to the opening of 2 new clinics. Adding CHWs improves access even further, with mean distance being 2km if all CHWs are included as potential supervisors. Finally, adding volunteers (stores, schools and churches) potentially reduces distance to 800m.

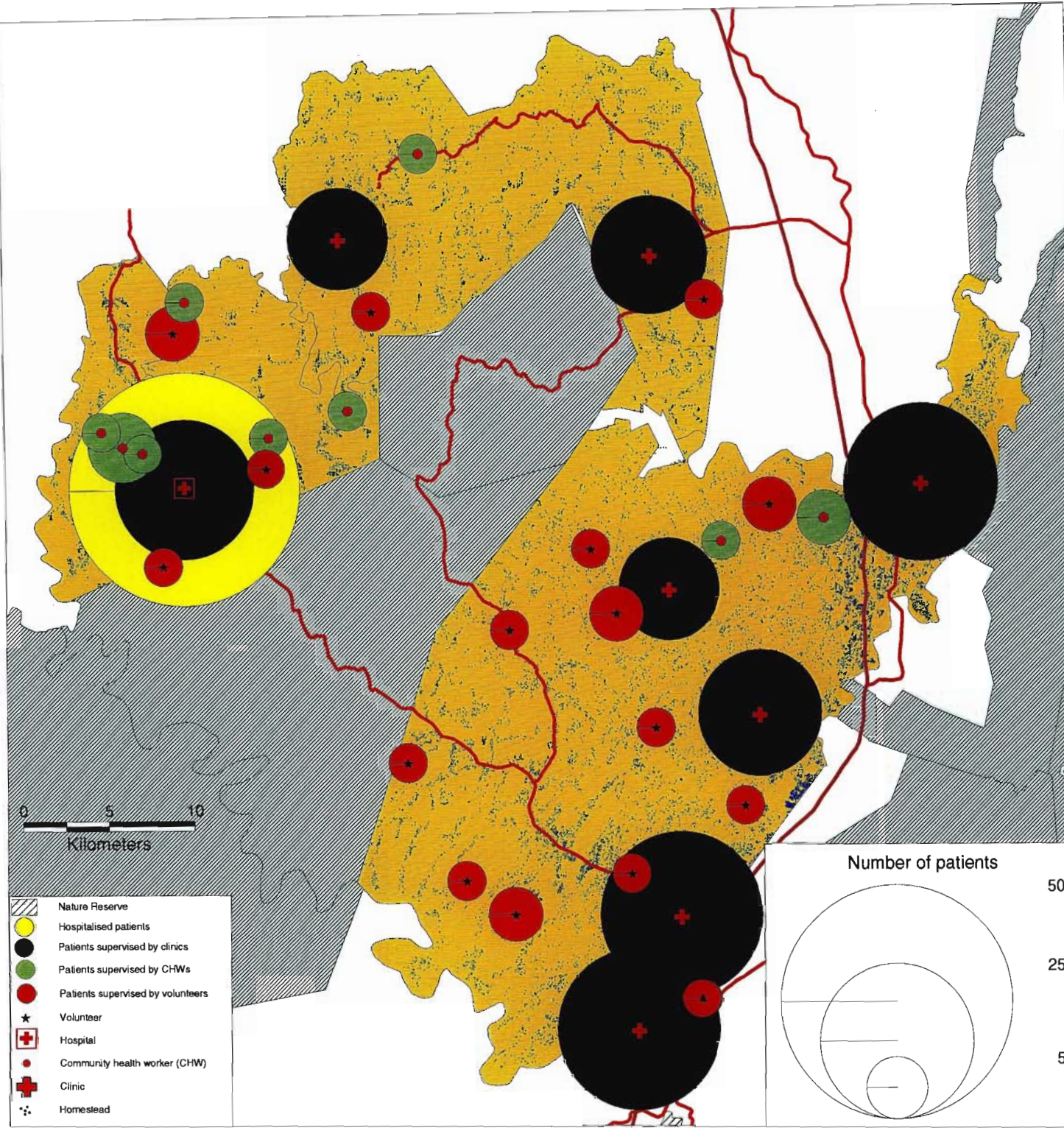


Figure 4.1: Treatment and supervision of tuberculosis patients in Hlabisa district, 1991

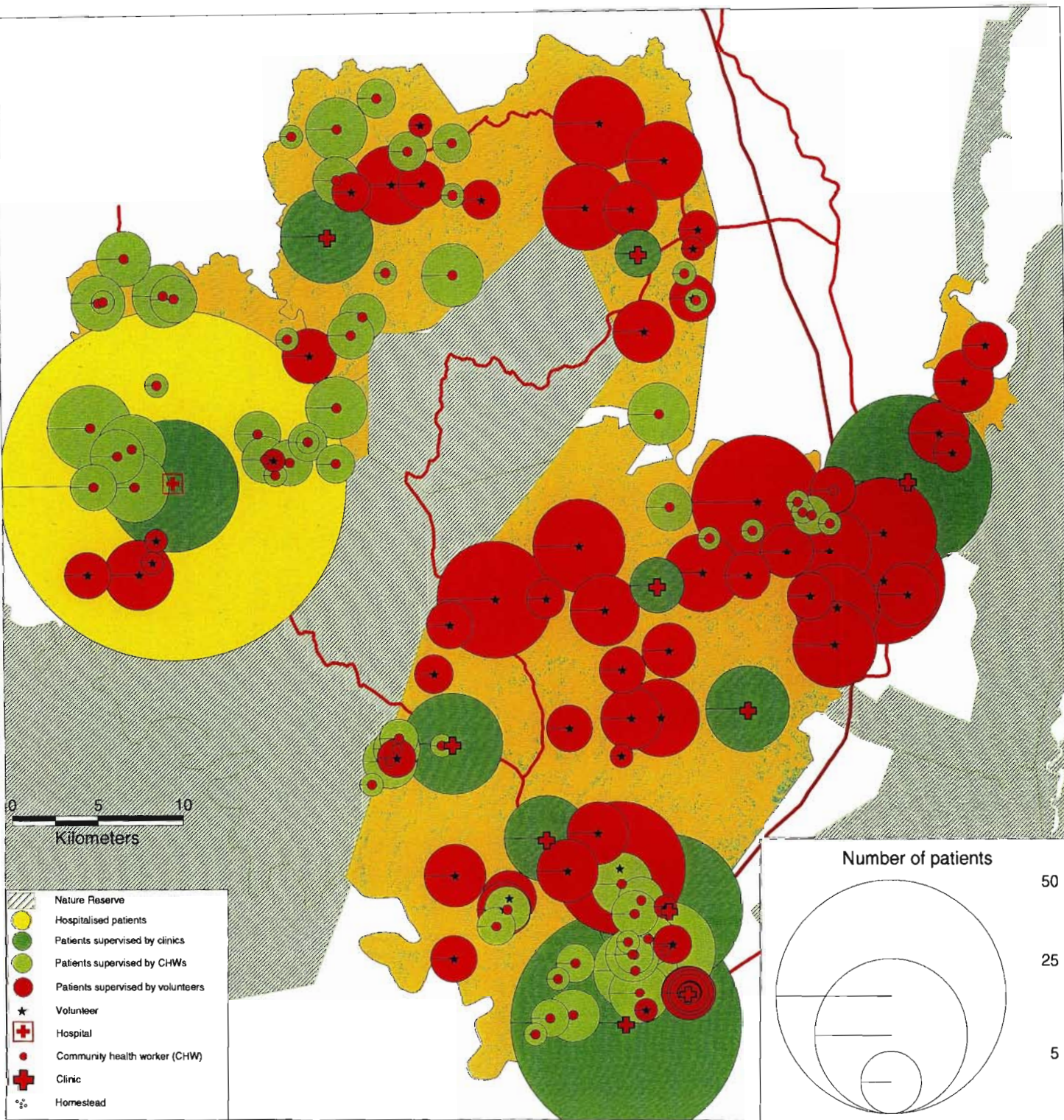


Figure 4.2: Treatment and supervision of tuberculosis patients in Hlabisa district, 1996

Table 4.1: Mean distance (km) from homestead to nearest actual and potential tuberculosis treatment points

Tuberculosis treatment point (mean, SD)	1991 actual supervision points	1996 actual supervision points	Potential supervision points
Hospital	29.7 (17.4)	29.7 (17.4)	29.7 (17.4)
Hospital and clinics	5.5 (3.7)	4.6 (2.7)	4.2 (2.7)
Hospital, clinics and CHWs	4.7 (3.7)	2.7 (2.2)	2.0 (1.8)
Hospital, clinics, CHWs and volunteers	2.3 (1.7)	1.5 (1.0)	0.8 (0.6)

4.5 DISCUSSION

These data further demonstrate the potential value of GIS/GPS technology in health and health research (Clarke *et al.*, 1996). We have documented and quantified substantial changes in the pattern of community treatment for tuberculosis over time in a health district. As greater use is made of more peripheral health facilities (clinics in addition to the hospital) and of truly community-based health services (community health workers), potential access to tuberculosis treatment increases substantially. Furthermore, a shift outside of the health system utilising community resources through the use of non-health worker volunteers potentially increases access even further. If all stores, churches and schools were used as treatment points, the average distance from any homestead in the district to a treatment point would be only 800m.

Our data has some limitations. Most importantly we were unable to geographically locate homesteads of patients with tuberculosis, and link them to their supervisors, because the GIS was established later than the tuberculosis programme. Instead we considered the relationship between each homestead in the district and the supervision points actually used in 1991 and 1996, and all potential points in 1996. A prospective study is underway to document actual proximity to treatment supervision among a large cohort of patients. Also, the GIS is limited to the new district boundaries, excluding approximately 15% of patients from the analysis. We were also unable to accurately locate 5% of patients to their supervisors because some CHWs had identical surnames.

Although used in various health fields (Clarke *et al.*, 1996), especially communicable diseases, GIS/GPS has been little used in the study and control of tuberculosis. With recent

advances in software and hardware, and with falling prices (Clarke *et al.*, 1996), GIS/GPS is no longer exclusively a research tool, but may be a cost-effective technology that can be used to drive development and health care provision in developing countries. In South Africa, for example, electricity supply companies use GIS to route pylons and to determine supply need, district boundaries are being plotted by GIS across the country, and the location of new primary care clinics is being guided by GIS.

Our experience suggests that GIS/GPS could have an important role to play in tuberculosis control programme management, service development, and research. In terms of planning and managing the service, how many supervision points should there be? How far apart should they be? How much choice is needed? There is likely to be some tension between increasing access and supervising and managing these supervision points (Wilkinson and Davies, 1997b). As the number of points grow, it may become more difficult for the programme to monitor all of them. Much remains to be understood about tuberculosis transmission dynamics in developing countries (Wilkinson *et al.*, 1997) and GIS/GPS will be a useful addition to molecular techniques and conventional epidemiology, in elucidating transmission pathways, and clusters of multi-drug resistant cases for example.

What lessons might there be for tuberculosis control in general? It is now widely recognised that community-based treatment is important if we are to cope with this re-emerging epidemic (Maher *et al.*, 1997). GIS/GPS might help rational development of community based care by providing maps, by locating potential supervision points, and by focussing on areas of particular need. In settings where this technology is not available, hand drawn maps, produced with the help of the community through participatory rural

appraisal techniques could yield similarly helpful data. GIS/GPS can also be used to locate cases and identify epidemics or localised outbreaks. Finally, further research will be needed to fully understand how important “reducing distance” is to “improving access to treatment”. In addition to locating treatment points close to patients’ homes or workplaces, the acceptability of particular supervisors is also likely to affect access.

B. GIS / GPS technology to document increased access to tuberculosis treatment

Wilkinson and Tanser (1999) *Lancet* (354) 9176, 394-5.

Effective community based tuberculosis treatment (Maher *et al.*, 1997) is likely to be necessary if the World Health Organisation's DOTS strategy (WHO, 1997) is to be successful, especially in view of the dramatic increase in tuberculosis caseload secondary to the HIV epidemic that has made institution based therapy untenable (Floyd *et al.*, 1997). Although long known to be safe and effective there is little modern experience with community based treatment strategies (Maher *et al.*, 1997). A district-wide community based treatment programme has produced high treatment completion rates in Hlabisa, South Africa, since 1991 (Wilkinson, 1994). Here, we report the novel use of geographical information system (GIS) and global positioning system (GPS) technology to measure the effect that developing a community based programme has on access to treatment.

The Hlabisa GIS comprises a series of layers digitised from 1:50 000 topographical maps using MapInfo (MapInfo Corporation, New York, 1998). Most homesteads (16,583; 68%) were located using differential GPS (Clarke *et al.*, 1996) to an accuracy of 2m and the rest were digitised from aerial photographs to an average accuracy of 30m. All health facilities, homes of community health workers, and potential volunteer tuberculosis treatment supervisors (stores, schools and churches (Wilkinson, 1994)) were located with differential GPS.

Figure 4.3a shows that 94% of district homesteads are located 5km or more from the district hospital (red and green areas). In Figure 4.3b, in which village clinics are included as treatment points, 36% of homesteads are located 5km or more away. Adding community health workers to the figure (c) as treatment supervisors ensures that only 3% of homesteads are 5km or more from treatment. Finally, with volunteers (Wilkinson, 1994) added, 68% of homesteads are within 1km of tuberculosis treatment, and all are within 5km of treatment (d).

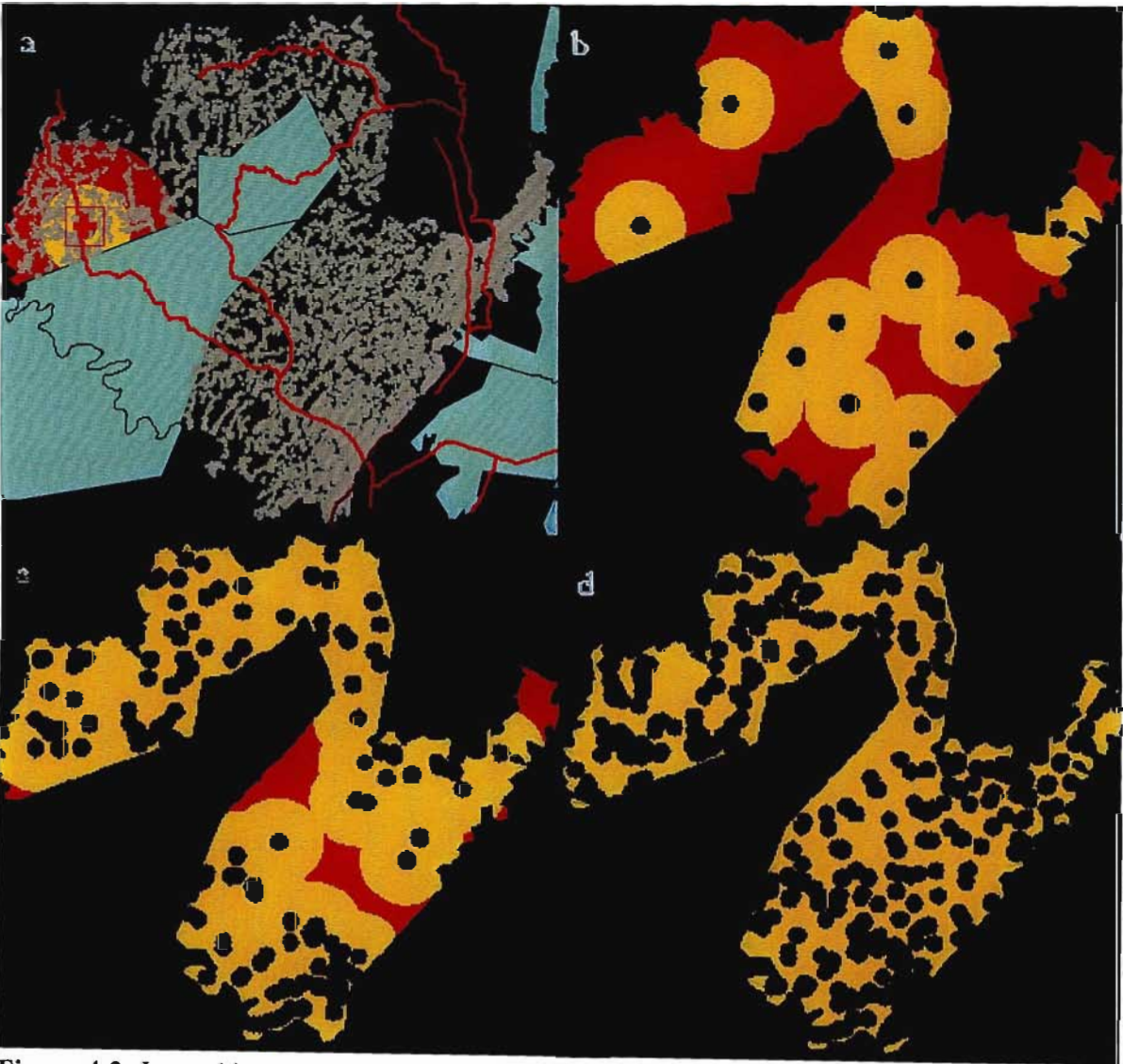


Figure 4.3: Image (a) represents the Hlabisa health district, with boundaries outlined in black and transected by a nature reserve. Major roads are in red, and the hospital is to the top left. In all 4 images blue represents parts of the district 0-0.9km from a tuberculosis treatment point, yellow 1-4.9km, red 5-9.9km, and green ≥ 10 km from a treatment point. In Image (b) village clinics are added to the hospital as treatment points, in Image (c) community health workers are added, and in Image (d), volunteers are added.

There is more to adherence to tuberculosis therapy than Euclidian distance between homestead and supervision point. Steep, vegetation-dense areas crossed by large rivers are more inaccessible than flat, open savannah with transport services. Furthermore, geographical accessibility alone will ensure neither access nor adherence: if the local clinic, community health worker, or volunteer is unable or unwilling to provide a user friendly service, proximity may be irrelevant. However, proximity of treatment is likely to be one important factor in promoting adherence to treatment. GIS/GPS may therefore have an important role to play in the rational design and management of community based tuberculosis programmes, as well as associated operational research. In Hlabisa, using an intermittent drug regimen and developing a network of supervisors, most of whom are volunteers (Figure 4.2d), a cost-effective and sustainable community based treatment service has been developed (Floyd *et al.*, 1997).

Chapter Five:

HIV heterogeneity and transport networks

Tanser *et al.*, (2000b) *Tropical Medicine and International Health* (5) 1, 40-46.

5.1 ABSTRACT

Objective: To describe heterogeneity of HIV prevalence among pregnant women in rural South Africa and to correlate this with proximity of homestead to roads

Setting: Hlabisa district, South Africa

Methods: HIV prevalence measured through anonymous surveillance among pregnant women and stratified by local village clinic. Polygons were created around each clinic, assuming women attend the clinic nearest their home. A geographical information system (GIS) calculated the mean distance from homesteads in each clinic catchment to nearest primary (1°) and to nearest primary or secondary (2°) road.

Results: Marked HIV heterogeneity by clinic catchment was observed (range 19-31% ($p < 0.001$)). A polygon plot demonstrated lower HIV prevalence in catchments remote from 1° roads. Mean distance from homesteads to nearest 1° or 2° road varied by clinic catchment from 1623 to 7569 metres. The mean distance from homesteads to 1° or 2° road for each clinic catchment was strongly correlated with HIV prevalence ($r^2 = 0.44$; $p = 0.002$).

Conclusions: The substantial HIV heterogeneity in this district is closely correlated with proximity to 1° or 2° road. GIS is a powerful tool to demonstrate and to start to analyse this observation. Further research is needed to better understand this relationship both at ecologic and individual levels, and to develop interventions to reduce the spread of HIV infection.

5.2 INTRODUCTION

The global HIV pandemic is composed of a series of several smaller epidemics (UNAIDS, 1998). Even within Africa, where levels of infection are the highest in the world, there is substantial heterogeneity of levels of infection (UNAIDS, 1998). While prevalence in many west and central African countries has remained relatively low and stable, eastern and southern Africa have experienced explosive epidemics with HIV prevalence exceeding 40% among pregnant women in some parts (UNAIDS, 1998). Within countries there may also be substantial heterogeneity: in Uganda for example the demographic impact of HIV is far from uniform geographically (Low-Beer *et al.*, 1997). The reasons for such marked variation are not fully understood, but both individual level risk factors (such as differing rates of unprotected sex with multiple partners) and ecologic or societal factors (such as the varying proportion of rural men who migrate for work) are likely to be important.

Even within regions and districts of a country infection levels may vary. In Uganda HIV prevalence was considerably higher in trading centres and roadside villages than more remote rural settings (Wawer *et al.*, 1991). These differences have been attributed, at least in part, to levels of sex work (Pickering *et al.*, 1997), and sexual networks that may be quite separate socio-geographically (Pickering *et al.*, 1996). In the rural district of Hlabisa, South Africa, 41.2% of pregnant women were HIV infected in late 1998 (Wilkinson *et al.*, 1999). We have observed substantial geographical heterogeneity of HIV infection in the district (Coleman and Wilkinson, 1997). Here, we report the use of a geographical information system (GIS) to display and to start to determine reasons for this heterogeneity. In particular we explore the relationship between HIV prevalence and the proximity of homesteads to primary (1°) and to primary or secondary (2°) roads. An exploration of the

causes of HIV heterogeneity is important as it may inform control efforts (Lurie *et al.*, 1997).

5.3 METHODS

Setting

Hlabisa district is situated in northern KwaZulu-Natal, South Africa and is home to 210,000 largely Zulu-speaking people who rely on migrant labour remittances, subsistence farming, and pensions. Annual per capita income is US\$1730, the literacy rate 69%, and life expectancy averages 63 years. Approximately 90% of the homesteads in the district have at least one male resident who spends most nights away from home and therefore who is classed as a migrant worker (V Hosegood, Africa Centre for Population Studies and Reproductive Health, personal communication). Most men travel to the mines around Johannesburg, but others travel to the major ports of Durban and Richards Bay (Figure 5.1, (Lurie *et al.*, 1997)).

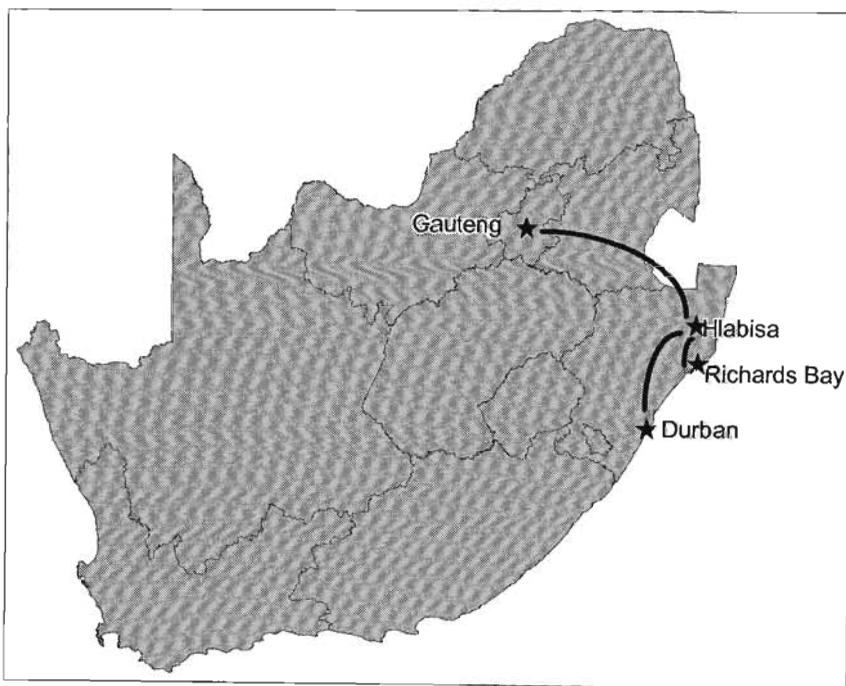


Figure 5.1: Diagrammatic representation of migrant worker destinations among men resident in Hlabisa.

HIV infection has spread rapidly in South Africa, and HIV prevalence among pregnant women in Hlabisa increased from 4.2% in 1992 to 14% in 1995 (Coleman *et al.*, 1997) and to 41.2% in 1998 (Wilkinson *et al.*, 1999).

HIV prevalence survey

Antenatal care is provided by the local district hospital and its village clinics.

Approximately 95% of pregnant women in the district receive antenatal care at these facilities (Wilkinson *et al.*, 1997). At their first antenatal visit women have blood taken to test for syphilis. For the HIV seroprevalence survey personal identifiers were removed from remaining serum and stored at 4°C until being frozen at -20°C within 48 hours. Data on the name of the clinic attended, age, marital status, and whether the woman's partner is a migrant were collected in the 1997 survey. Results of surveys done in 1992, 1993 and 1995 have been reported (Lurie *et al.*, 1997).

Two different ELISA tests were used to test for antibodies to HIV. Specimens were deemed HIV positive if both ELISAs were positive or if one positive ELISA was confirmed with an immunofluorescent assay. Confidential and voluntary HIV counselling and testing was available for women who requested it following the HIV education that is a routine part of antenatal care. Ethical approval for the study was given by the University of Natal Ethics Committee.

The Hlabisa GIS

A series of geographical layers of the district (including magisterial and nature reserve boundaries, roads and rivers) were digitised from 1:50 000 topographical maps using

MapInfo (MapInfo Corporation, New York, 1998). Primary roads (1°) are defined as national {N} roads and secondary (2°) roads are defined as regional {R} roads, remaining roads are tertiary (3°) roads.

Locating homesteads

Two methods were used to obtain the geographical position of every homestead in the district. The 16,583 homesteads in the largest of the four tribal authorities that make up the Hlabisa district were positioned by global positioning system (GPS). The United States Department of Defence introduce an intentional error to the system, typically around 30-100m (Clarke *et al.*, 1996). We differentially corrected for this against a local base station. By plotting the errors over time, it is possible to subtract these errors from a roving GPS in the field (Ardö and Pilesjö, 1992). Differential correction occurred subsequent to homestead positioning in the field. Comparison with trigonometric beacons in the district revealed all positions to be accurate within 2m. The 7741 homesteads occurring in the remainder of the district were digitised from 1:30 000 aerial photographs (captured in 1996) and corrected for geometric distortions. Comparison with differential GPS co-ordinates showed the average error to be 30m with a maximum error of 50m.

Creating the HIV GIS

We created raster images of all clinics used in the study as well as all 1°, 2° and 3° roads in the district (pixel resolution of 20m) in Idrisi version 2.0 (Clark Laboratories, Worcester, 1998).

Analysis

We first stratified HIV prevalence data by clinic attended. We then created polygons for these clinics, dividing space such that any particular home is allocated to its geographically nearest clinic. We then created distance images for the categories 1°, 2° and 3° roads. All 24,324 homesteads were overlaid onto the distance images and the distance of each homestead to the nearest road category in each clinic catchment extracted. Results are reported as mean (SD) distance per clinic catchment.

A simple regression analysis measured the correlation between mean distance from homesteads to roads and HIV prevalence, and a scatter plot was produced (BMDP, BMDP Statistical Software, 1994, Los Angeles, USA). A regression analysis weighted for sample size in each clinic catchment did not substantially differ from the crude analysis and hence here we report the crude analysis. Previous analyses have demonstrated that there is no statistically significant association between clinic catchment HIV prevalence and age, marital status, or partner status (submitted for publication), hence here we report unadjusted correlation between HIV prevalence and proximity to roads. We have analysed correlation of HIV prevalence with 1° roads alone, and with 1° or 2° roads.

5.4 RESULTS

Serum samples were available from 2013 women attending antenatal clinics between January and April 1997. For a 2 week period when approximately 350 specimens were collected, demographic data were inadvertently not obtained. HIV prevalence varied from a low of 19% among women attending one of the more rural clinics, to 31% (Chi square test, $p < 0.001$) among women attending a clinic that serves a large township next to a major national road (Table 5.1).

Table 5.1: Clinic-specific HIV prevalence among pregnant women in Hlabisa, and mean distance from homesteads to roads by clinic catchment.

Clinic	Number HIV positive	Number tested	HIV prevalence % (95%CI)	Mean (SD) distance (m) from homesteads to 1° or 2° roads	Mean (SD) distance (m) from homesteads to 1° roads
1. Nhlwathi	18	95	19 (12-28)	4,574 (2,620)	27,538 (6,334)
2. Ntondweni	13	68	19 (11-30)	7,569 (2,665)	14,397 (5,531)
3. Madwaleni	24	105	23 (16-32)	3,965 (3,031)	4,705 (3,423)
4. Hlabisa hospital	26	106	25 (17-33)	3,239 (2,631)	43,791 (7,038)
5. Mpukunyoni	44	168	26 (20-33)	1,623 (1,433)	3,001 (2,094)
6. Somkhele	25	93	27 (19-37)	3,192 (3,111)	11,467 (3,016)
7. Nkundusi	75	272	28 (23-33)	2,433 (2,540)	4,127 (3,353)
8. Makhowe	11	39	28 (16-44)	2,054 (1,704)	10,191 (4,805)
9. Machibini	11	36	31 (17-47)	2,498 (2,498)	20,720 (4,708)
10. Macabuzela	24	78	31 (21-42)	2,553 (1,898)	20,698 (3,145)
11. KwaMsane	112	363	31 (26-36)	1,822 (2,271)	5,220 (2,267)

As reflected in Figure 5.2, HIV prevalence tended to be highest in those clinic catchments through which the national (1°) road runs. Lowest HIV prevalence is observed in those clinic catchments through which neither 1° nor 2° roads run.

We measured a wide range of mean distance from homesteads to 1° and to 1° or 2° roads for the various clinic catchments (Table 5.1). For 1° or 2° roads the shortest mean distance was 1623 metres, reflecting the population and household density in this area, and its proximity to the national road. The greatest mean distance (7569 metres) was measured for a catchment around the relatively more isolated Ntondweni clinic (Figure 5.2; {2}).

Interestingly, although no 1° or 2° roads pass through this catchment, parts of it are only a few kilometres from the national road.

A scatter plot of mean distance from home to 1° or 2° road versus HIV prevalence (Figure 5.3) demonstrates a strong correlation between these two variables. We measured a r^2 of 0.44, ($p=0.002$). For 1° roads alone the r^2 was 0.05 ($p=0.45$).

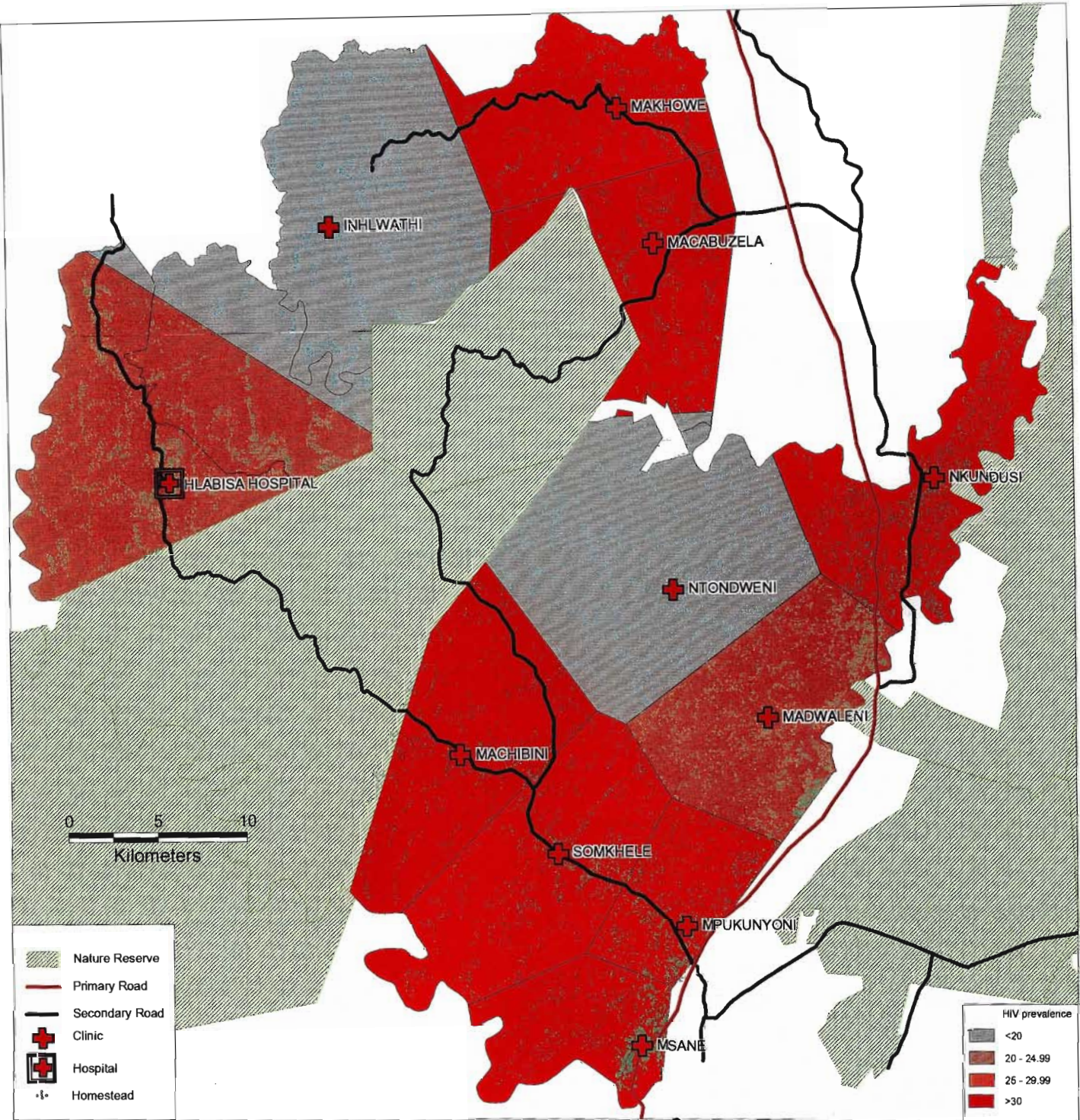


Figure 5.2: HIV prevalence among pregnant women by clinic catchment, Hlabisa district, 1997

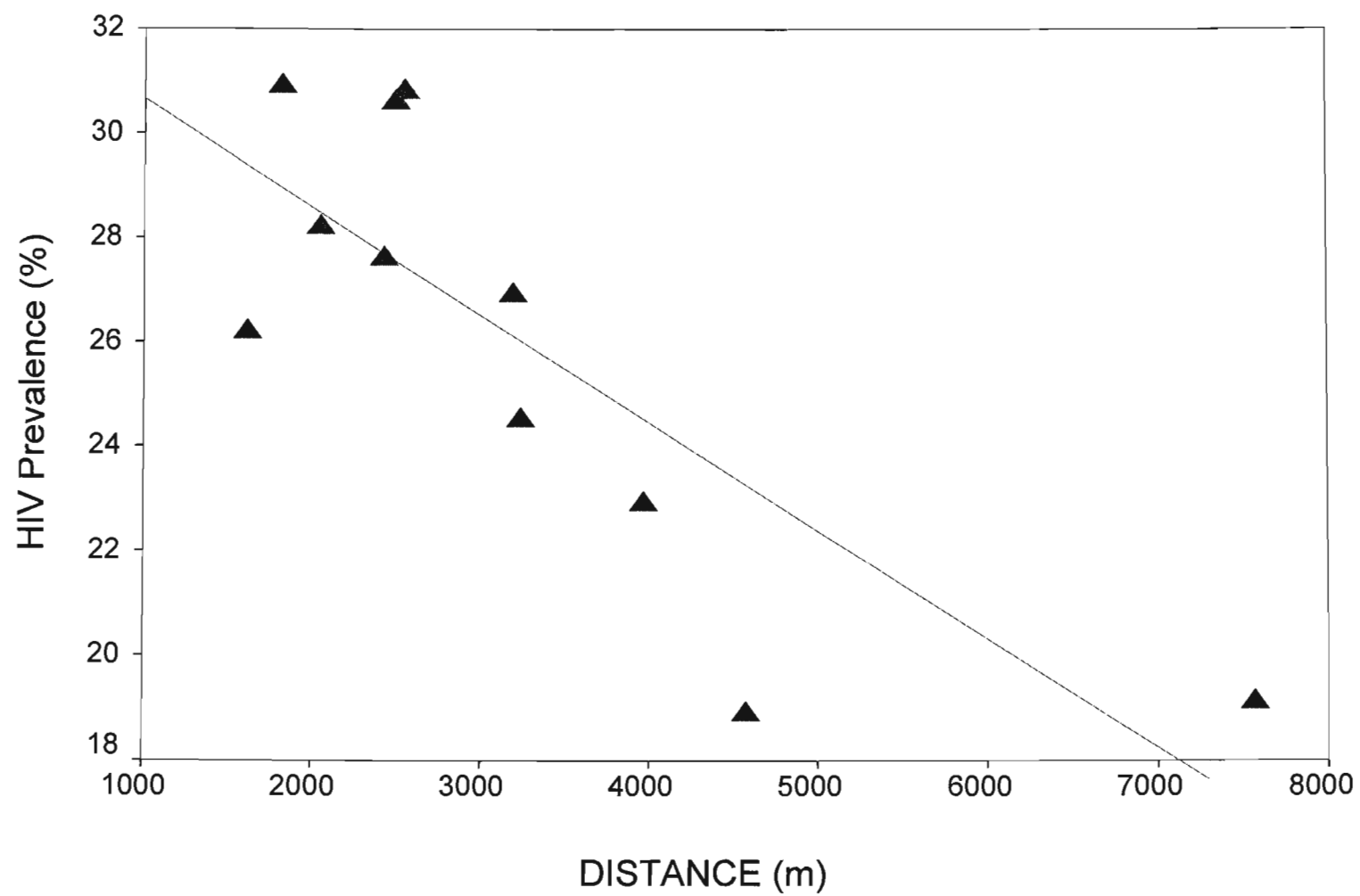


Figure 5.3: HIV prevalence versus average distance to primary and secondary roads by clinic catchment

Figure 5.4 illustrates the variation between clinic catchments, in levels of proximity to 1° or 2° roads. For example, the clinic catchments to the east of the district show high levels of proximity, whereas the more central and western catchments show much lower levels of proximity. Figure 5.4 also demonstrates substantial variation in proximity to 1° or 2° roads within each clinic catchment, but as we are unable to geo-locate individual pregnant women within their respective clinic catchments we are unable to explore this relationship further.

5.5 DISCUSSION

We have shown that HIV prevalence among pregnant women varies substantially within this district, when stratified by clinic catchment. Further, we have shown a close correlation between proximity of homesteads to 1° or 2° roads and HIV prevalence: those catchments with homesteads that are closer, on average, to 1° or 2° roads are more likely to have higher HIV prevalence. These findings support observations made in other parts of Africa (Wawer *et al.*, 1991; Killewo *et al.*, 1994; Soderberg *et al.*, 1994) and suggest that communities with better access to transport and transport routes are at higher risk of HIV. These observations may have implications for HIV prevention efforts.

There are some limitations to our data. Firstly we assumed that women attending a particular clinic also live within that clinic's catchment. We also assumed that geographic catchments, as defined by polygons, are equivalent to functional clinic catchments.

Through the further refinement of the demographic surveillance system being developed in the district we have been able to test these assumptions and have found that they hold well.

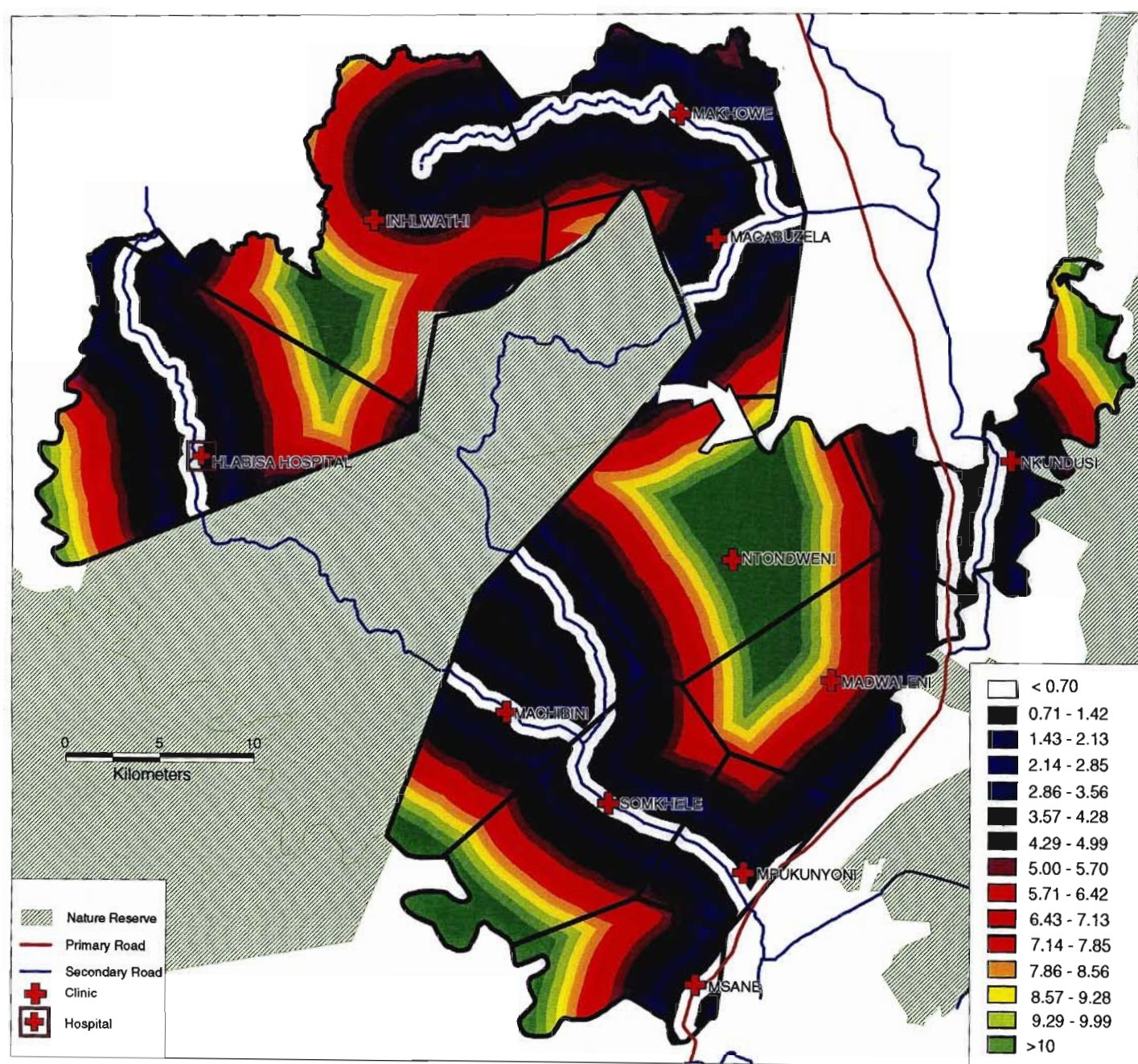


Figure 5.4: Proximity (kilometres) to primary and secondary roads by clinic catchment, Hlabisa district

Among 13,000 homesteads, 88% of respondents reported using the geographically nearest clinic, and preliminary analyses suggest that functional catchments are highly correlated with geographically defined catchments (unpublished data)⁶. We measured direct distances from homesteads to roads, but this may not accurately reflect actual ease of access to roads, especially in hilly parts of the district, and in those parts crossed by rivers. However, as the most populous parts of the district are quite flat and accessible this assumption may not affect our data too much. Lastly, we gave equal weight to proximity to 1° and 2° roads, and it is unlikely that this assumption is reasonable: further research is underway to determine what weighting should be applied.

Why does proximity to 1° and 2° roads confer HIV risk to communities? It may be that men living in such communities are more likely to be migrant workers. These men may migrate to different towns from their more rural counterparts, and may also find it easier to return home more frequently. This may then confer greater risk to their rural partners. Alternatively, or in addition, it may be that there is more sex work close to the major roads, especially the national road that crosses the east of the district, than in the more rural parts of Hlabisa. This national road is a major trucking route from the large coastal ports of Durban and Richards Bay to Swaziland, Mozambique and beyond. Although there are no major truck stops within the Hlabisa district, there is a small truck stop near the township (near KwaMsane clinic; Figure 5.2). It seems likely that the type of traffic carried by different roads, its volume, and whether it stops or not, are factors which might influence the relationship between proximity and HIV that we have described. We are working with

⁶ Subsequently submitted for publication in Tanser *et al.* (2000a, this thesis)

the Department of Transport to add traffic count, and traffic type, data to the GIS and to further explore these relationships.

Why was the correlation with 1° roads alone weaker than with 1° and 2° roads? Firstly there is only one 1° road in the district and as most residents will need to travel along it to reach home, there is little opportunity for discrimination in analysis. Further, this road only traverses a small proportion of the district. As noted above, the type of traffic on a road and its stopping frequency may be more important than road size: most of the traffic on this road does not stop in the district. It is possible that 1° roads act as important conduits for traffic to reach secondary roads, and that these roads then determine to a greater extent the penetration of HIV into more rural, isolated settings.

It has been shown that the risk of HIV in this area is highest amongst migrant men and their partners (Colvin *et al.*, 1995), and in a similar setting, it has been shown that people who had most recently moved into an area were more likely to be HIV infected (Abdool Karim *et al.*, 1992). These observations support similar ones made in Uganda (Wawer *et al.*, 1991) and elsewhere, and seem to suggest that within rural communities at least, sexual networks are relatively constrained (Pickering *et al.*, 1997). If they were not, we would expect there to be much less heterogeneity across the district.

What are the implications of these observations for HIV prevention? Although prevalence is high (and is rising rapidly) in all parts of this district, it seems that prevention efforts might usefully be targeted to certain areas. It seems reasonable to suggest that HIV was introduced to the district through transport routes. There are a small number of

well-defined transport nodes where the minibus taxis and bus services that operate in the area are based. It might be prudent to focus some of the limited human and financial resources that are available for prevention, at these sites. Already a few minibus taxis carry HIV prevention posters, but this could be enhanced to include distribution of written health educational material and condoms on the taxis and buses as well as at ticket and booking offices, for example. Furthermore, outreach efforts perhaps including clinics offering voluntary HIV counselling and testing and sexually transmitted disease treatment, sited at these transport nodes might be considered. When an epidemic has established itself in a district, localised prevention efforts may have a smaller role to play than at the start of an epidemic.

We have found GIS to be a powerful tool to display and to start to analyse reasons for HIV heterogeneity in this setting, further supporting its potentially important role in health, health services management and in research (Clarke et al,1996).

Chapter Six:

The equitable distribution of fieldworker workload in a large, rural health survey

Tanser (2000) *Submitted for publication*

6.1 ABSTRACT

A methodology is presented that has numerous applications to health systems provision in developing countries where limited physical access to primary health care is a major factor contributing to the poor health of populations. An accessibility model within a geographical information system (GIS) is used to predict average inter-homestead walking times and subdivide the study area into units of equal completion time. The methodology could be used to ergonomically design home-based care and tuberculosis DOT programmes and inform the siting of health facilities. The paper highlights the use of GIS technology as a powerful tool in developing countries.

6.2 INTRODUCTION

Geographical information system (GIS) technology has a wide range of applications in health, many of which are only emerging now. GIS has been applied to environmental health (Snow *et al.*, 1998), health system management (Wilkinson and Tanser, 1999, this thesis), and a range of communicable diseases (Clarke *et al.*, 1996), but its full potential remains largely unrealised. Accessibility can be defined as the ability for interaction or contact with sites of economic or social opportunity (Deichmann, 1997). Accessibility measures within a GIS have traditionally been used in measuring proximity to health care (Walsh *et al.*, 1997; Parker and Campbell, 1998; Tanser and Wilkinson, 1999, this thesis; Perry and Gesler, 2000). Limited physical access to primary health care is a major factor contributing to the poor health of populations in developing countries. In reality accessibility is determined by a complex inter-linkage of both physical and human factors in addition to mere proximity to target locations.

Conducting health surveys in heterogeneous, remote areas can be problematic. Social, physical and spatial heterogeneities pose a major challenge to the estimation of fieldworker requirements, cost, completion time and equitable distribution of labour. These problems are especially pronounced in longitudinal surveys where an inequitable division of a study area will have long-term consequences and will result in a decrease in overall labour productivity. Studies in Bangladesh have shown a substantial decrease in community health worker performance for every 1 sq. km increase in catchment size (Ali *et al.*, 1999). The authors conclude that health worker performance can be significantly improved by defining catchments through the use of GIS techniques and that without knowledge of the spatial distribution of population and the physical barriers to movement, allocating a fixed number

of clients per health worker may not be the most efficient approach. The dearth of literature on the equitable allocation of labour across an area, suggests that adjusting for the variable characteristics of a study area is often ignored or at best is done on a subjective basis.

A demographic surveillance system of an extremely heterogeneous area (both physically and socially) is being set up in a remote area in rural South Africa. The aim of the system is to collect demographic and epidemiological data on a population of 75,000 people and to monitor the effects of the HIV epidemic on the population longitudinally (Hosegood, 1998). The methodology of the system required that fieldworkers walk to every homestead in the study area every 60 working days and administer questionnaires to the occupants of the homesteads. The population is dispersed throughout the study area and is not concentrated into villages or compounds as in many other parts of Africa where similar work is being undertaken (Sauerborn *et al.*, 1996). The heterogeneities in the study area and the dispersed population present significant problems to the estimation and equitable distribution of labour. I use a fuzzy accessibility model within a GIS to adjust for the variable social and physical characteristics of the study area and produce an equitable subdivision of the area into sub-units (fieldworker areas) of equal completion time.

6.3 METHODS

Setting

The study area is located in the Hlabisa district in northern KwaZulu-Natal, South Africa and is 435 Km² in size. The population is approximately 75,000 Zulu-speaking people who rely on migrant labour remittances, subsistence farming, and pensions. Annual per capita income is US\$1730, the literacy rate 69%, and life expectancy averages 63 years. The area

is characterised by large variations in population density (0-6500 people per km²), altitude (20-300 m.a.s.l), terrain (flat to undulating to mountainous), vegetation (sparse grassland to thick forest) and proximity to transport networks. Socially, large variations in homestead size (1-100 people), access to electricity and municipal water and levels of westernisation exist.

Location of homesteads

All 10275 homesteads occurring in the study area were positioned by global positioning systems (GPS) (Trimble Geoexplorer II). The GPS system, owned by the United States Department of Defence, introduces an intentional error to the system, typically around 50-100m. For the purposes of the study this error was unacceptable as some homesteads are only 10m apart. I differentially corrected for this and other errors against a local base station. By plotting the errors over time, it is possible to subtract these errors from a roving GPS in the field. Differential correction occurred subsequent to homestead positioning in the field. Comparison with trigonometric beacons in the district revealed all positions to be accurate within 2m. All homesteads were uniquely numbered and a dataset collected around facility usage and data pertaining to the homestead itself, including the number of residents and the presence of tenants.

Factors affecting accessibility

By observing the progress of 12 fieldworkers during the homestead mapping exercise and in consultation with them, a number of factors emerged as having an impact on time taken to walk between homesteads. Homestead density is an important factor affecting inter-homestead walking time. The closer the homesteads are to each other the less the time

taken to walk between them. Terrain also contributes to walking time. Areas characterised by steep uneven terrain are more problematic and take longer to navigate than their flat counterparts and the most direct route between homesteads is often not available. Although the homesteads are negotiated on foot, the fieldworkers reported that road networks were an important variable affecting walking time. Roads provided conduits for the fieldworkers to traverse their allotted areas and the majority of homesteads tended to be located near the transport routes. A final factor affecting walking time was vegetation. The fieldworkers reported that in dense vegetation they had difficulty locating homesteads. In addition, the thick vegetation prevented the use of the most direct route and fieldworkers were often forced to use roundabout routes to reach some homesteads.

Preparation of data to be used in the accessibility model

A series of geographical layers of the district (including magisterial and nature reserve boundaries) were digitised from 1:50 000 topographical maps using MapInfo (MapInfo Corporation, New York, 1998).

To calculate an elevation image 20m contours in digital format were purchased and imported into Idrisi 2.0 (the Idrisi project, Clark University, Worcester, MA, USA). I superimposed the contours onto a blank raster surface (resolution = 20m) and interpolated the data into a continuous raster surface using a modified CONSURF algorithm (Eastman, 1997).

Elevation values do not have an impact on the time taken to walk between homesteads per se; rather it is the variations in elevation around each homestead that will affect travel time.

I therefore passed a moving 1km x 1km standard deviation filter across the elevation image. The end result is an image (with the same resolution as the original elevation image) which measures elevation variations in a 1km x 1km neighbourhood around each pixel.

I used a similar technique to calculate a homestead density image. I created a raster image of number of homesteads per pixel. I then passed a moving 1km x 1km filter across the image which summed the number of homesteads in the filter window and assigned the total to the central pixel. The result is a homestead density image in which the value of each pixel is the total number of homesteads in the surrounding 1km x 1km block.

The normalised difference vegetation index (NDVI) is a satellite-derived index that has been used to estimate green biomass by numerous authors (Tucker *et al.*, 1985; Bedard and LaPointe, 1987). High NDVI values are characteristic of densely vegetated areas, e.g. forests, sparsely vegetated areas by contrast, e.g. urban areas, result in low NDVI values. NDVI is based on the fact that growing vegetation has a high near infra-red reflectance due to internal reflectances involving green leaves coupled with low red reflectance due to absorption by chlorophyll and other plant pigments. I obtained geometrically and radiometrically corrected Advanced Very High Resolution Radiometer (AVHRR) NDVI imagery for the study area for June 1998 at a 1.1km resolution. The data were collected by the AVHRR on board the National Oceanic and Administration's NOAA-11 satellite (Cracknell, 1997). I selected the June 1998 (winter) NDVI image to ensure that the grass contribution to the overall NDVI spectral reflectance was negligible. I resampled the NDVI image to the same resolution as the other images (20m).

I obtained all 1st level (national), 2nd level (regional) and 3rd level (district) roads in MapInfo format from the department of roads. In addition, all 4th level roads in the study area were mapped using a differential GPS. I defined 4th level roads as additional roads which were of significant longitudinal length and were serviced by the minibus taxis in the area. I created raster images of all 1st - 4th level roads in Idrisi and created a 'distance to nearest road' image.

Estimating walking time

I scaled the variables between zero and one along a fuzzy sigmoidal (cosine) curve (Figure 6.1) to produce accessibility maps of fractions between zero (highly inaccessible threshold = I) and one (highly accessible threshold = A). The thresholds used as the fuzzy cut-offs represent values above or below which no significant difference in accessibility is likely to result. The thresholds were selected using a combination of knowledge and aggregated analyses of the homestead mapping exercise data. The sigmoidal membership function (Schmucker, 1982) is one of the most commonly used functions in fuzzy set theory. The shape of the curve mimics the relationship of the independent variable to accessibility. As the threshold limits are approached the fuzzy value /accessibility increases slowly in relation to the independent variable, but in the middle of the continuum, accessibility increases rapidly.

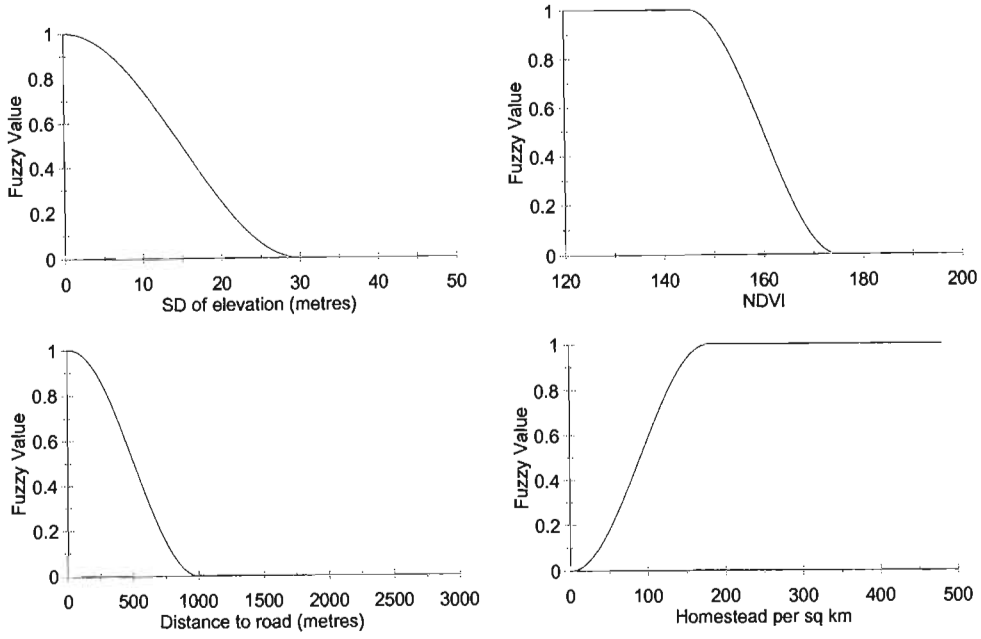


Figure 6.1: Graphs showing the fuzzy transformation of independent variables used to estimate average inter-homestead walking time.

The sigmoidal curve is defined as:

$$y = \cos^2 \left[\frac{x - A}{A - I} \times \frac{\pi}{2} \right]$$

where y is the fuzzy suitability of accessibility value x . In the decreasing curve (applied to standard deviation of elevation, distance to roads and NDVI), fuzzy value is equal to y , in the increasing curve (applied to homestead density) it is $(1 - y)$. A fuzzy value of zero in a particular variable represents a very low accessibility and is therefore conducive to a long walking time (i.e. thick vegetation, low homestead density, large variations in altitude or a large distance from the nearest road), whereas a value of one represents a high accessibility or short walking time. Fuzzy values located along the accessibility gradient (between zero and one) lie somewhere between highly inaccessible and highly accessible.

I grouped homesteads mapped across the study area into actual number of homesteads mapped per fieldworker per day (n=920 fieldworker days). I extracted the values of the independent fuzzy variables for each homestead and calculated the average fuzzy values for each group of homesteads mapped per fieldworker per day. I performed a multiple regression analysis on the average fuzzy variables to predict the number of homesteads mapped per fieldworker per day. The resulting equation was then applied to the fuzzy variables and an image produced of 'predicted number of homesteads mapped per fieldworker per day'. I then converted the resulting output to average inter-homestead walking time by dividing the average daily time spent working in the field (6 hours) by the resulting image and subtracting the average time taken to establish the coordinates of a homestead (12 minutes). I also applied the above methodology to the raw variables (without fuzzy scaling) for comparative purposes.

Validation of the accessibility model

The accuracy of the accessibility model is likely to be over-estimated if analysed using the original data used to build the regression equation. In addition, lack of recorded start and completion times in the input data would mitigate against an accurate validation. I therefore selected three areas (ranging between 16.44 km² and 2.64 km² in size and each containing between 189 and 245 homesteads) of contrasting physical and social characteristics to conduct an independent validation of the accessibility model. The areas comprised a peri-urban, semi rural and a deep rural area. I assigned each area to a group (of similar estimated average walking speed) of five fieldworkers and asked each group to walk to every homestead (as a group) in the assigned area in any chosen sequence and record inter-homestead walking times (n = 630 homesteads). I then compared the predicted

average daily walking time (the average of the predicted walking times for all homesteads visited by the group in a day) against actual average daily walking time (n = 16 days) and statistically analysed the results.

Estimating interview time

Pilot studies revealed that an average time of 45 minutes was required to administer a questionnaire within one family unit in each homestead and that each family unit consisted of an average of 6 residents. I therefore assigned an estimated interview time of 45 minutes per 6 people in a homestead. An additional 45 minutes interview time were assigned if the estimated number of family units was one but the homestead included tenants. The presence of tenants would require the administration of another set of questionnaires. Some homesteads were in the process of being built (2.2 %) or respondents were not available for interviewing (3.1%). In such instances, I used the average homestead interview time (54 minutes) across the study area.

Creating hard areas

The fieldworker areas had to be enclosed by features observable on the ground to facilitate easy allocation of new homesteads to fieldworker areas. I considered using polygons such as the census enumerator areas, Izigodi and local areas. However, these were often not delimited by hard boundaries as well as being too large.

I imported all roads (level 1-4) and rivers into Idrisi and superimposed them on a blank raster surface. I then subjected the resulting raster line features to an enclosed-area detection algorithm (written in Idrisi macro language) to identify areas which were

completely enclosed by any number of roads or rivers (Appendix 6). The algorithm identified contiguous groupings of pixels (excluding diagonal neighbours) of the same value. Cells belonging to the same contiguous grouping are given a unique integer identifier, numbered consecutively in the order found. I then filtered out the original line features using a 3 x 3 mode (majority) filter and removed insignificant areas of less than 50 pixels and replaced them with the value of the adjoining pixels. In this way I identified a number of significant areas that were fully bounded by roads and rivers. The resulting areas were converted to vector format and exported to MapInfo.

Creating the fieldworker areas

I superimposed all homesteads on the predicted average inter-homestead walking time image and extracted the average walking times for each homestead. Although an individual walking time is assigned to each homestead, in reality this value reflects the average inter-homestead walking time for the surrounding 1km x 1km neighbourhood. I then adjusted the walking times to account for the required members of the homesteads not being present at the time of interviewing, requiring a subsequent revisit by the fieldworker. Using data from the mapping of homesteads, I estimated that the increase in visits coupled with the extra distance the fieldworker had to walk to reach these homesteads would result in a 100% increase in total walking time. I therefore doubled all inter-homestead walking times to account for this combined effect, *viz.* revisits constitute half of the total walking time.

By summing all walking and interview times for all homesteads in the study area, I estimated that it would take one fieldworker in excess of 1,900 working days to complete the entire study area. I was therefore able to recommend that 48 fieldworkers should be used in each 60 working day cycle at an average completion time of 40.2 days per

fieldworker area. A 20 day cushion was incorporated to account for the growth of the number of homesteads over time, complete days lost to weather and to allow for the introduction of additional questionnaires at a later stage if required. The required number of fieldworkers computed by the model confirmed previous estimations using aggregated statistical methods.

I calculated a completion time for each area (enclosed by roads and rivers) by summing the interview and walking time (doubled to account for homestead revisits) of all homesteads that fell within the area. I then combined adjacent areas until a total within 5 hours of the 40.2 day average was reached. In densely populated areas, I used rivers in preference to roads where possible because they provide more definite separations (with less margin for error). This is because homesteads are seldom sited within 50m of a river (because of the danger of flooding) whereas they tend to be densely clustered along roads. In certain fieldworker areas ergonomics were sacrificed in favour of equitable workload distribution and due to the limited availability of hard boundaries. However, I attempted to make the fieldworker areas as non-elongated as possible to ensure the fieldworker was never excessively far from any one location within the fieldworker area. I didn't allocate a fieldworker area across more than one major river catchment. This prevented more than one major watershed feature, e.g. a mountain range, being allocated to a single fieldworker area. Once the preliminary fieldworker areas had been constituted, I identified isolated homesteads at the extremities of fieldwork areas and altered the boundaries (along roads and rivers) so that the homesteads were allocated to a neighbouring area where they were more ergonomically accessible. Once the final areas had been constituted, I digitised the new boundaries on-screen by 'snapping' them to the relevant roads and rivers. This smooths the 'jagged' appearance of the raster-derived boundaries and prevents the

misallocation of homesteads (occurring near the boundaries of the fieldworker area) to the incorrect area.

6.4 RESULTS

The fuzzy variables used to calculate the accessibility model are shown (Figure 6.2). The heterogenous nature of the study area is clearly illustrated.

The resulting reclassified outcome of the multiple regression equation (predicted average inter-homestead walking time) is shown (Figure 6.3). Homestead density proved to be the most significant factor in predicting inter-homestead walking time (40%), however NDVI (27%) and standard deviation of elevation (22%) also contributed notably. Distance to the nearest road was the least significant factor (11%).

The relationship between predicted and actual (independently recorded) average daily inter-homestead walking times ($r^2=0.864$, $p<0.001$) is shown (Figure 6.4). The predicted daily walking time between homesteads is more than double the actual walking time. This is to be expected as the predicted walking time is calculated using a regression equation derived from data that included stoppages for rain and waiting for respondents. The independent validity data included no time for stoppages and contained walking time only. Since fieldworkers will encounter similar stoppages once the survey is underway the predicted walking time provided by the accessibility equation is a more realistic estimation of walking time. The relationship of predicted walking times, derived from the raw variables, to actual walking times was poor ($r^2=0.14$). The application of fuzzy scaling to the raw variables therefore significantly improved the final result ($p<0.001$).

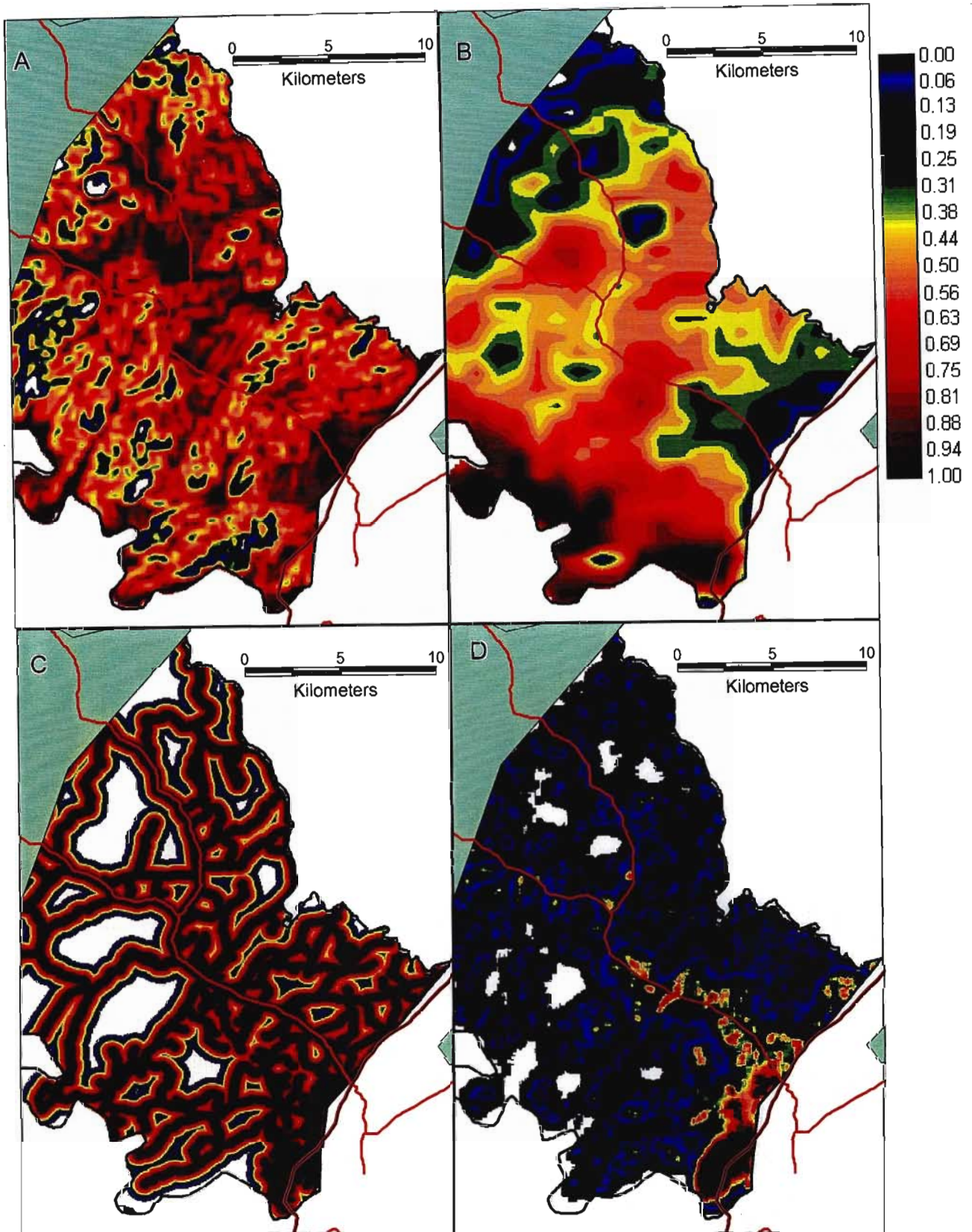


Figure 6.2: Fuzzy input images used to predict average inter-homestead walking time. A=standard deviation of elevation, b=NDVI, C=distance to roads, D=homestead density. A fuzzy value of zero is considered to be highly inaccessible and a value of one highly accessible. A nature reserve constitutes the western boundary and the main roads are superimposed for ease of reference.

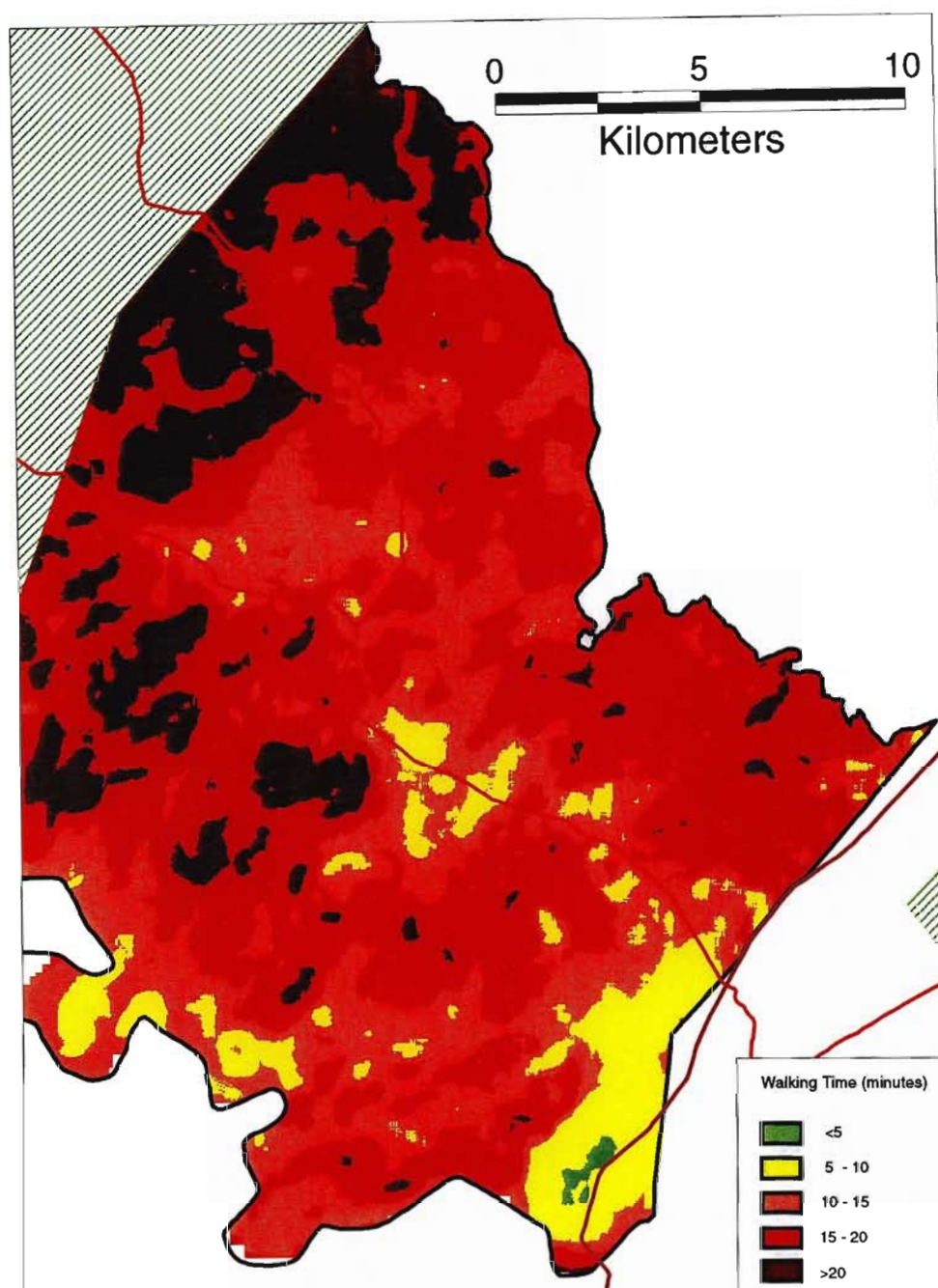


Figure 6.3: Reclassed image of predicted average inter-homestead walking time (minutes).

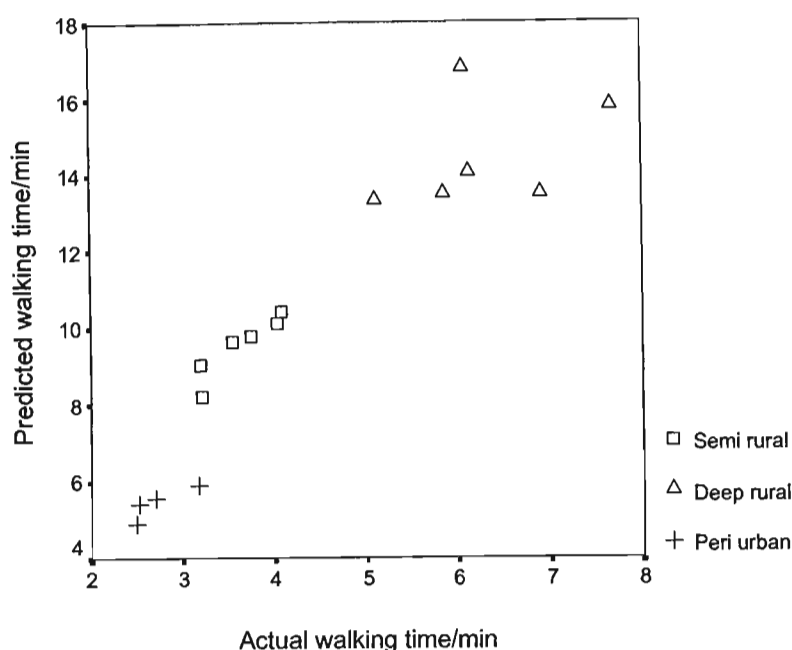


Figure 6.4: Predicted versus actual (derived from the accessibility model) average daily inter-homestead walking times in three physically and socially contrasting areas in the study area ($p < 0.001$, $r^2 = 0.864$)

The roads and rivers (Figure 6.5a), the resulting areas computed using the enclosed-area detection algorithm (Figure 6.5b) and the final workload-efficient fieldworker area delineation with homesteads superimposed (Figure 6.5c) are shown (mean completion time = 40.2 days, standard deviation = 3.8 hours).

The larger fieldworker areas contain fewer, more sparsely distributed homesteads than their smaller counterparts due to the greater amount of walking time involved. The number of homesteads in each fieldworker area ranges from 189 to 275 (average = 214 homesteads) with the highest number of homesteads allocated to fieldworkers in the most accessible urban/peri-urban areas. Average walking time in inaccessible areas can be up to 220% greater than their accessible counterparts.

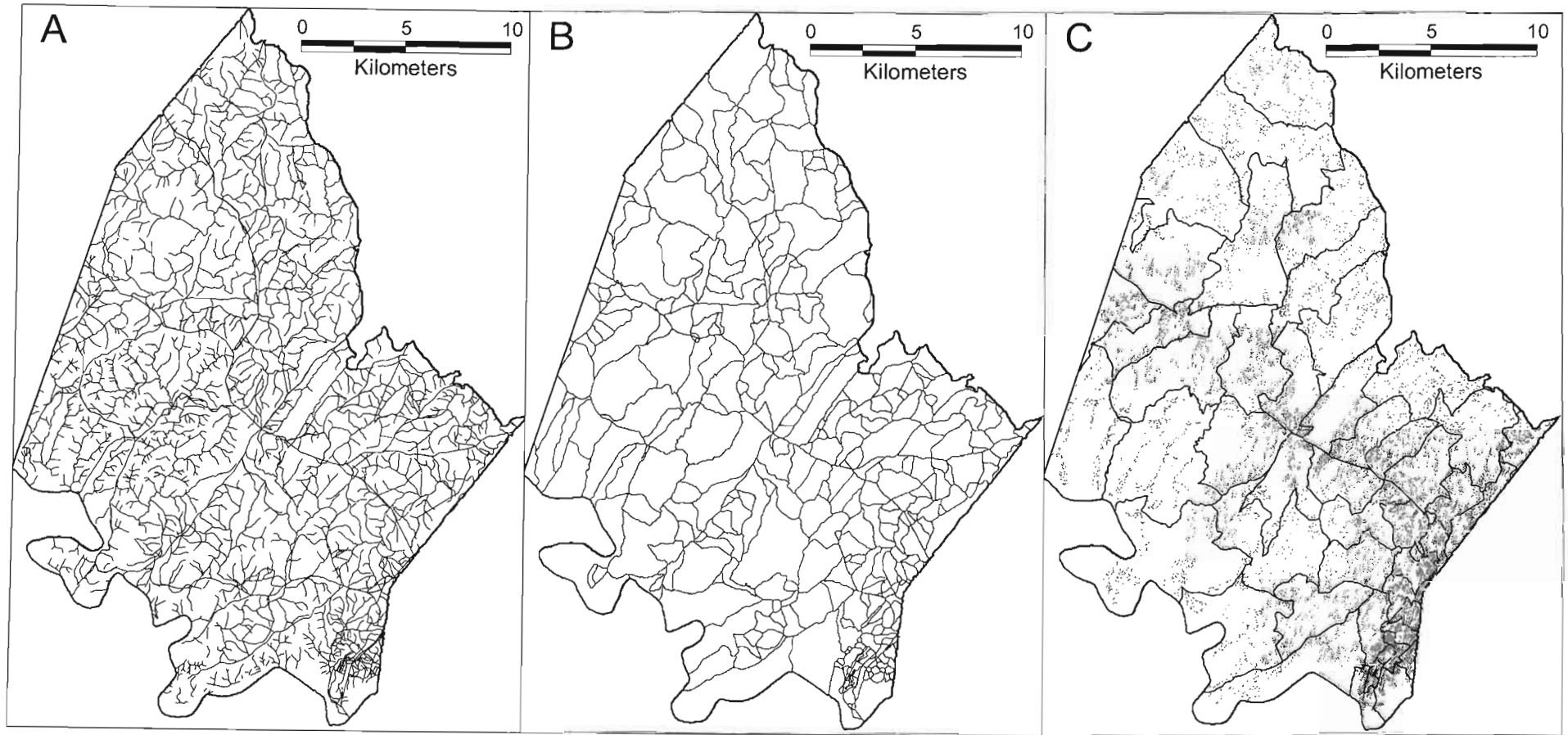


Figure 6.5: Stages in the delineation of 48 workload-equivalent fieldworker areas. A =All rivers and roads (level 1-4) in the study area. B = All significant polygons completely enclosed by roads and rivers (detected using a raster algorithm). C= The final workload-equivalent fieldworker area delineation with all homesteads superimposed.

6.5 DISCUSSION

I have used a fuzzy accessibility model to estimate average inter-homestead walking time in a heterogeneous, rural area. In addition, I estimated questionnaire administration time based on homestead composition. These two components were used to estimate completion time in a number of 'hard' areas which were combined to constitute fieldworker areas of equal workload/completion time. By employing a methodology that encompasses other equally important social and physical dimensions in addition to mere proximity to target locations, I have been in a position to estimate, cost and equitably distribute fieldworker workload across a heterogeneous landscape.

The concept of accessibility within a GIS has been applied to numerous health issues. It has been used to redefine sub-areas for the management of primary health care in England (Bullen *et al.*, 1996). The study used focal points of service provision, barriers to movement and various accessibility data such as journey to work, school and family doctor surgeries. GIS has been used by numerous authors to calculate the accessibility of patients to health services. In the KwaZulu-Natal province of South Africa GIS has been used to document the decrease in distance to nearest tuberculosis DOT dissemination point (Wilkinson and Tanser, 1999, this thesis), quantify a relationship between road accessibility and HIV prevalence (Tanser *et al.*, 2000b, this thesis) and calculate population per clinic bed ratios (Zwarenstein *et al.*, 1991). GIS has been used to assess and optimise ambulance response performance (Peters and Hall, 1999). Using a GIS, studies have measured the impact of travel time and visit frequency on the probability of receiving quality treatment for depression. Travel time was significantly associated with making fewer visits and a lower likelihood of receiving care (Fortney *et al.*, 1999).

A particularly encouraging aspect of the methodology has been the accurate prediction of inter-homestead walking times ($r^2 = 0.864$) across a wide range of varying social and physical landscapes, despite the fact that a homestead visit sequence was not imposed on the fieldworkers. It is this aspect of the methodology that makes it more robust and computationally-efficient than ‘travelling salesman’ (Voudouris and Tsang, 1999) algorithms, with or without ‘genetic’ optimisations. These computationally intensive algorithms determine the most optimal visit sequence of homesteads. However, this requires that a pre-determined visit sequence be imposed on the fieldworker. While this may theoretically allow the fieldworkers to complete their areas in slightly quicker times, it is neither practical nor necessary. Using this methodology the fieldworker is relatively free to decide her own visit sequence⁷. One of my assumptions therefore is that the fieldworker will make intelligent choices regarding this sequence.

It is important to note that the model is predicting *average* inter-homestead walking time and not actual inter-homestead walking times (as this would require a predetermined visit sequence). The model works on the simple premise that areas with low homestead densities, thick vegetation, uneven terrain and which are far from roads (fuzzy values approaching zero) are predisposed to having a high inter-homestead walking time whilst those areas with characteristics near the other end of the fuzzy scale will be predisposed to having a short inter-homestead walking time. The model only indirectly considers distance between homesteads (in the form of a wide area average of homestead density). Each pixel

⁷ The fieldworker areas were subsequently divided into 12 sub-units. Fieldworkers have to complete the sub-units in a prescribed sequence but have freedom to choose the visit sequence of homesteads within an individual sub-unit.

is a product of the characteristics of its surrounding 1km x 1km neighbourhood and it is therefore unnecessary to engage in any form of complex route analysis. Thus, although an inter-homestead walking time is assigned to each homestead, this represents an average walking time for the surrounding 1km x 1km neighbourhood. For example, in an inaccessible area (fuzzy values approaching zero) of 1km x 1km size which contains two homesteads directly next to each other, the model may assign approximately 20 minutes estimated walking time to each homestead. In reality the fieldworker may actually walk 40 minutes to the first homestead and under a minute from the first homestead to the next. The integrity of the wide area average technique is preserved as the average walking time is still approximately 20 minutes.

A shortcoming of the model is that walking times may be under-computed for isolated homesteads occurring at the periphery of fieldworker areas as a result of an over-exaggerated homestead density calculation. This may arise where a group of homesteads is split between two fieldworker areas with the vast majority occurring in one. However, by identifying these isolated homesteads and reassigning them to a neighbouring fieldworker area by adjusting the boundary (using roads and rivers) this problem is largely overcome. The travel time between the fieldworker's residence and work (most reside in their respective fieldworker areas) is only partially accounted for in the model (only the time taken to travel between the last homestead of the current day and the first homestead of the following day offsets this travel time). Fieldworkers in larger areas will therefore have greater travel times to and from work. However, all fieldworkers are expected to start and finish work at the same time, so this effect will not affect total completion times. When combining discrete segments to make up fieldworker areas, I considered optimal

regionalisation algorithms (Macmillan and Pierce, 1994). However, a manual combination method gave me greater control over the final form of the fieldworker areas and allowed me to preserve social identities within a fieldworker area.

The formula used to calculate walking time in this research is not universally applicable. The fuzzy thresholds, the relative contribution of each variable and the variables themselves may differ depending on physical characteristics, mode of transport used, and settlement patterns of the study area. For the same methodology to be applied to rural areas elsewhere, a sample survey (similar to the one used in the validation of walking time) must be conducted (in contrasting areas) to build the accessibility-walking time relationship.

The fieldworker area delineation has now been implemented at the study site. The fieldworkers have since completed their fieldworker areas in the prescribed 60 days and initial indications are good. The performance of the model is difficult to accurately judge however, because questionnaire administration in the initial round is substantially longer than in subsequent rounds (for which the model was configured). This means that accessible areas with a greater number of homesteads will take longer to complete in the first round than their more inaccessible counterparts. Assessment of the model will take place in subsequent rounds.

In addition to the accurate estimation of cost, labour (and optimal allocation of that labour) and time in large rural health surveys, a host of potential applications exist relating to accessibility in the planning of health service provision in remote, rural areas. Limited physical access to primary health care is a major factor contributing to the poor health of

populations in developing countries (Perry and Gesler, 2000). The methodology could be used to ergonomically create community health worker areas, site tuberculosis DOT supervisors or constitute home-based care catchments. It could also be extended to determine actual walking times to nearest health care facility and could thus inform the siting of new facilities. I am working with the National Malaria Control Programme to divide a neighbouring area into surveillance units of equal residual spraying time. The methodology could also be employed at larger scales, for example, it could be used to demarcate national census tracts.

Some may argue that rural health services are unlikely to afford such technology or have access to the data required. The accuracy of GPS has now improved by an order of magnitude since the 1st May 2000 when the intentional error previously imposed by the United States government was abolished. Relatively inexpensive GPS units are now capable of mapping to a very high accuracy and location of homesteads in developing countries can be carried out significantly more cheaply. All other data used in this research may be inexpensively obtained. This study is a practical example of the ability of GIS to integrate disparate data sets to answer a spatial question. With recent advances in software and hardware, and with falling prices (Clarke *et al.*, 1996), GIS is no longer exclusively a research tool, but may be a cost-effective technology that can be used to design health care provision in developing countries.

Chapter Seven:

Malaria seasonality and population exposure in Africa

Tanser *et al.* (2000c) *Submitted for publication*

7.1 ABSTRACT

Background Until recently malaria was the single largest cause of mortality in Africa. Cases in Africa account for approximately 90% of malaria cases in the world. Knowledge of malaria seasonality is particularly important for malaria control.

Methods We use high-resolution long-term rainfall and temperature data to produce the first malaria seasonality (length, start and end of transmission season(s)) maps for Africa. We relate the model to population data and estimate the population exposure in a variety of transmission settings. We investigate the relationship between length of transmission season and parasite ratio from 2335 geo-referenced studies of children < 10 years across Africa. We recompute the model to estimate the potential temporal, spatial and population exposure changes in the disease likely to occur as a result of global warming.

Findings The seasonality model corresponds well with historical expert opinion maps and case data. A significant logarithmic relationship was detected between predicted length of transmission season and parasite ratio ($r^2=0.712$, $p=0.001$). The model predicts that during 1995, a total of approximately 440 million people (80 million children; 0-4 years of age) were living in malarious areas. Assuming a static population, a continental temperature increase of 1°C/3.5°C would result in an additional 25/58 million people being exposed to the disease, many of whom live in highland areas.

Interpretation The seasonality model constitutes an important first step towards an estimate of continental intensity of transmission and provides a powerful tool to inform current malaria control strategies and provide a framework to plan future control measures in the face of global climatic change.

7.2 INTRODUCTION

Until recently malaria was the single largest cause of mortality in Africa. Cases in Africa account for approximately 90% of malaria cases in the world (WHO, 1996). Control of malaria is becoming increasingly difficult and manifestations of the disease appear to be more severe than in the past. An upsurge of malaria in endemic areas coupled with explosive epidemics in 14 countries of sub-Saharan Africa between 1994-1996 caused a high number of deaths, many in areas previously free of the disease (OAU, 1997).

Changing climatic patterns, spread of malaria parasite drug resistance and changes in vector behaviour coupled with complex social factors (e.g. migration of non-immune populations, civil strife, high birth rates) are responsible for the upsurge (Nchinda, 1998). In addition, availability and quality of malaria mortality and morbidity statistics in Africa are notoriously poor and variable.

The effect of climate on malaria-distribution is well-known (Martens *et al.*, 1995; Lindsay and Birley, 1996). Prior to the advent of geographical information systems (GIS) some examples of maps defining the global distribution of malaria exist (Lysenko and Beljaev, 1968; Lysenko and Semashko, 1969). More recently, several authors have used climatic models to estimate distributions of malaria vectors and parasites (Hay *et al.*, 1998; Snow *et al.*, 1998; Craig *et al.*, 1999). A number of studies have also examined the implications of

climate change on these distributions (Loevinsohn, 1994; Jetten *et al.*, 1996; Lindsay and Martens, 1998; Rogers and Randolph, 2000). However, high resolution climatic models have never been applied in the estimation of onset, completion and length of malaria transmission season at a continental scale. Knowledge of malaria seasonality has important implications for optimising control programme operations, such as vector spraying regimens, dipping of insecticide-treated bednets and optimal and timely allocation of finite resources.

GIS technology is a powerful tool ideally suited to the manipulation of climatic data and to the modelling of infectious disease patterns (Clarke *et al.*, 1996). The primary objective of the research was to use a GIS to produce the first climate-based seasonality model of malaria transmission in Africa. We use the model to investigate the relationship between length of transmission season and actual parasite ratio data and to estimate population exposure within different seasonality classes. The international panel for climate change predict that the mean surface temperature of the earth will increase by around 1-3.5°C over the coming century (IPCC, 1996). The phenomenon of climate change is likely to hit hardest in Africa, even though the continent produces only about 7% of the world's green house gases. Greater rainfall variability will result in more floods and more drought, thus greater food insecurity and problems with environmental diseases such as malaria (World Bank, 2000b). Understanding of seasonality of disease is particularly important in the accurate prediction of the effects of climate change on disease distribution and incidence (McMichael *et al.*, 1996). We provide the first spatial, temporal and population exposure change estimates within different seasonality classes that will occur under simple global temperature increase scenarios.

7.3 METHODS

The effect of climate on malaria

The relationship between climate and malaria distribution has been described before (Macdonald, 1957; Detinova, 1962). Briefly, sustained transmission depends on favourable environmental conditions for both vector and parasite. The effect of temperature on the duration of the sporogonic cycle of the malaria parasite and vector survival (Onori and Grab, 1980; Molineaux, 1988) is particularly important. The higher the temperature, the shorter the duration of the sporogonic cycle of the malaria parasite and the higher the proportion of vectors surviving sporogony. For example, at a temperature of 22°C, sporogony of the *Plasmodium falciparum* parasite is completed in less than three weeks and mosquito survival is sufficiently high (15%), whereas at 18°C sporogony takes eight weeks with mosquito abundance being limited by the long larval duration (Detinova, 1962).

In addition, it is important that average temperatures be sustained close to or above the required temperature threshold to facilitate transmission. A sporadic month of 'suitable' climatic conditions (bordered by unsuitable months) is not adequate for malaria transmission. We defined stable malaria using an adaption of Bruce-Chwatt's (1999) definition. Malaria is described as stable when there is a measurable incidence both of cases and of natural transmission throughout the year and over a succession of years. Our analysis of stable and seasonal climatic profiles revealed that lower monthly temperatures can sustain transmission of malaria in stable malarious areas. These differences are a function of the annual variations in temperature. In seasonal areas (higher latitudes and altitudes) vector and parasite populations need to be fully regenerated after the cold winter

months to facilitate transmission. In stable areas (lower latitudes and altitudes) temperatures hover around the threshold mark for much of the year, therefore lower temperatures can sustain transmission on account of the existing 'parasite reservoir'. The effect of frost on vector populations is also important. Once minimum temperatures approach freezing, African vector populations are effectively obliterated (Leeson, 1931; De Meillon, 1934; Stuckenberg, 1969).

Studies of anopheline mosquitos have shown a close association between breeding site availability and precipitation (Sloof, 1961; Bouma, 1995). In addition, rainfall is intimately related to soil moisture status, an important factor in mosquito survival (Molineaux and Gramiccia, 1980). However, a significant lag can exist between a precipitation event and suitable soil moisture status being attained. It is possible for suitable vector breeding sites to occur in an area that has recorded a low (or nil) rainfall value for the current month on the strength of preceding precipitation events. Conversely, latent moisture levels are likely to be depressed during a month of average rainfall but preceded by low rainfall conditions. Several authors (Hay *et al.*, 1998; Patz *et al.*, 1998) have confirmed this 'lag-effect' by showing that preceding moisture condition is a good predictor of current malaria cases.

Our analysis of climatic profiles in both seasonal and stable malaria areas has revealed the need for a catalyst month (unpublished data). A month of highly suitable rainfall conditions is required to provide adequate vector breeding sites and regenerate the vector population.

Climate data

We utilised long-term mean monthly rainfall and temperature climate data as the basis for the seasonality model (Hutchinson *et al.*, 1995). The raster (composed of pixels) surfaces were based on weather station data from between 1920 to 1980 and have a spatial resolution of 5 x 5 km. The temperature data have standard errors of 0.5°C and monthly mean precipitation data have errors of 10-30%.

Computing the seasonality model

We used the geographical information system (GIS) IDRISI (version 32, Clark Laboratories, Clark University, Worcester, MA, USA) to compute the seasonality model. We adopted a 3-month preceding moving-average approach (e.g. the value of March is the average of January, February and March) for both temperature and rainfall inputs into the model to temporally smooth the data, eradicate sporadic fluctuations and account for the time lag between suitable climatic conditions and the occurrence of malaria. This approach also accounts for the need for temperature consistency by ensuring that near-suitable temperature conditions are maintained for three months before malaria-status will be assigned. Similarly, the approach allows rainfall from the previous two months to contribute to a more accurate moisture-status estimate in the current month.

We calculated a differential temperature cut-off across the entire continent of Africa that takes into account the annual variations in temperature (Table 7.1). At a consistent temperature of 19.5°C, the duration of the sporogonic cycle is 32 days with 4% of the total vector cohort surviving (Detinova, 1962). The other thresholds used to generate the seasonality model are given (Table 7.1). The thresholds are designed to delimit high-

probability malarious areas as the use of long-term mean data precludes the delimitation of occasional epidemic areas. All requirements (moving average temperature, minimum annual temperature and moving average rainfall and the presence of a catalyst month) had to be met for a pixel to be classed as malarious in a particular month. In areas where the climatic suitability thresholds predicted a one month transmission interruption (e.g. between two malaria seasons), the errant month was assigned transmission status on the strength of the climatic suitability of the bordering months and the existing parasite reservoir. This rule was applied irrespective of the climatic characteristics of the month.

Table 7.1: Criteria used to compute months suitable for malaria transmission in Africa.

Simulated effect	Variable	Threshold
Parasite development & vector survival	Moving average temperature	$\geq (19.5^{\circ}\text{ C} + \text{annual standard deviation of average monthly temperature})$
Frost	Minimum annual temperature	$\geq 5^{\circ}\text{ C}$
Availability of vector breeding sites	Moving average rainfall	$\geq 60\text{ mm}$
Catalyst Month	Moving average rainfall	At least one month $\geq 80\text{ mm}$
Parasite reservoir (also simulated by the differential temperature thresholds imposed across the continent)	1 month interruption in transmission (as predicted by climatic thresholds)	Automatically assigned transmission status

The final model was used to calculate the onset and completion month of the malaria season(s) and the total number of malarious months in an average climatic year. Isolated pixels predicted as having two malaria seasons were replaced with the majority transmission pattern of the surrounding pixels (isolated pixels of markedly different

transmission patterns to their neighbours are unlikely to exist in the real world and are of no value from a continental control perspective). The Idrisi macro used to calculate the seasonality model is given (Appendix 7).

Validation of the seasonality model

We compared our model against existing historical maps (South Africa, Zimbabwe, Botswana, Namibia, Kenya and Tanzania) to ascertain its accuracy in terms of raw distribution, transmission season length (Eastern Africa) and transmission intensity (using predicted number of suitable months as a proxy) (Southern Africa). The expert opinion maps for East Africa (Wilson, 1956; Nelson, 1959) were derived from knowledge of malaria transmission in populated areas and rainfall patterns in remote areas. Although the validity of the historical maps is questionable in certain instances, they nevertheless provide a reasonable comparison base. The Southern African maps are based on unpublished expert opinion from case data (Namibia and Zimbabwe), district level microscope-confirmed case data (Botswana) and historical maps (South Africa).

Analysis

2335 parasite ratio studies (of 328,325 children <10 years) conducted across Africa were collected from a variety of published and unpublished studies (Figure 7.1). The data were geo-referenced using the Africa Data Sampler (WRI, 1995) and other methods to match the study locations and extract the co-ordinates (MARA, 1998). We plotted the mean parasite ratio (weighted by total cohort size) against the predicted number of months suitable for transmission (as calculated by the seasonality model) and tested the statistical significance of the relationship.

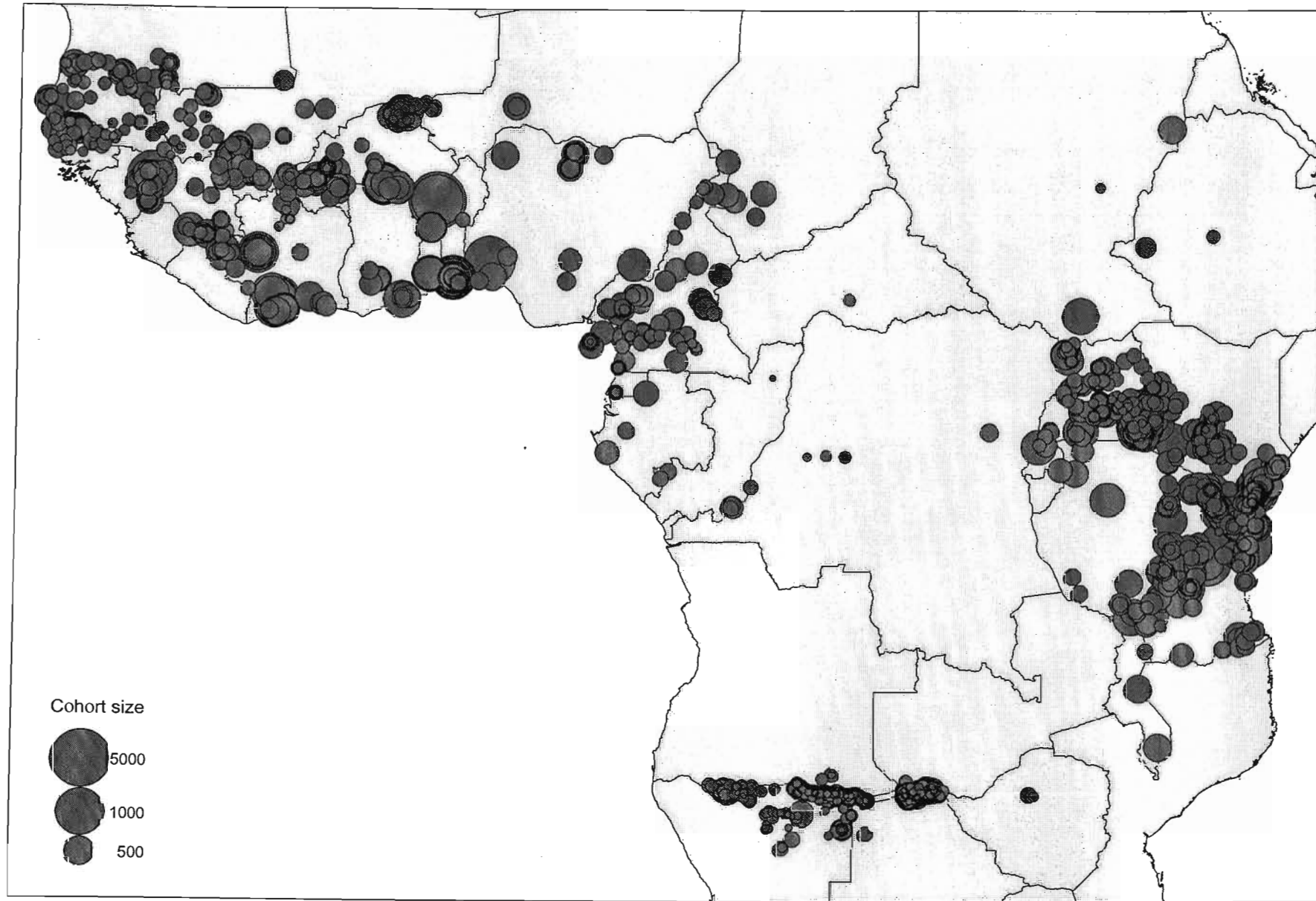


Figure 7.1: Geographical distribution and size of 2335 parasite ratio surveys (total of 328,325 children <10 years tested) across Africa. The diameter of the data point is logarithmically proportional to the cohort size.

Estimation of population exposure

We superimposed an interpolated population surface⁸ (Deichmann, 1996) on the seasonality maps to establish the total and childhood (0-4 years) population exposed to malaria in each length of season class. The paucity of accurate mortality data in different transmission settings mitigated against realistic mortality estimates.

The implications of climate change on malaria distribution and seasonality

The seasonality model provides a useful tool for evaluating the distributional and seasonality changes that will occur as a result of global warming. We recomputed the model using a simple 1°C and 3.5°C rise in average temperature (IPCC, 1996). We investigated the effects of such an increase on the distribution and length of transmission season of malaria as well as the concomitant increase in population exposure (assuming a static population) within different seasonality classes. The primary objective of this approach is to demonstrate the utility of the model in computing changes in exposure and distribution of the disease given a change in climate and not to give a definitive answer regarding the effect of global climatic scenarios on malaria. Clearly the effect of global warming is more complex than the scenario we have modelled but predicting the effects of complex global warming scenarios on malaria would constitute a valid study in its own right.

⁸ The population surface was interpolated using a spatial interaction model which incorporated information on the location and size of major towns, transport infrastructures and uninhabited areas. Overall, uncertainty in these population estimates is likely to be significant but remains within the usual error bounds associated with census figures for developing countries (Snow *et al.*, 1999a).

7.4 RESULTS

The predicted onset (Figure 7.2a) and completion (Figure 7.2b) of the malaria season(s), as calculated by our seasonality model is shown. It is important to distinguish between a bimodal transmission pattern and two discrete malaria transmission periods. Whereas a bimodal transmission pattern refers to the existence of two definite peaks in transmission intensity, our model shows those areas in which two complete breaks (≥ 2 months) in annual transmission exist. It is possible for a bimodal situation to exist within one complete transmission period (season). The reclassified image of transmission season length is shown (Figure 7.3).

A comparison between predicted transmission season length and historical maps is shown for Eastern and Southern Africa (Figure 7.4). Although there is clearly some category mismatch in Southern Africa, the resemblance is striking, both in terms of raw distribution, transmission season length (Eastern Africa) and season length as a proxy for transmission intensity (Southern Africa). We have omitted any occasionally epidemic categories from the historical maps, as comparison with our model, which uses long term climatic data, would be meaningless.

There was a significant relationship between mean parasite ratio and the log of transmission season length ($r^2=0.712$, $p=0.001$) (Figure 7.5). When the data are aggregated into weighted two monthly groups to increase sample size the fit of the regression is improved ($r^2=0.931$). We also performed a linear regression for comparative purposes. The relationship was not as significant ($r^2=0.651$, $p=0.004$) and is not as plausible biologically.

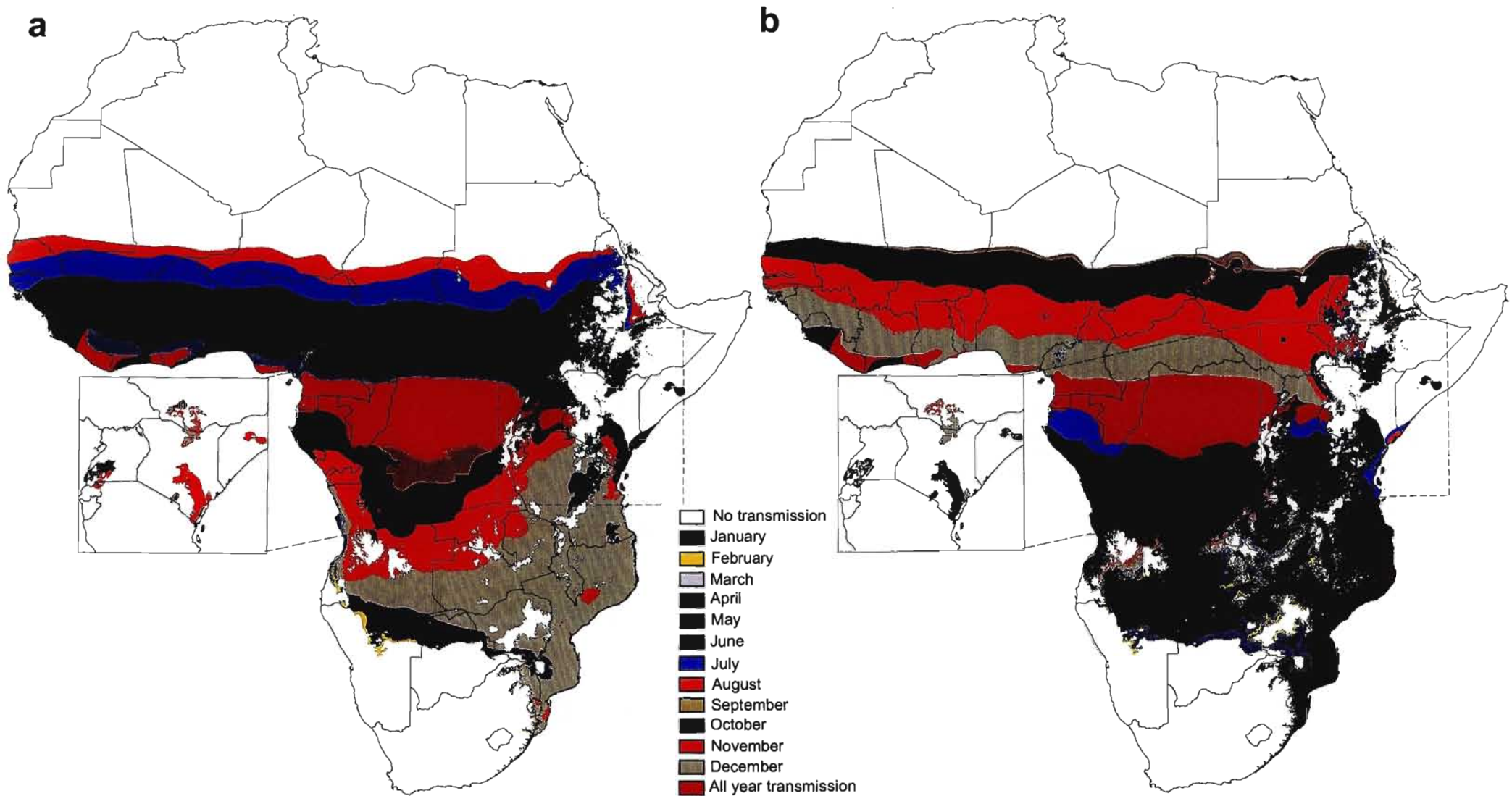


Figure 7.2: The onset month (a) and completion month (b) of the malaria transmission season(s) in Africa. The onset and completion month of areas characterised by two discrete malaria seasons (each malaria season bordered by transmission interruptions ≥ 2 months) are shown as insets. Isolated pixels predicted as having two malaria seasons were replaced with the majority transmission pattern of the surrounding pixels (as they are of no value from a continental control perspective).

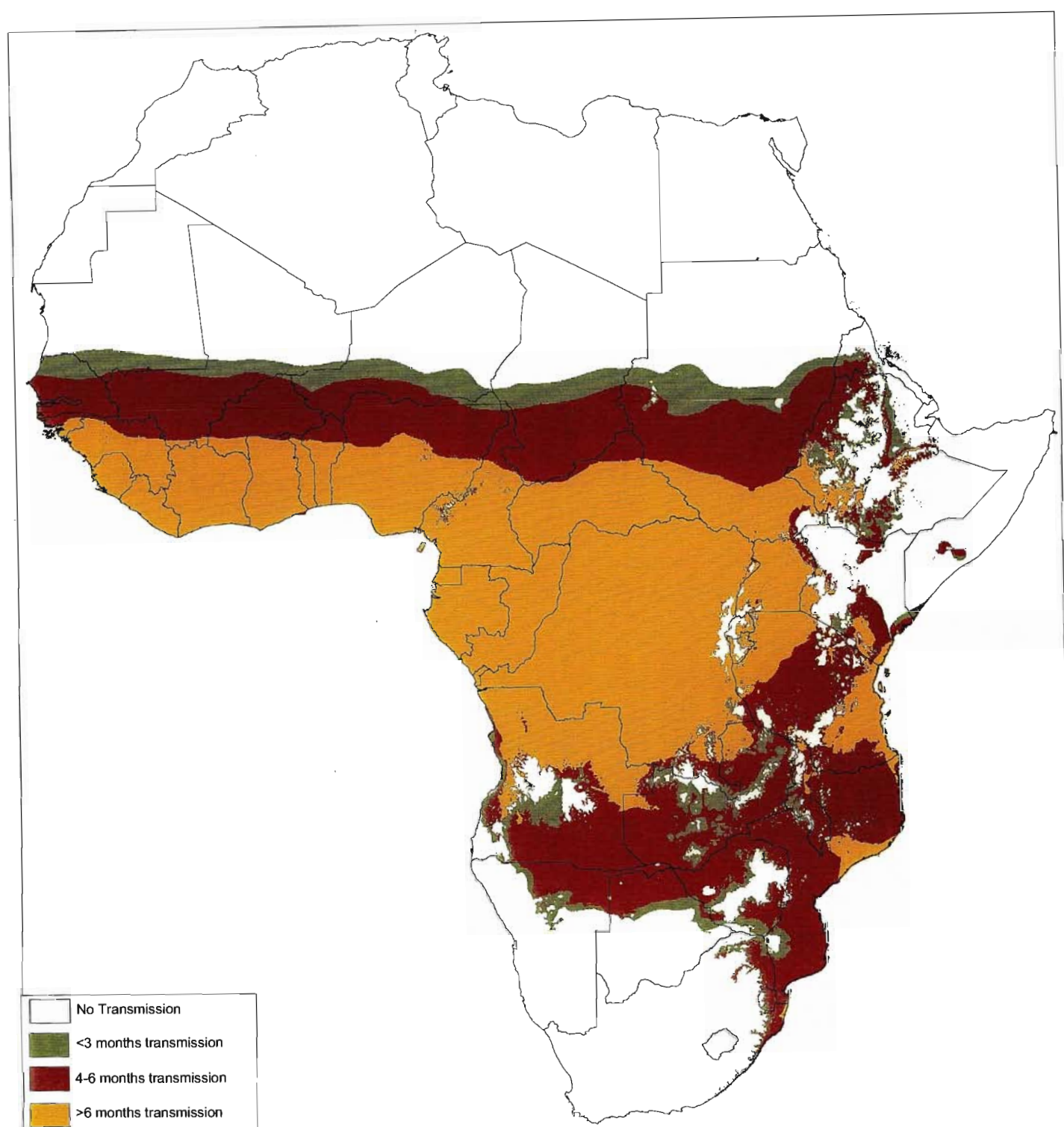


Figure 7.3: Predicted number of months suitable for malaria transmission in Africa.

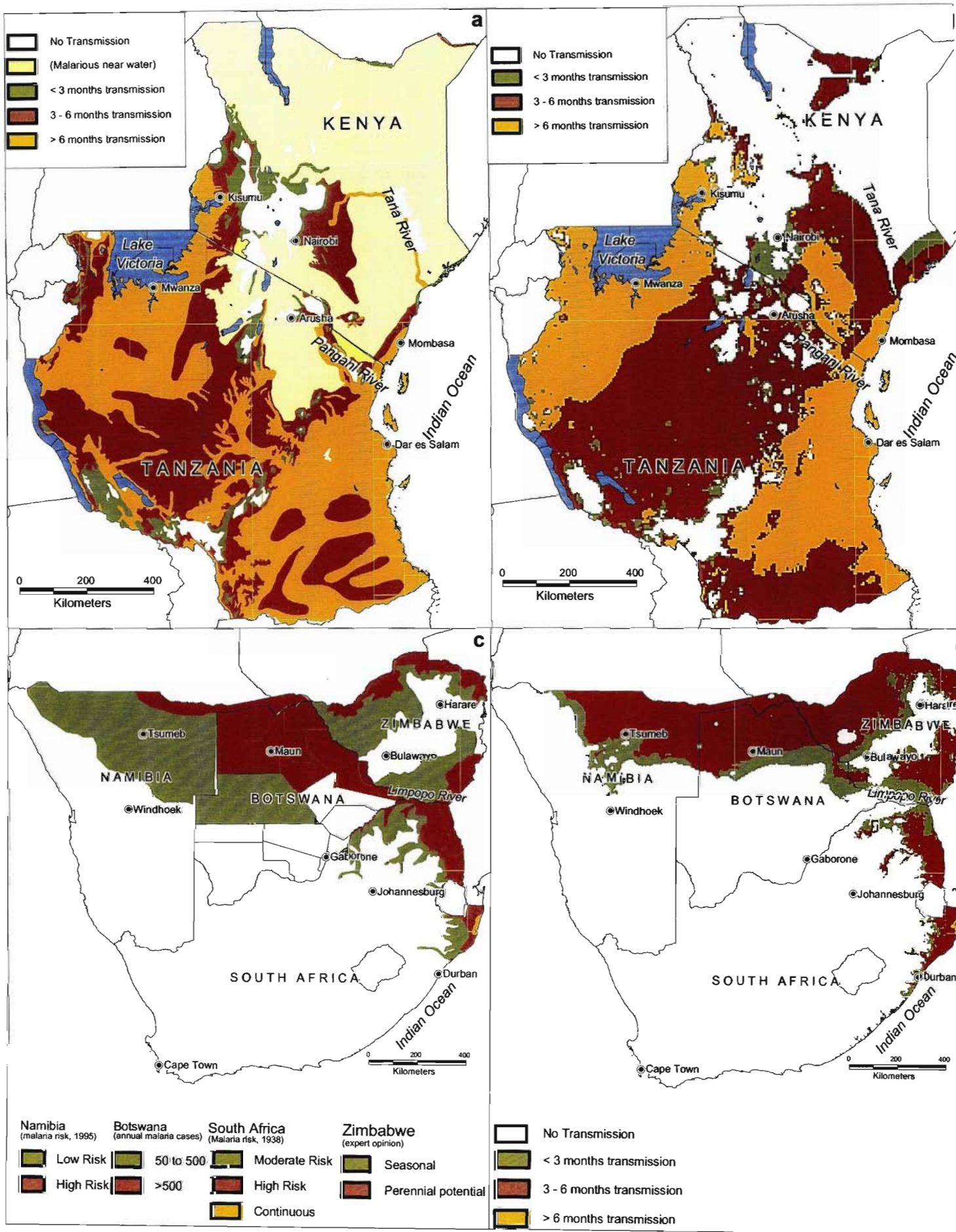


Figure 7.4: Comparison between the seasonality model (b & d) and historical maps and case data (a & c) for Eastern and Southern Africa.

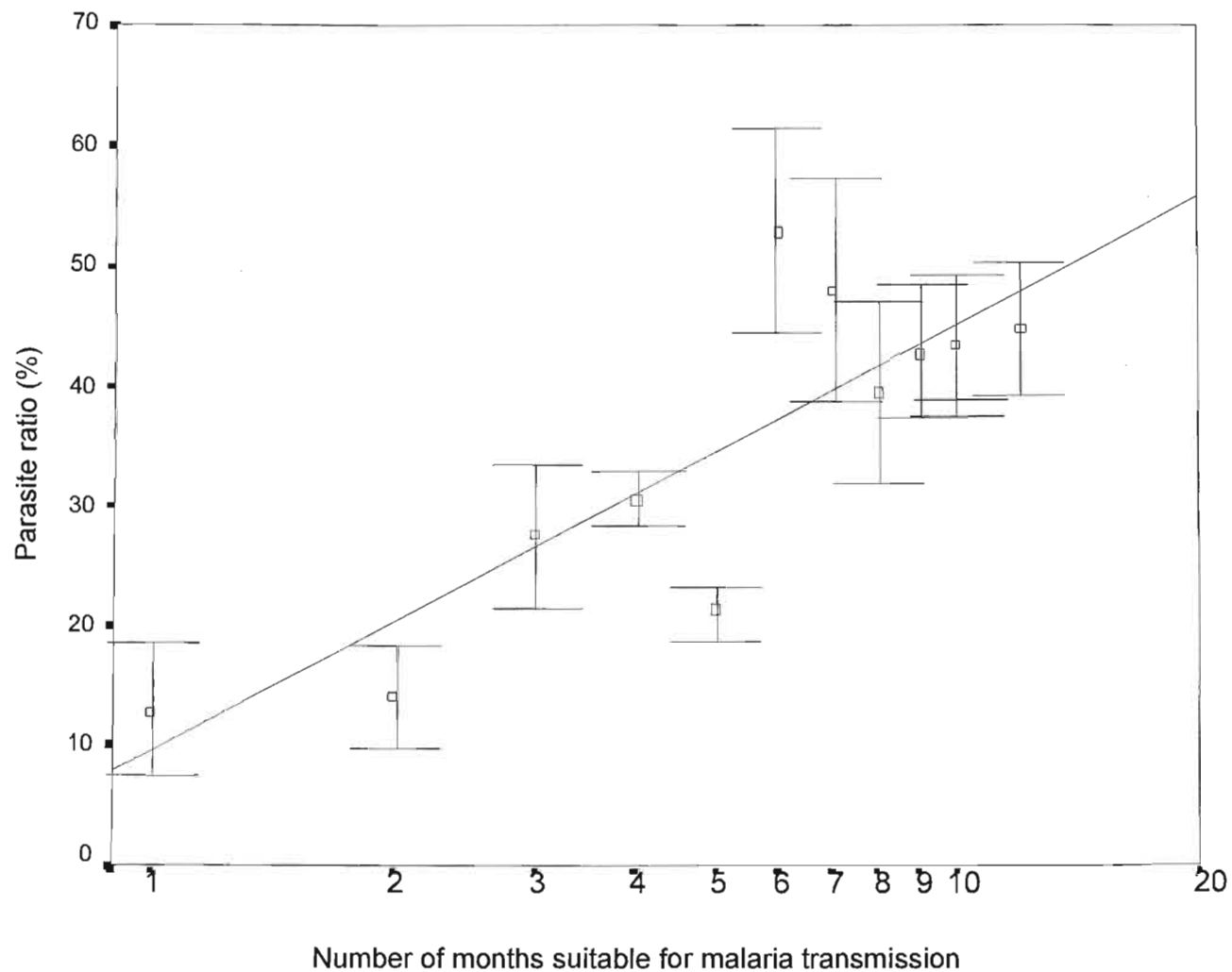


Figure 7.5: Mean parasite ratio (weighted by cohort size) from 2335 studies across Africa (total number children <10 years tested = 328,325) plotted against the log of predicted transmission season length ($r^2=0.712$, $p=0.001$). Two standard errors either side of the mean are shown.

The changes in distribution and length of season, following a 1°C and 3.5°C rise in average monthly temperature (IPCC, 1996) are shown (Figure 7.6). Selected populated centres in or close to affected areas are labelled. Areas depicted as having had ‘no change’ as a result of the temperature increase may still have shown an increase in season length *within* a class. Previously malaria-free, large highland cities such as Harare (Zimbabwe) would be affected by the temperature increase. Lack of immunity in these populations could lead to a high mortality rate in such areas.

The 1995 disease population exposure estimates in each of the seasonality categories (under current climatic conditions and after a global rise in average temperature) are shown (Table 7.2). During 1995, a 1°C and 3.5°C rise in average temperature would have resulted in an additional 25 million (6%) and 58 million (13%) people respectively being exposed to the disease. The global temperature increase would result in a decrease in the population exposed in the 1-3 month zone (although this is partly a function of our assumption that there will be no change in minimum annual temperature), thus, the overall mortality rate is likely to increase under such conditions.

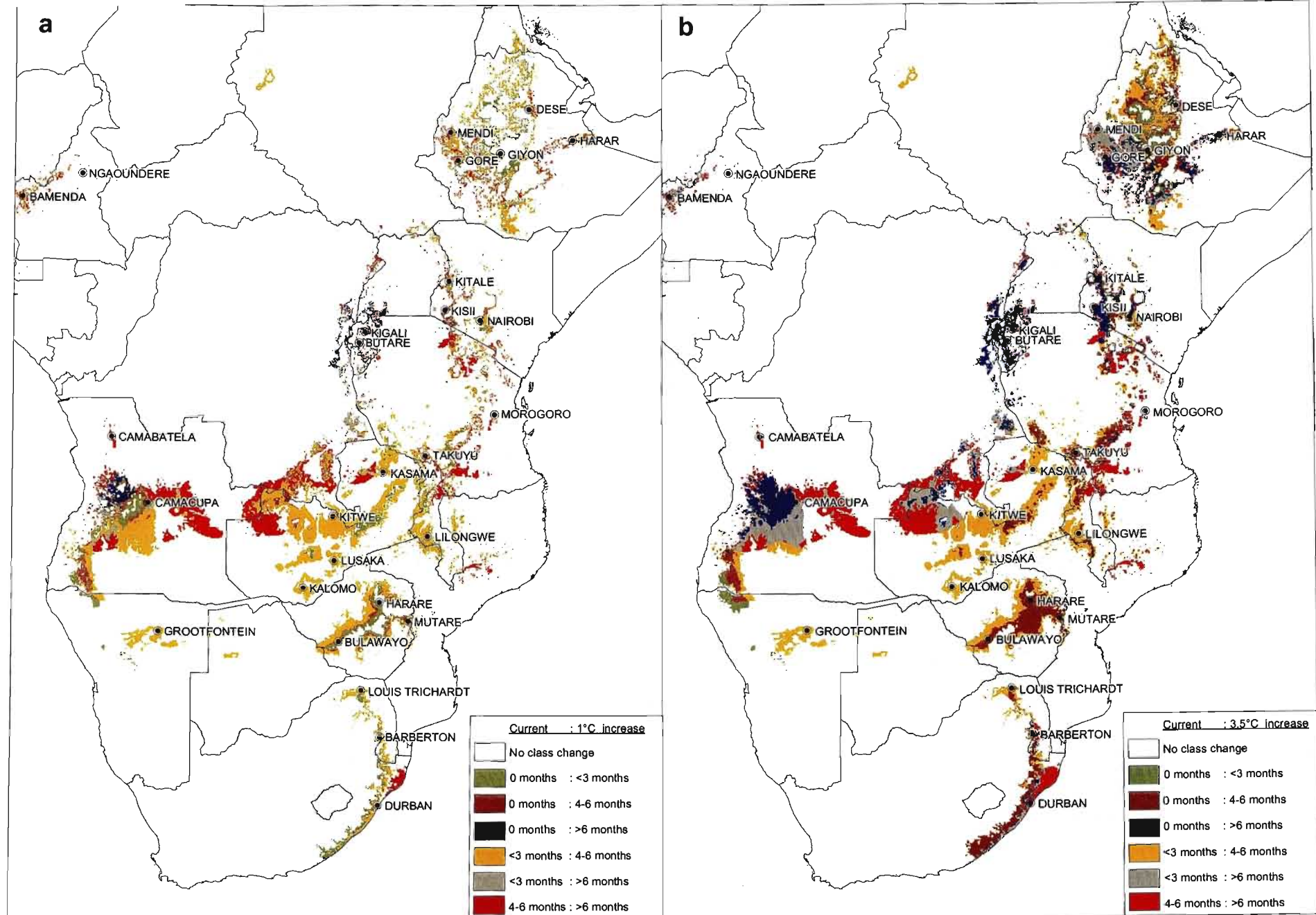


Figure 7.6: Changes in malaria distribution and length of transmission season associated with a 1°C (a) and 3.5°C (b) rise in average monthly temperature.

Table 7.2: Estimated total (childhood; 0-4 years) population (millions) exposed to malaria in Africa in 1995 under current climatic conditions and after a 1°C and 3.5°C rise in average temperature.

Length of transmission season	Current climatic conditions	1°C increase in monthly average temperature	3.5°C increase in monthly average temperature
< 3 months	45.79 (8.12)	38.82 (6.82)	25.40 (4.51)
4-6 months	154.08 (27.79)	170.09 (30.60)	180.34 (32.51)
> 6 months	238.16 (43.44)	254.02 (46.37)	290.10 (52.76)
Total	438.03 (79.35)	462.93 (83.79)	495.84 (89.78)

7.5 DISCUSSION

We have produced the first high-resolution model to estimate the onset, completion and length of malaria transmission season in Africa and related it to transmission intensity and population exposure at a large scale. Our model compared well with historical maps both in terms of raw distribution, predicted length of transmission season and predicted length of transmission season as a proxy for transmission intensity. We established a significant relationship between parasite ratio and length of transmission season ($p=0.001$). The model was extended to produce the first estimates within different seasonality classes of changes in distribution and population exposure associated with a global rise in average temperature. Assuming a median childhood mortality rate of 9.4 per 1000 per year, across the entire continent (Snow *et al.*, 1999b), the increase in average temperature would have lead to an approximate increase in childhood deaths from 746 000 (current conditions) to 788 000 (1°C increase) to 844 000 (3.5°C increase) during 1995.

Recently there have been a number of attempts at modelling the distribution and occurrence of malaria as well as a large amount of debate regarding the effect of global warming on malaria distribution (Reiter, 1998). Authors have estimated that by the latter half of the century, the percentage of people living within the potential malaria transmission zone will have increased from 45% to 60% given a 3°C rise in temperature (Martens *et al.*, 1995). Rogers and Randolph (2000) used a multivariate approach to estimate the impact of climate change (using global circulation models) on the global distribution of malaria. The authors estimated that by the year 2050 the difference in distribution of malaria to that of the present day would only be of the order of 1%. The study used low resolution data and used a crude expert opinion map to validate their model. Snow and colleagues performed a discriminant analysis on a combination of long-term climatic (temperature and rainfall) and the normalised difference vegetation index (NDVI) data to discriminate between three stable malaria endemicity categories (on the basis of childhood parasite prevalence) in Kenya (Snow *et al.*, 1998). The number of months of malaria risk in Kenya have been estimated by calculating the number of times a year a monthly fourier processed NDVI threshold was exceeded (Hay *et al.*, 1998). Common to both these studies was their limited applicability at a larger scale. A fuzzy classification of long-term temperature and rainfall data has however been used to model the probability of occurrence of malaria in sub-Saharan Africa (Craig *et al.*, 1999). The model showed a good resemblance to historical expert opinion maps.

In contrast to previous attempts at malaria seasonality modelling, our model is robust enough to be applied across the entire continent of Africa. We achieved this by applying a differential temperature threshold across the continent. In addition, we were able to

overcome a number of the disadvantages associated with static Boolean-type models (that do not make allowance for temporal interactions) by integrating temporal smoothing into the model (to account for the lag effect associated with soil moisture retention as well as the need for temperature consistency) and the need for a catalyst month. We extended the model to compute not only the transmission season length but also the onset and completion dates and related our model to parasite ratio data at a continental level. Our model uses all 12 months of data to produce the final result and does not only focus on fixed-length 'transmission windows'. Understanding of malaria seasonality is critical to the accurate prediction of the effects of global warming (McMichael *et al.*, 1996). Our model therefore provides a more robust and informative method of determining these changes than previous attempts.

Recent attempts at the modelling of malaria distribution have had to define zones (within which different rules are applied) to account for the continental discrepancies between malarious areas. For example, Craig and colleagues incorporated an artificial boundary (based on latitude) separating those areas where 3/5 months of suitable conditions were required to facilitate malaria transmission (Craig *et al.*, 1999). Using the same model to estimate burden of disease, Snow and colleagues defined a discontinuity (using country boundaries) where a fuzzy value of $\geq 0.2/\geq 0.5$ defined areas of stable *Plasmodium falciparum* transmission in stable/Southern African areas respectively (Snow *et al.*, 1999b). It is our belief that a smooth mathematically facilitated transition should be incorporated into such models as abrupt discontinuities do not exist in the real world.

The basis for our model is climatic, and in this regard it has some limitations. For example, areas adjacent to perennial water bodies may fail to meet the required monthly rainfall threshold, but may provide good vector breeding grounds. An example of such an area is the Limpopo valley (the border between South Africa and Zimbabwe). We make no attempt to take local demographic and socioeconomic circumstances into account nor make provision for the impact of malaria control on transmission intensity. In estimating the population exposure changes that are likely to occur as a result of a global temperature increase, we assume a static population distribution. This is unlikely to be the case as an increase in transmission intensity will cause population movements to malaria-free areas. Consequently, our 'population exposure' estimates are to be interpreted as 'potential' rather than 'actual'.

Parasite ratio is believed to be a crude approximation of transmission intensity (Metselaar and van Theil, 1959). However, the relationship between parasite ratio and the log of season length ($r^2=0.712$, $p=0.001$) yielded good results. There is likely to be some bias in parasite ratios on account of most surveys being carried out during high transmission months (this effect will be greatest in areas with a low number of months suitable for transmission). Although there was some scatter within each length of season class (on account of the small area and temporal variation) the results show that length of transmission season is an important variable in the prediction of transmission intensity. Our findings are in agreement with recent research that has shown a significant logarithmic relationship between Entomological inoculation rate (an accurate measure of transmission intensity) and parasite ratio (Beier *et al.*, 1999). Other factors that are not incorporated into

our model, such as the amount by which the climatic threshold value is regularly exceeded are also important in the prediction of transmission intensity.

Both the duration and the start and end of the malaria season(s) are important in informing malaria control efforts. The duration of the season will affect the dynamics of transmission with longer seasons allowing more intense transmission and higher levels of infection in the human population. Short duration exposure periods lend itself to a waning immune response and fatal outcomes. Duration of the transmission season is an important factor in informing suitable control strategies. For example, in an area with seven months of transmission, impregnation of insecticide treated bednets needs to be carried out just prior to the onset of the season and with a residual effect of at least seven months. In addition, it is often important to know not only the number of months of risk but also the timing. In the above example an area characterised by one malaria season of seven month duration would require a very different strategy from an area consisting of two distinct malaria seasons of four and three months respectively. Malaria control (in the form of residual spraying) is carried out in six countries in Southern Africa. Studies have shown that such control measures are only effective if one treatment is applied prior to the malaria season onset and has an effective residual life for the entire malaria season (Sharp and le Sueur, 1996). A continental temperature increase may therefore render such measures cost-ineffective in certain areas. There is a current trend towards the judicious use of pesticides and their application at the appropriate time. The seasonality model will help in the correct planning of such measures.

The global malaria strategy recently adopted by WHO recognised the need to improve understanding of how climate-related and other ecological factors affect the spread and severity of malaria (WHO, 1993). We believe that seasonality maps should form an integral component of this strategy. The seasonality model constitutes an important first step towards an estimate of continental intensity of transmission. Once a better understanding of global climate dynamics is achieved, the model provides a robust tool for determining the malaria distributional and seasonality changes that will occur in the face of complex global climatic change scenarios.

Chapter Eight:

Conclusions

The overall goal of this thesis was to demonstrate the potential of GIS to be an effective, relevant and powerful tool for health research and development in Africa. I have accomplished this through the achievement of the research objectives outlined in *chapter 1.4*. In this conclusion I review the major research findings and their implications for health policy and suggest some directions for future research. I then complete this chapter with some general conclusions regarding the status and future of GIS health research in Africa.

8.1 TUBERCULOSIS

I used GIS technology to document and quantify improved access to tuberculosis treatment through a community-based programme in the face of a tuberculosis epidemic (chapter 4). GIS effectively documented and quantified the impact of community-based tuberculosis treatment on physical access to treatment.

The results of the study suggest that GIS could have an important role to play in tuberculosis control programme management, service development, and research. In terms of planning and managing the service, GIS can assist in the planning of the number and distribution of the supervision points. Proximity of treatment is one important factor in promoting adherence to treatment. Further research will be needed to fully understand how important “reducing distance” is to “improving access to treatment”. Much remains to be

understood about tuberculosis transmission dynamics in developing countries (Wilkinson *et al.*, 1997) and GIS will be a useful addition to molecular techniques and conventional epidemiology, in elucidating transmission pathways, and clusters of multi-drug resistant cases for example.

8.2 HIV

I used GIS to produce quantifiable evidence of a relationship between proximity to roads and HIV prevalence (chapter 5). The mean distance from homesteads to a primary or secondary road in each clinic's distance catchment was strongly correlated with HIV prevalence. Further research is needed to better understand this relationship both at ecologic and individual levels, and to develop interventions to reduce the spread of HIV infection.

Although prevalence is high (and is rising rapidly) in all parts of Hlabisa the results indicate that prevention efforts might usefully be targeted in certain areas. It seems reasonable to suggest that HIV was introduced to the district through transport routes. There are a small number of well-defined transport nodes where the minibus taxis and bus services that operate in the area are based. It might be prudent to focus some of the limited human and financial resources that are available for prevention, at these sites. Furthermore, outreach efforts perhaps including clinics offering voluntary HIV counselling and testing and sexually transmitted disease treatment, sited at these transport nodes might be considered. It seems likely that the type of traffic carried by different roads, its volume, and whether it stops or not, are factors which might influence the relationship between proximity and HIV that has been described. Future research should incorporate traffic

count, and traffic type, data into GIS models to improve predictions. GIS has been a powerful tool to display and to start to analyse reasons for HIV heterogeneity in Hlabisa, further supporting its potentially important role in the study of the spread of infectious diseases in Africa.

8.3 MALARIA

I produced the first malaria seasonality (length, start and end of transmission season(s)) model for Africa using high-resolution long-term rainfall and temperature data within a GIS (chapter 7). The variable temperature threshold (that took into account annual temperature variations) used in the model was a significant improvement on earlier malaria modelling work. The seasonality model corresponded well with historical expert opinion maps and case data. A significant logarithmic relationship was detected between predicted length of transmission season and parasite ratio in studies conducted on children < 10 years of age across Africa. Although there was some scatter within each length of season class (on account of the small area and temporal variation) the results showed that length of transmission season is an important variable in the prediction of transmission intensity. The findings are in agreement with recent research that has shown a significant logarithmic relationship between entomological inoculation rate (an accurate measure of transmission intensity) and parasite ratio (Beier *et al.*, 1999). The research is the first to correlate actual malaria survey data with model predictions at a continental scale. I related the model to population data and estimated population exposure in a variety of transmission settings. I recomputed the model to estimate the potential temporal, spatial and population exposure changes in the disease likely to occur under simple global warming scenarios.

Knowledge of both the duration and the start and end of the malaria season(s) are important in informing malaria control efforts. The duration of the season will affect the dynamics of transmission with longer seasons allowing more intense transmission and higher levels of infection in the human population. Short duration exposure periods lends itself to a waning immune response and fatal outcomes. Duration of the transmission season is an important factor in informing suitable control strategies. For example, in an area with seven months of transmission, impregnation of insecticide treated bednets needs to be carried out just prior to the onset of the season and with a residual effect of a least seven months. In addition, it is often important to know not only the number of months of risk but also the timing. In the above example an area characterised by one malaria season of seven month duration would require a very different strategy to an area consisting of two distinct malaria seasons of four and three months respectively.

Malaria control (in the form of residual spraying) is carried out in six countries in Southern Africa. Studies have shown that such control measures are only effective if one treatment is applied prior to the malaria season onset and has an effective residual life for the entire malaria season (Sharp and le Sueur, 1996). A continental temperature increase may therefore render such measures cost-ineffective in certain areas. There is a current trend towards the judicious use of pesticides and their application at the appropriate time. The seasonality model will help in the correct planning of such measures. The model constitutes a repeatable, rational and transparent product that can inform current malaria control strategies and provide a framework to plan future control measures in the face of global climatic change. It also represents an important first step towards a continental estimate of intensity of transmission. The model has been disseminated in hard copy form

to a number of Ministries of Health throughout the continent. Feedback so far has been extremely positive. There is a possibility that the model could be improved on by incorporating satellite-derived indices of moisture status (e.g. the normalised difference vegetation index (NDVI)). However, indices such as the NDVI are not without caveats (Tanser and Palmer, 1999). The chapter showed GIS to be a powerful tool for identifying infectious disease ‘suitability windows’ and evaluating ‘what if’ scenarios.

8.4 HEALTH SYSTEMS

My investigation of large-scale usage patterns of multiple primary health care services across an integrated health unit was the first to be undertaken in Africa (chapter 3). I presented new approaches to the spatial analysis of primary health care usage patterns. This included the development of the distance usage index (DUI) which is a composite spatial measure of facility usage in relation to the size of facility’s distance-defined catchment. The DUI proved to be a powerful and informative composite measure of clinic usage and can contribute significantly to health provision and resource allocation in Africa. The results showed that in a rural South African setting, mode clinic usage patterns can be predicted with a strong degree of accuracy using proximity to clinic and that there is a logarithmic decline in usage with increasing distance from a clinic. This is an exceedingly useful finding for health planning. It is unclear whether these findings are applicable to other settings in the developing world.

Geographically stratified sampling techniques of small populations can be employed by the health services to facilitate calculation of the indices. Alternatively, patients attending clinics over a specified time period could be geo-located. This method would ensure that

the sample was weighted by frequency of clinic attendance as well as geographic distribution. Health managers should strive towards DUI values close to 100% at all health facilities. Clinics exhibiting low DUI values should be further investigated to determine whether quality of service differs from other clinics or whether the differences are merely a function of physical accessibility. There are more data required for successful health planning than spatial indices alone can provide and they should be combined with demographic profiles and detailed health-seeking behaviour data. Future research should focus on the calculation of the DUI in different settings and stratified at an individual level, by age, sex and diagnosis. The indices should be weighted by frequency of clinic attendances. There is likely to be an increase in the indices with the shift from a homestead to an individual level as more deviant usage behaviour is revealed. The indices could be improved by the construction of polygons which incorporate other factors affecting physical accessibility (e.g. public transport access) into their boundaries.

In chapter six I presented a methodology that has numerous applications to health systems provision in developing countries. Limited physical access to primary health care is a major factor contributing to the poor health of populations and walking is often the primary mode of transport. An accessibility model was used to predict average inter-homestead walking times and subdivide the study area into units of equal completion time. The methodology could be extended to ergonomically design home-based care and tuberculosis directly observed treatment (DOT) programmes and inform the siting of health facilities.

The methodologies employed in this thesis suggest that GIS could have a significant role to play in the analysis and improvement of health systems in Africa.

8.5 GENERAL CONCLUSIONS

I used GIS to analyse primary health care patterns, measure patient access to tuberculosis treatment, quantify a relationship between HIV prevalence and proximity to transport networks, equitably distribute fieldworker workload in a large rural health survey and produce a continental model of malaria seasonality. The diversity of the research undertaken and the results obtained demonstrate the considerable promise of GIS as a research and planning tool and for providing a basis for intervention in infectious diseases in Africa.

Africa is generally held to be in crisis and the quality of life for the majority of the continent's inhabitants has been declining in both relative and absolute terms (World Bank, 2000b). The health problems are different to those in the developed world and if GIS is to be used for the health challenges facing Africa, then it must respond to these realities and priorities. Due to infrastructural and cost constraints, there is a lack of reliable statistics and disease reporting in Africa. Where data do exist, they tend to be clinically (as opposed to diagnostically) based. Disease estimates in Africa can therefore range between educated guesses and wild speculation (Snow *et al.*, 1999b). GIS can help significantly in this area by filling the gaps through empirical disease modelling techniques.

GIS trends relevant to Africa

GIS is largely technologically (as opposed to research) driven. Some of these global technological trends are irrelevant to health research in Africa at the present time.

However, some global trends (both technological and non-technological) are of significant relevance to Africa's health crisis.

There has been significant debate regarding the definition of GIS a tool versus a science (Goodchild, 1992; Wright et al., 1997). This is due in part to the wide range of possible applications of GIS as well as the lack of agreement about what exactly constitutes a science. It is my view that although GIS started out as a technological tool, it is rapidly evolving into a science in its own right, albeit in embryonic form. At present it lies somewhere along the continuum between the two. As software becomes increasingly powerful and new datasets become available and GIS is increasingly used to understand and forecast the dynamics of (particularly environmental) disease, this evolution is likely to continue. A parallel exists between GIS and epidemiology. In the same way that epidemiology is only recently evolving into a science in its own right (Rothman, 1986), GIS is beginning to be recognised as a science. Like epidemiology its tenets have been established piecemeal (Rothman, 1986) with contributions coming from a number of different disciplines, in particular the earth sciences. It is now time to draw the different facets of GIS together under the umbrella of geographic information science.

Computer hardware is becoming increasingly cheaper and more powerful, so that even complex analyses of GIS and image data can be carried out on a desktop computer. At the same time, commercial software has been developed into stand-alone solutions capable of performing increasingly complex tasks through increasingly user-friendly interfaces. Whilst there is an increasing amount of free software, the commercially available comprehensive packages remain expensive (Clarke *et al.*, 1996).

Since the 1st May 2000 the accuracy of off-the-shelf global positioning systems (GPS) has improved by an order of magnitude. Low cost units can now perform tasks that they

previously weren't suitable for. This development is likely to result in a sharp increase in the number of geo-referenced health projects making use of GPS technology in the near future.

Obstacles to the advancement of GIS in health in Africa

The paucity of qualified staff, which has prevented many GIS projects from surviving the donor involvement phase, is a major problem in Africa (Taylor, 1991). GIS applications in Africa are often found to be initiatives funded or supported by international aid agencies and many are pilot or research projects as opposed to operational systems. They also tend to be controlled by outsiders, not by African scientists (Nijkamp and De Jong, 1987). If GIS are to be useful and effective, then they must be introduced by local scientists who understand both the technological and the socio-economic context in which the systems are to operate. Training creates capacity and leads to an increase in needs in terms of data needs. It however also provides the capacity to fulfill these needs and the new products that result are often of value to many other sectors. Capacity development of African staff should therefore be prioritised.

In addition to lack of capacity, a lack of suitable GIS data sets is a major impediment to the growth of GIS in Africa. The access to spatial data (which are fundamental to any GIS application) continues to be difficult and expensive (Briggs and Elliot, 1995). This is not specific to health but to all sectors that utilise GIS. There are similarities in the field requirements for using GIS between forestry, ecology, archeology and epidemiology that could provide substantial benefits by the sharing of experiences and the pooling of resources (Clarke *et al.*, 1996). However, much of the spatial data collection efforts within

Africa have been conducted in a decentralised and uncoordinated manner. Inter-sectoral collaboration initiatives should therefore be encouraged and receive funding priority.

African data sets used in this research include the African data sampler (WRI, 1995), long-term rainfall and temperature (Hutchinson *et al.*, 1995) and population data (Deichmann, 1996). In addition to these, a large number of remotely sensed data sets, which have been already used extensively in health are available free of charge or at nominal cost.

Development of such data sets are of paramount importance to ensure the growth of all sectors of GIS in Africa. With the emergence of new technologies and techniques within remote sensing, there is likely to be a great improvement in the quality of such data sets and parallel improvement of GIS and related research products (Hay *et al.*, 2000b).

Nevertheless, it is also true to say that so far, our ability to extract meaning and make useful decisions from remotely-sensed data has not kept pace with the developments in this field.

Further development is needed in the creation of digital data sets, for example, the digitalisation of 1:250 000 and 1: 50 000 cartographic maps for countries that have them should be a priority. Similarly, national geo-referenced health facility databases should be established. Widespread availability of small scale digital data (< 1: 50 000) for many countries within Africa is unlikely to ever become a reality. The most cost-effective and appropriate method to examine disease patterns at small scales is the establishment of geo-referenced sentinel surveillance sites (such as the Hlabisa demographic surveillance system). This will enable the elucidation of small-scale disease patterns (e.g. diffusion dynamics) that could be modelled using coarser resolution data and the coverage extended.

For example, the HIV heterogeneity exposed across the Hlabisa district (chapter five) will be examined at a much higher resolution using the surveillance system.

The issue of scale is one that is poorly understood in the disease arena. Diseases patterns and processes evident at one scale are not necessarily evident at another. Moreover, correlations between explanatory variables and outcomes may even be (seemingly) reversed at different scales. This has led to a significant amount of confusion when hypotheses are rejected at one scale and not at another. Sometimes it is advisable to use coarser resolution data to mask out small scale heterogeneity. For example, the malaria seasonality component of this thesis was conducted using 5km resolution data. Higher resolution satellite data (sub kilometre) may obscure continental malaria patterns by exposing unnecessary small area variation. Ideally the resolution of the data should be driven by the application. However, given Africa's geographic data deficits, future research is needed to establish how applicable coarse resolution data sets are to modelling high resolution disease-specific dynamics and vice-versa. The above issues are as applicable to temporal resolution as they are to spatial resolution.

Another obstacle remaining to the growth of GIS in health in Africa is to convince role players (often from cash-strapped organisations) of the potential uses and cost-effectiveness of GIS in the health arena. GIS cost/benefit analyses within different organisations have demonstrated that at the very least the technology gives a full return on the investment (benefit/cost ratio = 1:1), but when extensively used has given a large return on the investment (benefit/cost ratio = 7:1) (Korte, 1996). Even amongst the international scientific community, significant scepticism still exists surrounding the use of GIS

technology in health. This problem will diminish in size as GIS continues to evolve. The parallel with epidemiology again warrants mentioning: In the same way that scepticism greeted epidemiologists who hypothesised that a relationship existed between smoking and lung cancer in the 1950s (Rothman, 1986), so too will scepticism continue to plague GIS until it is firmly established as a science.

The 'mapping malaria risk in Africa' (MARA) research collaboration is an African research endeavour that makes extensive use of GIS technology. The collaboration has been highly successful in collating malaria data from around the continent, and producing a large number of scientific publications on a limited budget. The collaboration overcame significant data deficits by creating its own base data sets and created a significant amount of GIS capacity in its five regional centres throughout the continent. During the setting up of the collaboration, significant scepticism was expressed by influential malaria scientists as to the ultimate value of a GIS approach, its logistical feasibility and cost effectiveness (Le Sueur, 1998). The collaboration is a testament to the fact that successful GIS initiatives can be undertaken in Africa.

Viable GIS health applications in Africa

The current software and hardware trends in combination with the realities faced in Africa have given rise to essentially, two broad categories of long-term feasible GIS health applications in Africa. The outputs of the categories will inform one another and are not mutually exclusive and may overlap. The first category involves the use of GIS as a research tool. These applications should seek to provide new insights into the spatial dimensions of disease and new methodologies to more cost-effectively allocate resources

to health services. These types of applications will normally use high-end systems with significant analytical functionality and will usually involve a significant amount of additional data collection. An example of such an application is the equitable distribution of fieldworker workload methodology (chapter six).

The second category of long-term viable GIS application concerns the use of GIS as a health planning and management tool and for exploratory data analysis. Generally speaking this kind of system will involve a low-end GIS. The primary goal of such a system will be to simply display and overlay basic health data concerning both health care facilities and disease patterns. These systems (normally vector-based) permit rapid manipulations of spatial data and display of the results so that the decision maker can use them for policy decisions. A further step could involve limited spatial queries and analysis such as buffering. The display of tuberculosis directly observed treatment supervisors and the number of associated patients (chapter four), for example would be a useful tool for the programme manager.

The outputs of the different categories of application will inform one another. As the data is geographically displayed using a management GIS and research questions are derived, collaborations can be initiated with institutions undertaking GIS research to test hypotheses and model disease distributions. Similarly, research GIS applications will inform GIS management applications. For example a variant of the workload distribution model (chapter six), calculation of the distance usage index (chapter three) and malaria seasonality model (chapter seven) could be instituted on management GIS systems to inform optimal resource allocation and intervention strategies respectively.

The nature of Africa's disease burden

The results of the case-studies in this thesis combined with the review of the health literature in Africa revealed the GIS bias towards so called 'environmental' diseases. In certain diseases, such as the vector borne diseases (e.g. malaria, schistosomiasis, human helminth infections and trypanosomiasis) the environmental component in the determination of factors such as transmission intensity is extremely high. In other diseases, especially in the non-communicable category (e.g. multiple sclerosis) links to the environment are weak or non-existent. Some infectious diseases such as HIV and tuberculosis have moderately strong links to the environment. Not only does Africa have the highest burden of disease of all the continents (WHO, 2000), but it is the continent in which the greatest component of the burden is contributed by so called 'environmentally dependent' diseases. In addition, the phenomenon of climate change is likely to hit hardest in Africa (World Bank, 2000b) on account of its greater rainfall variability and the proportion of 'ecothermic infectious diseases'. This makes the potential applications of GIS in health particularly relevant to Africa, i.e. GIS in health has greater relevance and inherent potential in Africa than it does in the United States or Europe for example. Unfortunately, this reality is not reflected in the literature or in practice. Thus there exists a continuum of diseases, on the one end there are those diseases in which GIS has little or no application and on the other there are those in which GIS is highly applicable. This continuum does not relate to the availability of ancillary data sets but rather to the inherent nature of the disease itself.

The ability to map spatial and temporal variation in disease risk is more important than ever given the ever-increasing disease burden in Africa. GIS allows the planning of control

strategies and the delivering of interventions where the need is greatest, and sustainable success is most likely. This thesis has demonstrated that despite some obstacles, GIS holds considerable promise for health research and development in Africa. The global trend towards faster, more powerful computers, user-friendly software and falling prices combined with the magnitude and nature of Africa's disease burden and lack of reliable disease statistics makes it a viable, relevant and powerful technology for health research and management in Africa.

References

- Abdool Karim Q, Abdool Karim SS, Abdool Karim BS, Short R and Ngxongo S (1992) Seroprevalence of HIV infection in rural South Africa. *Aids* (6), 1535-1539.
- Airey T (1992) The impact of road construction on the spatial characteristics of hospital utilization in the Meru district of Kenya. *Soc Sci Med* 34 (10), 1135-46.
- Ali M, de Francisco A, Khan M, Chakraborty J and Myaux J (1999) Factors affecting the performance of family planning workers: importance of geographical information systems in empirical analysis. *Int J Pop Geog* 5 (1), 19-29.
- Amat-Roze JM (1993) Geographic inequalities in HIV infection and AIDS in sub-Saharan Africa. *Soc Sci Med* 36 (10), 1247-56.
- Anderson J, Maclean M and Davies C (1996) *Malaria research. An audit of international activity*. Wellcome Trust Publishing, London
- Ardö J and Pilesjö P (1992) On the accuracy of the global positioning system - A test using a hand-held receiver. *International Journal of Remote Sensing* 13 (16), 3229-3233.
- Bailey T (1994) A review of statistical spatial analysis in geographical information systems. In: Fotheringham S and Rogerson P (Editors), *Spatial analysis and GIS*. Taylor and Francis, London, 13-44.
- Bayer R and Wilkinson D (1995) Directly observed therapy for tuberculosis: history of an idea. *Lancet* 345 (8964), 1545-8.
- Bedard J and LaPointe G (1987) The estimation of dry green biomass in hayfields from canopy spectroreflectance measurements. *Grass Forage Science* 1 (42), 73-78.
- Beier JC, Killeen GF and Githure JI (1999) Short report: entomologic inoculation rates and *Plasmodium falciparum* malaria prevalence in Africa. *Am J Trop Med Hyg* 61 (1), 109-13.
- Beyers N, Gie RP, Zietsman HL, Kunneke M, Hauman J, Tatley M and Donald PR (1996) The use of a geographical information system (GIS) to evaluate the distribution of tuberculosis in a high-incidence community. *S Afr Med J* 86 (1), 40-1, 44.
- Bishai WR, Graham NM, Harrington S, Pope DS, Hooper N, Astemborski J, Sheely L, Vlahov D, Glass GE and Chaisson RE (1998) Molecular and geographic patterns of tuberculosis transmission after 15 years of directly observed therapy. *Jama* 280 (19), 1679-84.
- Bouma MJ (1995) *Epidemiology and control of malaria in Northern Pakistan, reference to the Afgan refugees , climate change and the El Nino Sourthern Oscillation*, PhD Thesis, Leiden University, Leiden, Netherlands.
- Briggs DJ and Elliott P (1995) The use of geographical information systems in studies on environment and health. *World Health Stat Q* 48 (2), 85-94.

- Brown KS (1997) Scientific journal editors say polished prose clarifies research. *The Scientist* **11** (2), 16.
- Bruce-Chwatt LJ (1999) *Essential Malariology*. Arnold, London
- Bullen N, Moon G and Jones K (1996) Defining localities for health planning: a GIS approach. *Soc Sci Med* **42** (6), 801-16.
- Chadee DD and Kitron U (1999) Spatial and temporal patterns of imported malaria cases and local transmission in Trinidad. *Am J Trop Med Hyg* **61** (4), 513-7.
- Charlwood JD and Bryan JH (1987) A mark-recapture experiment with the filariasis vector *Anopheles punctulatus* in Papua New Guinea. *Ann Trop Med Parasitol* **81** (4), 429-36.
- Clarke KC (1995) *Analytical and computer cartography*. Prentice Hall, New Jersey
- Clarke KC, McLafferty SL and Tempalski BJ (1996) On epidemiology and geographic information systems: a review and discussion of future directions. *Emerg Infect Dis* **2** (2), 85-92.
- Cliff A and Haggett P (1988) *Atlas of disease distribution, analytic approaches of epidemiological data*. Basil Blackwell Ltd, Oxford
- Coetzee M, Craig M and le Sueur D (2000) Distribution of African malaria mosquitoes belonging to the *Anopheles gambiae* complex. *Parasitol Today* **16** (2), 74-7.
- Coleman RL and Wilkinson D (1997) Increasing HIV prevalence in a rural district of South Africa from 1992 through 1995. *J Acquir Immune Defic Syndr Hum Retrovirol* **16** (1), 50-3.
- Colvin M, Abdool Karim SS and Wilkinson D (1995) Migration and AIDS. *Lancet* **346** (8985), 1303-4.
- Cracknell AP (1997) *The Advanced Very High Resolution Radiometer*. Taylor & Francis, London
- Craig MH, Snow RW and le Sueur D (1999) A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitol Today* **15** (3), 105-11.
- Davies GR, Connolly C, Sturm AW, McAdam KP and Wilkinson D (1999) Twice-weekly, directly observed treatment for HIV-infected and uninfected tuberculosis patients: cohort study in rural South Africa. *Aids* **13** (7), 811-7.
- De Cock KM, Soro B, Coulibaly IM and Lucas SB (1992) Tuberculosis and HIV infection in sub-Saharan Africa. *Jama* **268** (12), 1581-7.
- De Meillon B (1934) Observations on *Anopheles funestus* and *Anopheles gambiae* in the Transvaal. *Publications of the South African Institute Medical Research* (6), 195.
- De Savigny D, Arsenault L and Wijeyaratne P (1995) Preface. In: De Savigny D and Wijeyaratne P (Editors), *GIS for health and the environment*. IDRC, Ottawa, v-vi.

- Deichmann U (1996) *Africa population database*. National Centre for Geographic Information and Analysis and United Nations Environment Programme, World Resources Institute, <http://grid2.cr.usgs>
- Deichmann U (1997) *Accessibility indicators in GIS*. United Nations Statistics Division, New York.
- Department of National Health (1996) Sixth National HIV survey of women attending antenatal clinics of the public health services in the Republic of South Africa, October 1995. *Epidemiol Comm* (26), 3-18.
- Detinova TS (1962) *in Age Grouping Methods in Diptera of Medical Importance, with Special Reference to Some Vectors of Malaria*. World Health Organisation, pp. 120-150.
- Eastman JR (1997) *Idrisi . Version 2.0*. Clark University, Worcester
- Egunjobi L (1983) Factors influencing choice of hospitals: a case study of the northern part of Oyo State, Nigeria. *Soc Sci Med* **17** (9), 585-9.
- Fiedler JL (1981) A review of the literature on access and utilization of medical care with special emphasis on rural primary care. *Soc Sci Med* **15** (3), 129-42.
- Floyd K, Reid RA, Wilkinson D and Gilks CF (1999) Admission trends in a rural South African hospital during the early years of the HIV epidemic. *Jama* **282** (11), 1087-91.
- Fortney J, Rost K, Zhang M and Warren J (1999) The impact of geographic accessibility on the intensity and quality of depression treatment. *Med Care* **37** (9), 884-893.
- Gatrell A and Bailey T (1995) *Can GIS be made to sing and dance to an epidemiological tune?*, International Symposium on Computer Mapping Tampa, FL.
- Gesler W (1986) The uses of spatial analysis in medical geography: a review. *Soc Sci Med* **23** (10), 963-73.
- Goodchild M (1992) Geographical information science. *Int J GIS* **6** (1).
- Graff P (1994) Tuberculosis in high prevalence countries. In: Davies P (Editor), *Clinical Tuberculosis*. Chapman Hall, London, 325-329.
- Habib OS and Vaughan JP (1986) The determinants of health services utilization in southern Iraq: a household interview survey. *Int J Epidemiol* **15** (3), 395-403.
- Hay SI, Snow RW and Rogers DJ (1998) Predicting malaria seasons in Kenya using multitemporal meteorological satellite sensor data. *Trans R Soc Trop Med Hyg* **92** (1), 12-20.
- Hay SI, Omumbo JA, Craig MH and Snow RW (2000a) Earth observation, geographic information systems and Plasmodium falciparum malaria in sub-Saharan Africa. *Adv Parasitol* **47** 173-215.
- Hay SI, Randolph SE and Rogers DJ (2000b) *Remote sensing and geographical information systems in epidemiology*. Academic Press, London

- Hightower AW, Ombok M, Otieno R, Odhiambo R, Oloo AJ, Lal AA, Nahlen BL and Hawley WA (1998) A geographic information system applied to a malaria field study in western Kenya. *Am J Trop Med Hyg* **58** (3), 266-72.
- Hosegood V (1998) *The Hlabisa DSS pilot study - Results from the household composition exercise*. Africa Centre for Population Studies and Reproductive Health, Mtubatuba
- Hutchinson MF, Nix HA, McMahan JP and Ord KD (1995) *Africa - A topographic and climatic database, CD-ROM (1)*. Centre for Resource and Environmental Studies, Australian National University.
- IPCC (1996) *climate change 1995. The science of climate change*. Contribution of Working Group I to the second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, New York
- Jetten TH, Martens WJ and Takken W (1996) Model stimulations to estimate malaria risk under climate change. *J Med Entomol* **33** (3), 361-71.
- Jolly R and King M (1966) The organisation of health services. In: King M (Editor), *Medical Care in Developing Countries*. Oxford University Press, Oxford.
- Joseph A and Phillips D (1984) *Accessibility and Utilization: Geographical Perspectives on Health Care Delivery*. Harper and Row, New York
- Kabel R (1990) *Predicting the next map with spatial adaptive filtering*, Proceedings of the fourth international symposium in medical geography University of East Anglia, Norwich, UK.
- Kalipeni E (2000) Health and disease in southern Africa: a comparative and vulnerability perspective. *Soc Sci Med* **50** (7-8), 965-83.
- Killewo J, Dahlgren L and Sandstrom A (1994) Socio-geographical patterns of HIV-1 transmission in Kagera Region, Tanzania. *Soc Sci Med* **38** (1), 129-34.
- Kleinschmidt I, Bagayoko M, Clarke GP, Craig M and Le Sueur D (2000) A spatial statistical approach to malaria mapping. *Int J Epidemiol* **29** (2), 355-61.
- Kloos H (1990) Utilization of selected hospitals, health centres and health stations in central, southern and western Ethiopia. *Soc Sci Med* **31** (2), 101-14.
- Kloos H and Zein ZA (1993) *The ecology of health and disease in Ethiopia*. Westview Press, Boulder, Colorado
- Koh A and Edwards E (1996) *Differential Global Positioning Systems [DGPS] for Natural Resource Monitoring*, Unpublished Report.
- Korte G (1996) Weighing GIS benefits with financial analysis. *Government Finance Review* **12** (5), 48-52.
- Krishna S (1997) Science, medicine, and the future. Malaria. *Bmj* **315** (7110), 730-2.

- Latkin C, Glass GE and Duncan T (1998) Using geographic information systems to assess spatial patterns of drug use, selection bias and attrition among a sample of injection drug users. *Drug Alcohol Depend* **50** (2), 167-75.
- le Sueur D (1998) *Background*. In: *Towards an atlas of malaria risk in Africa: First technical report of the MARA/ARMA collaboration*, Durban, x-xi.
- Leeson HS (1931) *Anopheline Mosquitos in Southern Rhodesia*, The London School of Hygiene and Tropical Medicine.
- Lindsay SW and Birley MH (1996) Climate change and malaria transmission. *Ann Trop Med Parasitol* **90** (6), 573-88.
- Lindsay SW and Martens WJ (1998) Malaria in the African highlands: past, present and future. *Bull World Health Organ* **76** (1), 33-45.
- Loevinsohn ME (1994) Climatic warming and increased malaria incidence in Rwanda. *Lancet* **343** (8899), 714-8.
- Loslier L (1994) Geographical information systems (GIS) from a health perspective. In: De Savigny D and Wijeyaratne P (Editors), *GIS for health and the environment*. IDRC, Ottawa, 13-20.
- Low-Beer D, Stoneburner RL and Mukulu A (1997) Empirical evidence for the severe but localized impact of AIDS on population structure. *Nat Med* **3** (5), 553-7.
- Lurie M, Harrison A, Wilkinson D and Abdool Karim SS (1997) Circular migration and sexual networking in rural KwaZulu/Natal: implications for the spread of HIV and other sexually transmitted diseases. *Health Transition Review* **7** (s3), 17-27.
- Lysenko AJ and Beljaev AE (1969) An analysis of the geographical distribution of *Plasmodium ovale*. *Bull World Health Organ* **40** (3), 383-94.
- Lysenko AY and Semashko IN (1968) *The structure of the modern area of malaria (map)*. Manual of micorbiology, clinical aspects and epidemiology of infectious disease, Moscow
- Macdonald G (1957) *The epidemiology and control of malaria*. Oxford University Press
- Macmillan B and Pierce T (1994) Optimization Modelling in a GIS Framework: The Problem of Political Redistricting. In: Fotheringham S and Rogerson P (Editors), *Spatial analysis and GIS*. Taylor & Francis, Bristol, 221-246.
- Maher D, Hausler HP, Raviglione MC, Kaleeba N, Aisu T, Fourie B and Nunn P (1997) Tuberculosis care in community care organizations in sub-Saharan Africa: practice and potential. *Int J Tuberc Lung Dis* **1** (3), 276-83.
- MARA (1998) *Towards an atlas of malaria risk in Africa: First technical report of the MARA/ARMA collaboration*, Durban.
- Marks G (1971) *The Medieval Plague: The Black Death of the Middle Ages*. Doubleday, New York

- Marsh K and Snow RW (1999) Malaria transmission and morbidity. *Parassitologia* **41** (1-3), 241-6.
- Marshall R (1991) A review of methods for the statistical analysis of spatial patterns of disease. *J R Statist Soc A* **154** (3), 421-441.
- Martens WJ, Niessen LW, Rotmans J, Jetten TH and McMichael AJ (1995) Potential impact of global climate change on malaria risk. *Environ Health Perspect* **103** (5), 458-64.
- Mayer JD (1983) The role of spatial analysis and geographic data in the detection of disease causation. *Soc Sci Med* **17** (16), 1213-21.
- McLafferty S (1988) Predicting the effect of hospital closure on hospital utilization patterns. *Soc Sci Med* **27** (3), 255-62.
- McMichael AJ, Haines A, Sloof R and Kovats J (1996) *Climate change and human health*. WHO, Geneva
- Metselaar D and van Theil PM (1959) Classification of malaria. *Tropical and Geographical Medicine* (11), 157-161.
- Molineaux L and Gramiccia G (1980) *The Garki project: research on the epidemiology and control of malaria in the Sudan savanna of West Africa*. WHO.
- Molineaux L (1988)., *Malaria: Principles and Practice of Malariology*. Churchill Livingstone, 919-998.
- Moore DA and Carpenter TE (1999) Spatial analytical methods and geographic information systems: use in health research and epidemiology. *Epidemiol Rev* **21** (2), 143-61.
- Morrill R and Earickson R (1968) Hospital variation and patient travel distances. *Inquiry* (5), 26-34.
- Morrill R and Earickson R (1970) Factors influencing distances travelled to hospitals. *Econ Geog* (46), 161-171.
- Müller I, Smith T, Mellor S, Rare L and Genton B (1998) The effect of distance from home on attendance at a small rural health centre in Papua New Guinea. *Int J Epidemiol* **27** (5), 878-84.
- Murray CJ and Lopez AD (1997) Mortality by cause for eight regions of the world: Global Burden of Disease Study. *Lancet* **349** (9061), 1269-76.

- Nchinda TC (1998) Malaria: a reemerging disease in Africa. *Emerg Infect Dis* **4** (3), 398-403.
- Nelson GS (1959) *Atlas of Kenya*, Crown Printers, Nairobi.
- Nijkamp P and De Jong W (1987) Training needs in information systems for local and regional development. *Regional Development Dialogue* **8** (1), 72-119.
- OAU (1997) *Harare declaration on malaria prevention and control in the context of African economic recovery and development*. In: Proceeding of the 33rd Ordinary Session of the Assembly of Heads of State and Government, Harare, Zimbabwe.
- Omumbo J, Ouma J, Rapuoda B, Craig MH, le Sueur D and Snow RW (1998) Mapping malaria transmission intensity using geographical information systems (GIS): an example from Kenya. *Ann Trop Med Parasitol* **92** (1), 7-21.
- Onori E and Grab B (1980) Indicators for the forecasting of malaria epidemics. *Bull World Health Organ* **58** (1), 91-8.
- Openshaw S, Craft AW, Charlton M and Birch JM (1988) Investigation of leukaemia clusters by use of a Geographical Analysis Machine. *Lancet* **1** (8580), 272-3.
- Parker EB and Campbell JL (1998) Measuring access to primary medical care: some examples of the use of geographical information systems. *Health Place* **4** (2), 183-93.
- Patz JA, Strzepek K, Lele S, Hedden M, Greene S, Noden B, Hay SI, Kalkstein L and Beier JC (1998) Predicting key malaria transmission factors, biting and entomological inoculation rates, using modelled soil moisture in Kenya. *Trop Med Int Health* **3** (10), 818-27.
- Perry B and Gesler W (2000) Physical access to primary health care in Andean Bolivia. *Soc Sci Med* **50** (9), 1177-88.
- Peters J and Hall G (1999) Assessment of ambulance response performance using a geographic information system. *Soc Sci Med* **49** (11), 1551-66.
- Pickering H, Okongo M, Bwanika K, Nnalusiba B and Whitworth J (1996) Sexual mixing patterns in Uganda: small-time urban/rural traders. *Aids* **10** (5), 533-6.
- Pickering H, Okongo M, Ojwiya A, Yirrell D and Whitworth J (1997) Sexual networks in Uganda: mixing patterns between a trading town, its rural hinterland and a nearby fishing village. *Int J STD AIDS* **8** (8), 495-500.
- Rahaman MM, Aziz KM, Munshi MH, Patwari Y and Rahman M (1982) A diarrhea clinic in rural Bangladesh: influence of distance, age, and sex on attendance and diarrheal mortality. *Am J Public Health* **72** (10), 1124-8.

- Raviglione MC, Dye C, Schmidt S and Kochi A (1997) Assessment of worldwide tuberculosis control. WHO Global Surveillance and Monitoring Project. *Lancet* **350** (9078), 624-9.
- Reader S (1994) The present state of GIS and future trends. In: De Savigny D and Wijeyaratne P (Editors), *GIS for health and the environment*. IDRC, Ottawa, 1-13.
- Reiter P (1998) Global warming and vector-borne disease: Is warmer sicker? Verbal presentation to Competitive Enterprise Institute, <http://www.cei.org/CHBReader.asp?ID=539>
- Remy G (1993a) Epidemiologic distribution of HIV2 human immunodeficiency virus infection in sub-Saharan Africa. *Med Trop (Mars)* **53** (4), 511-6.
- Remy G (1993b) Geographic distribution of HIV-1 infection in Central Africa: remarkable discontinuities. *Ann Soc Belg Med Trop* **73** (2), 127-42.
- Rhind D, Goodchild M and Maguire D (1991) Epilogue in geographical information systems. In: Maguire D, Goodchild M and Rhind D (Editors), *Geographical Information Systems*. Longman, London, 313-327.
- Ribeiro JM, Seulu F, Abose T, Kidane G and Teklehaimanot A (1996) Temporal and spatial distribution of anopheline mosquitos in an Ethiopian village: implications for malaria control strategies. *Bull World Health Organ* **74** (3), 299-305.
- Richards JA (1993) *Remote Sensing Digital Image Analysis*. Springer-Verlag., Berlin
- Richards TB, Henriques WD, Croner CM, Brown CK, Saccenti JC and Berry P (1999) Toward a GIS sampling frame for surveys of local health departments and local boards of health. *J Public Health Manag Pract* **5** (4), 65-75.
- Rogers DJ and Randolph SE (2000) The global spread of malaria in a future, warmer world. *Science* **289** (5485), 1763-6.
- Rothman KJ (1986) *Modern Epidemiology*. Little, Brown and Company, Boston/Toronto
- Sauerborn R, Nougara A and Diesfeld HJ (1996) *Les Coûts Economiques De La Maladie Pour Les Ménages Au Mileau Rural Du Burkina Faso*. Peter Lang-Verlag., Frankfurt
- Schellenberg JA, Newell JN, Snow RW, Mung'ala V, Marsh K, Smith PG and Hayes RJ (1998) An analysis of the geographical distribution of severe malaria in children in Kilifi District, Kenya. *Int J Epidemiol* **27** (2), 323-9.
- Schmucker KJ (1982) *Fuzzy sets. Natural Language Computations and Risk Analysis*. Computer Science Press
- Scholten HJ and de Lepper MJ (1991) The benefits of the application of geographical information systems in public and environmental health. *World Health Stat Q* **44** (3), 160-70.
- Shannon G, Bashur R and Metzner C (1969) The concept of distance as a factor in accessibility and utilisation of health care. *Med Care Review* (26), 143-161.

- Shannon G and Dever G (1974) *Health Care Delivery: Spatial Perspectives*. McGraw-Hill, New York
- Shannon GW, Skinner JL and Bashshur RL (1973) Time and distance: the journey for medical care. *Int J Health Serv* **3** (2), 237-44.
- Sharp BL and le Sueur D (1996) Malaria in South Africa - the past, the present and selected implications for the future. *S Afr Med J* **86** (1), 83-9.
- Sloof R (1961) Field observations on the biting activity of *Anopheles Koliensis* Owen. *Tropical and geographical medicine* (13), 67-76.
- Smith T, Charlwood JD, Takken W, Tanner M and Spiegelhalter DJ (1995) Mapping the densities of malaria vectors within a single village. *Acta Trop* **59** (1), 1-18.
- Smith W (1994) *Hippocrates*. Harvard University Press, Cambridge
- Snow J (1855) *On the mode of communication of cholera*. Churchill Livingstone, London. Reproduced in *Snow on Cholera*, Commonwealth Fund, New York, 1936.
- Snow RW, Gouws E, Omumbo J, Rapuoda B, Craig MH, Tanser FC, le Sueur D and Ouma J (1998) Models to predict the intensity of *Plasmodium falciparum* transmission: applications to the burden of disease in Kenya. *Trans R Soc Trop Med Hyg* **92** (6), 601-6.
- Snow RW, Craig M.H., Deichman, U., Le Sueur, D (1999a) A continental risk map for malaria mortality among African children. *Parasitol Today* **15** (3), 99-104.
- Snow RW, Craig M, Deichmann U and Marsh K (1999b) Estimating mortality, morbidity and disability due to malaria among Africa's non-pregnant population. *Bull World Health Organ* **77** (8), 624-40.
- Soderberg S, Temihango W, Kadete C, Ekstedt B, Masawe A, Vahlne A and Horal P (1994) Prevalence of HIV-1 infection in rural, semi-urban and urban villages in southwest Tanzania: estimates from a blood-donor study. *Aids* **8** (7), 971-6.
- Sokal DC, Buzingo T, Nitunga N, Kadende P and Standaert B (1993) Geographic and temporal stability of HIV seroprevalence among pregnant women in Bujumbura, Burundi. *Aids* **7** (11), 1481-4.
- Stock R (1983) Distance and the utilization of health facilities in rural Nigeria. *Soc Sci Med* **17** (9), 563-70.
- Stock R (1985) Health care for some: a Nigerian study of who gets what, where and why? *Int J Health Serv* **15** (3), 469-84.
- Stock R (1995) *Africa South of the Sahara: a geographic interpretation*. Guilford Press, New York
- Stuckenberg BR (1969) Effective temperature as an ecological factor in Southern Africa. *Zool. Afr.* (4), 145-197.

- Tanser FC and Palmer AR (1999) The application of a remotely-sensed diversity index to monitor degradation patterns in a semi-arid heterogeneous South African landscape. *Journal of Arid Environments* (43), 477-484.
- Tanser FC and Wilkinson D (1999) Spatial implications of the tuberculosis DOTS strategy in rural South Africa: a novel application of geographical information system and global positioning system technologies. *Trop Med Int Health* 4 (10), 634-8.
- Tanser FC (2000) A model to equitably distribute fieldworker workload in a large, rural South African health survey. *Submitted for publication*.
- Tanser FC, Hosegood V, Benzler J and Solarsh G (2000a) New approaches to spatially analyse primary health care utilisation patterns in rural South Africa. *Submitted for publication*.
- Tanser FC, Le Sueur D, Solarsh G and Wilkinson D (2000b) HIV heterogeneity and proximity of homestead to roads in rural South Africa: an exploration using a geographical information system. *Trop Med Int Health* 5 (1), 40-46.
- Tanser FC, le Sueur D and Sharp B (2000c) Malaria seasonality and population exposure in Africa: a high resolution climatic model. *Submitted for publication*.
- Taylor DRF (1991) GIS and developing nations. In: Maguire D, Goodchild M and Rhind D (Editors), *Geographical information systems*. Longman, London, 71-84.
- Thomas CJ and Lindsay SW (2000) Local-scale variation in malaria infection amongst rural Gambian children estimated by satellite remote sensing. *Trans R Soc Trop Med Hyg* 94 (2), 159-63.
- Thomson M, Connor S, Bennett S, D'Alessandro U, Milligan P, Aikins M, Langerock P, Jawara M and Greenwood B (1996b) Geographical perspectives on bednet use and malaria transmission in The Gambia, West Africa. *Soc Sci Med* 43 (1), 101-12.
- Thomson MC, Connor SJ, Milligan PJ and Flasse SP (1996a) The ecology of malaria--as seen from Earth-observation satellites. *Ann Trop Med Parasitol* 90 (3), 243-64.
- Thomson MC, Connor SJ, D'Alessandro U, Rowlingson B, Diggle P, Cresswell M and Greenwood B (1999) Predicting malaria infection in Gambian children from satellite data and bed net use surveys: the importance of spatial correlation in the interpretation of results. *Am J Trop Med Hyg* 61 (1), 2-8.
- Trape JF, Pison G, Preziosi MP, Enel C, Desgreess du Lou A, Delaunay V, Samb B, Lagarde E, Molez JF and Simondon F (1998) Impact of chloroquine resistance on malaria mortality. *C R Acad Sci III* 321 (8), 689-97.
- Tuberculosis Chemotherapy Centre Madras (1959) A concurrent comparison of home and sanatorium treatment of pulmonary tuberculosis in south India. *Bull World Health Organ* (21), 51-144.
- Tucker CJ, Vanpraet CL, Sharman MJ and Vam Ottersi G (1985) Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel. 1980-1984. *Remote Sensing of Environment* 1 (17), 233-245.

- Twigg L (1990) Health based geographical information systems: their potential examined in the light of existing data sources. *Soc Sci Med* **30** (1), 143-55.
- UNAIDS (1998) *AIDS epidemic update: December 1998*. UNAIDS, Geneva.
- Van der Stuyft P, Sorensen SC, Delgado E and Bocaletti E (1996) Health seeking behaviour for child illness in rural Guatemala. *Trop Med Int Health* **1** (2), 161-70.
- van Rie A, Beyers N, Gie RP, Kunneke M, Zietsman L and Donald PR (1999) Childhood tuberculosis in an urban population in South Africa: burden and risk factor. *Arch Dis Child* **80** (5), 433-7.
- Vine M (1998) Geographic information systems: their use in environmental epidemiological research. *J Environ Health* **61** (3), 7-10.
- Voudouris C and Tsang E (1999) Guided local search and its application to the travelling salesman problem. *European Journal of Operational Research* **1** (113), 469-499.
- Walsh SJ, Page PH and Gesler WM (1997) Normative models and healthcare planning: network-based simulations within a geographic information system environment. *Health Serv Res* **32** (2), 243-60.
- Walter SD (1993) Visual and statistical assessment of spatial clustering in mapped data. *Stat Med* **12** (14), 1275-91.
- Warren R, Hauman J, Beyers N, Richardson M, Schaaf HS, Donald P and van Helden P (1996) Unexpectedly high strain diversity of Mycobacterium tuberculosis in a high-incidence community. *S Afr Med J* **86** (1), 45-9.
- Wawer MJ, Serwadda D, Musgrave SD, Konde-Lule JK, Musagara M and Sewankambo NK (1991) Dynamics of spread of HIV-I infection in a rural district of Uganda. *Bmj* **303** (6813), 1303-6.
- WHO (1993) *A global strategy for malaria control*. World Health Organisation, Geneva.
- WHO (1994) *TB - a global emergency. WHO report on the TB epidemic*. World Health Organisation, Geneva
- WHO (1996) *The world health report 1996: fighting disease fostering development*. World Health Organisation, Geneva.
- WHO (1997) *Global tuberculosis control*. World Health Organisation, Geneva
- WHO (2000) *The World Health Report 2000. Health Systems: Improving performance*. World Health Organisation, Geneva
- Wilkinson D (1994) High-compliance tuberculosis treatment programme in a rural community. *Lancet* **343** (8898), 647-8.
- Wilkinson D (1999) Eight years of tuberculosis research in Hlabisa--what have we learned? *S Afr Med J* **89** (2), 155-9.

- Wilkinson D, Davies GR and Connolly C (1996) Directly observed therapy for tuberculosis in rural South Africa, 1991 through 1994. *Am J Public Health* **86** (8 Pt 1), 1094-7.
- Wilkinson D and Moore DA (1996) HIV-related tuberculosis in South Africa--clinical features and outcome. *S Afr Med J* **86** (1), 64-7.
- Wilkinson D, Pillay M, Crump J, Lombard C, Davies GR and Sturm AW (1997) Molecular epidemiology and transmission dynamics of *Mycobacterium tuberculosis* in rural Africa. *Trop Med Int Health* **2** (8), 747-53.
- Wilkinson D and Davies GR (1997a) The increasing burden of tuberculosis in rural South Africa--impact of the HIV epidemic. *S Afr Med J* **87** (4), 447-50.
- Wilkinson D and Davies GR (1997b) Coping with Africa's increasing tuberculosis burden: are community supervisors an essential component of the DOT strategy? Directly observed therapy. *Trop Med Int Health* **2** (7), 700-4.
- Wilkinson D, Connolly C and Rotchford K (1999) Continued explosive rise in HIV prevalence among pregnant women in rural South Africa. *Aids* **13** (6), 740.
- Wilkinson D and Tanser FC (1999) GIS/GPS to document increased access to community-based treatment for tuberculosis in Africa. *Lancet* **354** (9176), 394-5.
- Wilson DB (1956) *Atlas of Tanzania*, Survey Division, Department of Lands and Surveys, Government Printers, Dar es Salaam.
- World Bank (1993) *World development report, 1993*. World Bank, Washington D.C.
- World Bank (2000a) *World development report, 2000*. World Bank, Washington D.C.
- World Bank (2000b) *Overview of the World Bank's work in sub-Saharan Africa*. World Bank, Washington D.C.
- WRI (1995) *Africa Data Sampler. CD-ROM edition 1*. World Resources Institute, Washington D.C.
- Wright D, Goodchild M and Proctor J (1997) Demystifying the persistent ambiguity of GIS as a "tool" versus "science". *The Annals of the Association of American Geographers* **87** (2), 346-362.
- Zwarenstein M, Krige D and Wolff B (1991) The use of a geographical information system for hospital catchment area research in Natal/KwaZulu. *S Afr Med J* **80** (10), 497-500.

Appendix 1: Attribute data collected at each facility

Facility Type	Data Collected
Fixed clinic or hospital	Name, location, sister in charge, names of other clinic staff, telephone number, isigodi ⁹ , 24 hour service (Y/N), ambulance access, antenatal service (Y/N), number of antenatal attendances ¹⁰ , number of deliveries, well baby clinic (Y/N), number of family planning visits, waiting mothers area (Y/N)
Mobile clinic point	Name, location, sister in charge, names of other clinic staff, isigodi, number of antenatal attendances, family planning service (Y/N), number of family planning visits
Community health worker (CHW)	Name, location, name of household head, Isigodi where CHW works, Isigodi where CHW lives
Shop	Name, location, owner, telephone number
School	Name, location, circuit, telephone, principal, enrolments for grade 0 - 12
Church	Name, location, denomination, name of leader, number of congregants, telephone number
Induna	Name, location, isigodi, tribal authority, telephone, contact person
Traditional Healer	Name, location, type of healer, registered (Y/N), name of healer's association, telephone

⁹ The geographical area that falls under a tribal chief (Induna)

¹⁰ All data incorporating a frequency component is measured per annum

Appendix 2: Attribute data collected at each homestead

Homestead Attribute data
ID, location, owner’s name, number of people, non-migrant couples (Y/N), associated facility (e.g. shop, church), fixed clinic preference, mobile clinic preference, secondary school preference, primary school preference, CHW name, isigodi, local name (neighbourhood), tag affixed (Y/N), fieldworker name, date, time

Appendix 3: A data dictionary file

Ordinary Homestead (point)

ID (numeric, 0, 10000, 14999, 10000, required)
Address (text, 30)
Owner's family name (menu)
.....
Other family name (text, 30)
.....
Owner's First Name (text, 30)
Number In Homestead (numeric, 0, 1, 99, 10, required)
Non-migrant couples? (menu, required)
Yes
No, default
Don't know
Associate feature(s) (menu, required)
.....
Isigodi (menu, required)
.....
Local Name (text, 30)
CLInlc preference (menu, required)
.....
Mobile preference (menu, required)
.....
CHW name (menu, required)
.....
Sec school pref (menu, required)
.....
Pri school pref (menu, required)
.....
tag affixed? (menu, required)
yes, default
no
Mapped By (menu, required)
.....
Date (date, auto, dmy)
Time (time, auto, 24)

Absent Home (point)

ID (numeric, 0, 10000, 14999, 10000, required)
Address (text, 30)
Mapped By (menu, required)
.....
Date (date, auto, dmy)
Time (time, auto, 24)

Refusal Home (point)

ID (numeric, 0, 10000, 14999, 10000, required)
Address (text, 30)
Mapped By (menu, required)
.....
Date (date, auto, dmy)
Time (time, auto, 24)

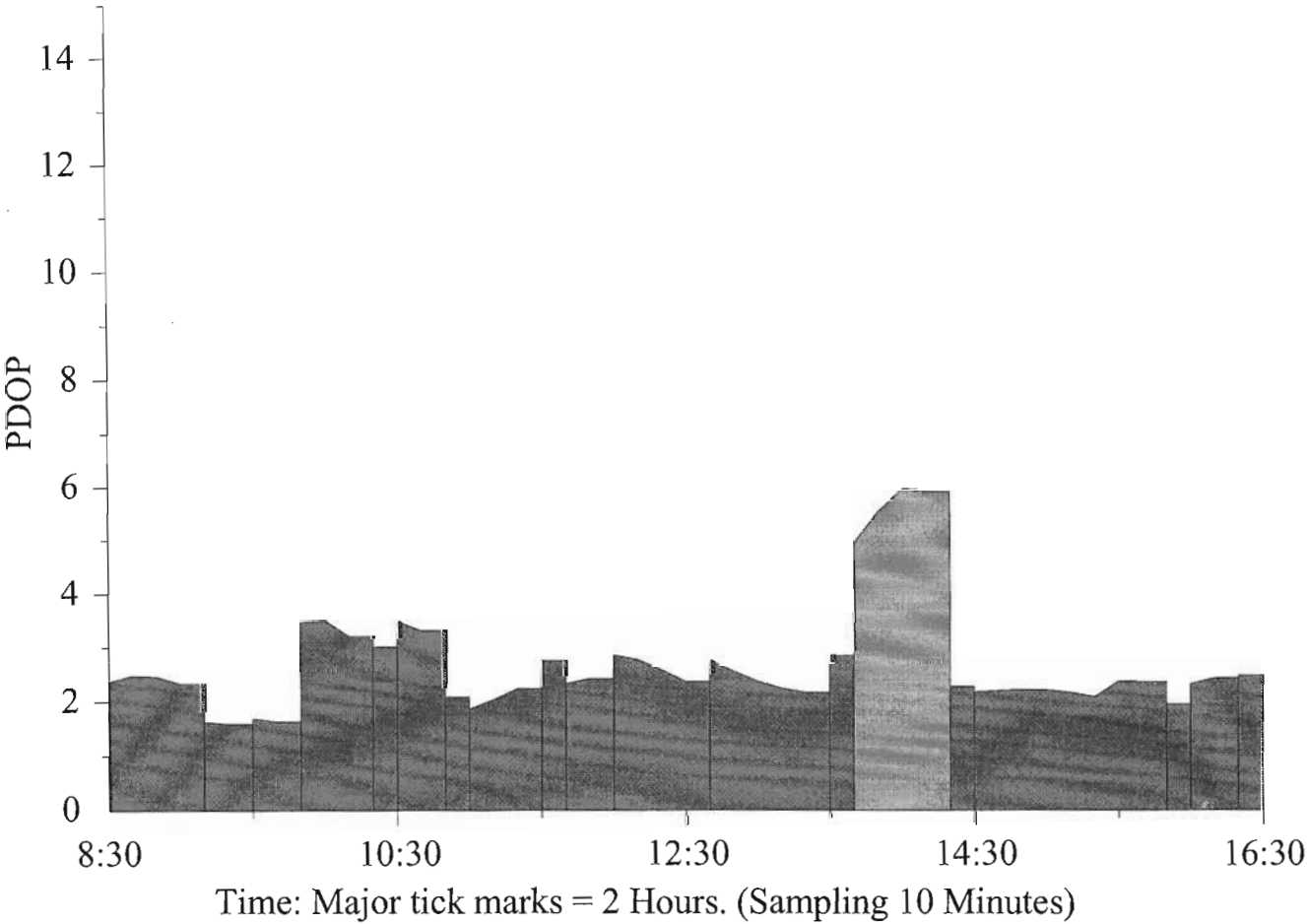
Under Construction (point)

ID (numeric, 0, 10000, 14999, 10000, required)
Address (text, 30)
Mapped By (menu, required)
.....
Date (date, auto, dmy)
Time (time, auto, 24)

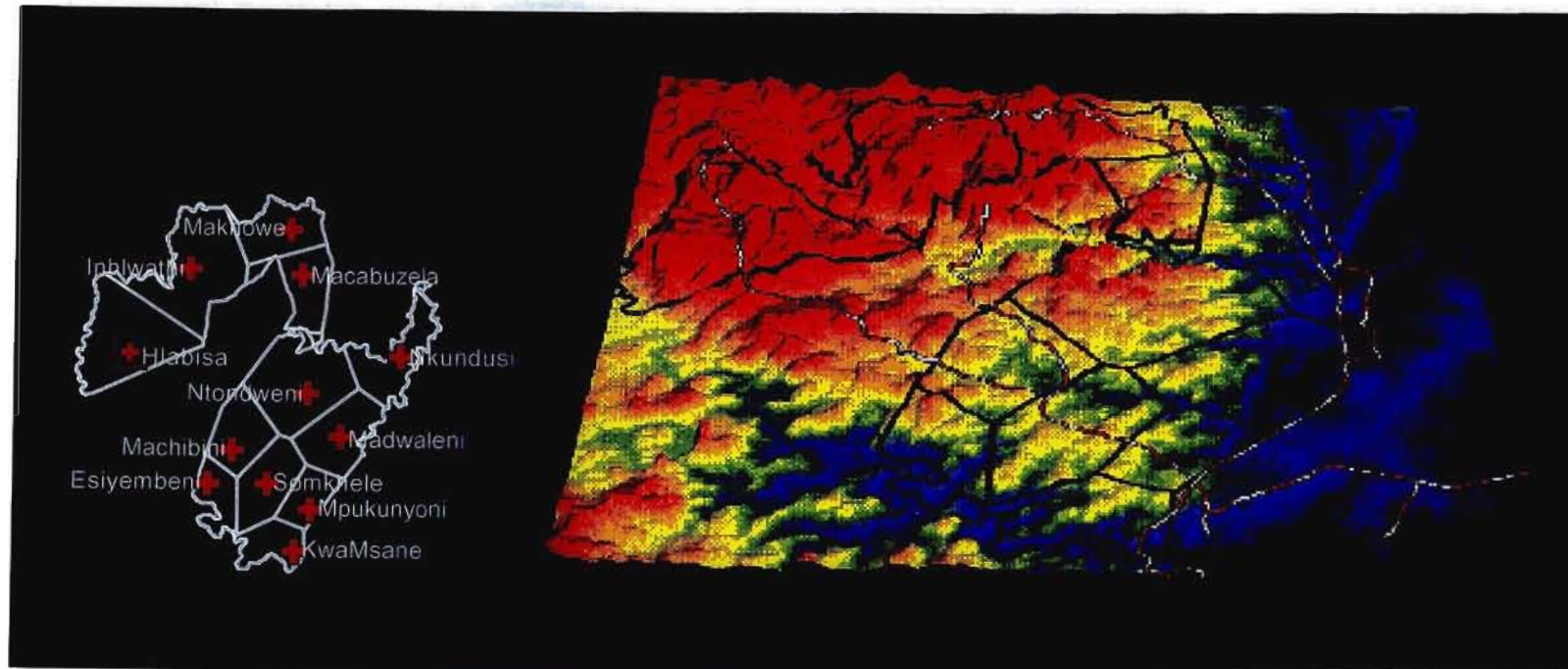
Abandoned Home, point

Mapped By (menu, required)
.....
Date (date, auto, dmy)
Time (time, auto, 24)

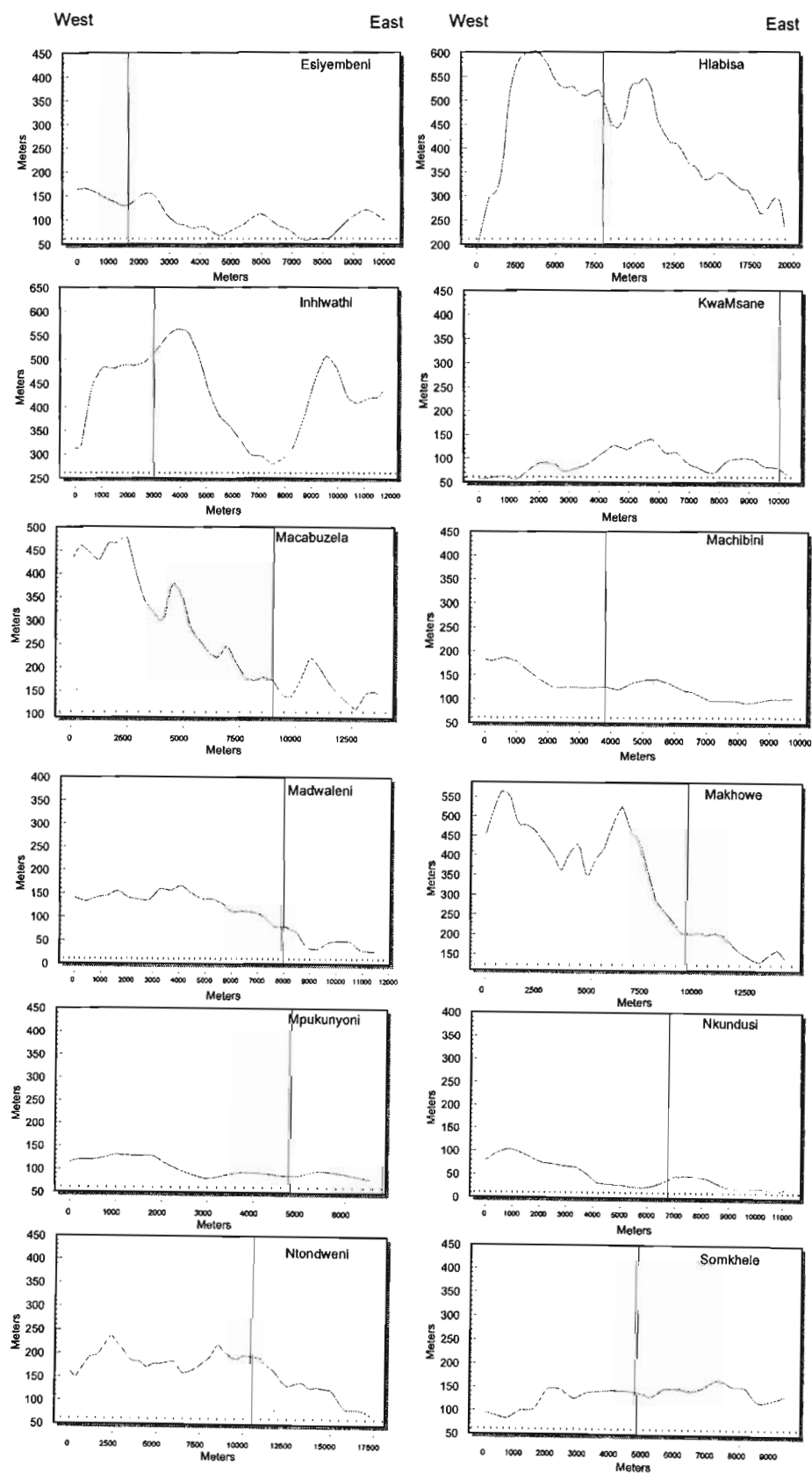
Appendix 4: A PDOP graph



Appendix 5a: Orthographic comparison of topography in each distance clinic catchment



Appendix 5b: Topographic cross-section across each distance clinic catchment



Appendix 6: Idrisi enclosed area detection algorithm

```
REM PRODUCE LINE IMAGE
REM 'initial x poly 1 1 0 1 poly ID'
LINERAS X rivers_all*POLY
LINERAS X ROAD_1*POLY
LINERAS X ROAD_2*POLY
LINERAS X ROAD_3*POLY
LINERAS X ROAD_4*POLY
RECLASS X I*POLY*TEMP*2*1*1*100000*-9999
COPY X TEMP.rst*POLY.rst
COPY X TEMP.rdc*POLY.rdc
OVERLAY X 3*POLY*DSS_MPK*TEMP
COPY X TEMP.rst*POLY.rst
COPY X TEMP.rdc*POLY.rdc
LINERAS X DSS_MPK*POLY

REM PRODUCE GROUP IMAGE
GROUP X POLY*N*GROUP

REM REMOVE LINES
FILTER X GROUP*GRP_MD_3*3
OVERLAY X 3*POLY*GRP_MD_3*COVER
OVERLAY X 7*COVER*GROUP*TEMP
GROUP X TEMP*N*GROUP

REM FILTER OUT SMALL AREAS OF PIXELS
FILTER X GROUP*GRP_MD_7*3*7
AREA X GROUP*1*1*AREA
OVERLAY X 3*AREA*DSS_MPK*TEMP
COPY X TEMP.rst*AREA.rst
COPY X TEMP.rdc*AREA.rdc
RECLASS X I*AREA*AREA_REC*2*1*1*50*0*50*100000*-9999
OVERLAY X 3*AREA_REC*GRP_MD_7*COVER
OVERLAY X 7*COVER*GROUP*TEMP
OVERLAY X 3*TEMP*DSS_MPK*GROUP
GROUP X GROUP*Y*TEMP
COPY X TEMP.rst*GROUP.rst
COPY X TEMP.rdc*GROUP.rdc

AREA X GROUP*1*1*AREA
OVERLAY X 3*AREA*DSS_MPK*TEMP
COPY X TEMP.rst*AREA.rst
COPY X TEMP.rdc*AREA.rdc
RECLASS X I*AREA*AREA_REC*2*0*1*20*1*20*100000*-9999
OVERLAY X 3*AREA_REC*GROUP*TEMP
GROUP X TEMP*N*GROUP

REM PERFORM ANOTHER 2 LOOPS OF THE ABOVE
FILTER X GROUP*GRP_MD_7*3*7
AREA X GROUP*1*1*AREA
OVERLAY X 3*AREA*DSS_MPK*TEMP
RECLASS X I*TEMP*AREA*2*0*100000*9000000*-9999
RECLASS X I*AREA*AREA_REC*2*1*1*50*0*50*100000*-9999
OVERLAY X 3*AREA_REC*GRP_MD_7*COVER
OVERLAY X 7*COVER*GROUP*TEMP
OVERLAY X 3*TEMP*DSS_MPK*GROUP
GROUP X GROUP*Y*TEMP
COPY X TEMP.rst*GROUP.rst
COPY X TEMP.rdc*GROUP.rdc

FILTER X GROUP*GRP_MD_7*3*7
AREA X GROUP*1*1*AREA
OVERLAY X 3*AREA*DSS_MPK*TEMP
RECLASS X I*TEMP*AREA*2*0*100000*9000000*-9999
RECLASS X I*AREA*AREA_REC*2*1*1*50*0*50*100000*-9999
OVERLAY X 3*AREA_REC*GRP_MD_7*COVER
OVERLAY X 7*COVER*GROUP*TEMP
OVERLAY X 3*TEMP*DSS_MPK*GROUP
GROUP X GROUP*Y*TEMP
COPY X TEMP.rst*GROUP.rst
COPY X TEMP.rdc*GROUP.rdc

REM PRODUCE VEC FILE AND EXPORT
POLYVEC X GROUP*GROUPVER*Y*0*N
MIFIDRIS X 2*GROUPVER*GROUPVER*5*ID*4*0
```

Appendix 7: Idrisi malaria seasonality macro

```
rem calculate the 3 month moving rainfall images m_rain01 etc (march_rain = (jan + feb + march)/3)
rem calculate the 3 month moving tempr images m_tavg01 etc (march_tempr = (jan + feb + march)/3)
rem calculate annual standard deviation of tavg and name the resulting image sd_tempr
rem name the frost image tminmin
rem produce values files 1-12 "01.val = 1 1" "02.val = 1 2" etc
rem produce a values file "13.val" containing "0 13"
```

```
rem calculate rain and temp suitable temperatures
RECLASS X I'M_RAIN01'R_RAIN01*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN02'R_RAIN02*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN03'R_RAIN03*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN04'R_RAIN04*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN05'R_RAIN05*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN06'R_RAIN06*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN07'R_RAIN07*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN08'R_RAIN08*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN09'R_RAIN09*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN10'R_RAIN10*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN11'R_RAIN11*2*0*0*60*1*60*9000*-9999
RECLASS X I'M_RAIN12'R_RAIN12*2*0*0*60*1*60*9000*-9999
```

```
OVERLAY X 2*M_TAVG01'SD_TEMPR'SD_M_TAVG01
OVERLAY X 2*M_TAVG02'SD_TEMPR'SD_M_TAVG02
OVERLAY X 2*M_TAVG03'SD_TEMPR'SD_M_TAVG03
OVERLAY X 2*M_TAVG04'SD_TEMPR'SD_M_TAVG04
OVERLAY X 2*M_TAVG05'SD_TEMPR'SD_M_TAVG05
OVERLAY X 2*M_TAVG06'SD_TEMPR'SD_M_TAVG06
OVERLAY X 2*M_TAVG07'SD_TEMPR'SD_M_TAVG07
OVERLAY X 2*M_TAVG08'SD_TEMPR'SD_M_TAVG08
OVERLAY X 2*M_TAVG09'SD_TEMPR'SD_M_TAVG09
OVERLAY X 2*M_TAVG10'SD_TEMPR'SD_M_TAVG10
OVERLAY X 2*M_TAVG11'SD_TEMPR'SD_M_TAVG11
OVERLAY X 2*M_TAVG12'SD_TEMPR'SD_M_TAVG12
```

```
RECLASS X I'SD_M_TAVG01'R_TAVG01*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG02'R_TAVG02*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG03'R_TAVG03*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG04'R_TAVG04*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG05'R_TAVG05*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG06'R_TAVG06*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG07'R_TAVG07*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG08'R_TAVG08*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG09'R_TAVG09*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG10'R_TAVG10*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG11'R_TAVG11*2*0*-1000*195*1*195*90000*-9999
RECLASS X I'SD_M_TAVG12'R_TAVG12*2*0*-1000*195*1*195*90000*-9999
```

```
rem calculate frost suitability
RECLASS X I'TMINMIN'FRST_MSK*2*0*-1000*50*1*50*10000*-9999
```

```
rem suitability image rainfall suitability * temp suitability * frost suitability
OVERLAY X 3'R_RAIN01'R_TAVG01*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT01
OVERLAY X 3'R_RAIN02'R_TAVG02*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT02
OVERLAY X 3'R_RAIN03'R_TAVG03*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT03
OVERLAY X 3'R_RAIN04'R_TAVG04*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT04
OVERLAY X 3'R_RAIN05'R_TAVG05*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT05
OVERLAY X 3'R_RAIN06'R_TAVG06*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT06
OVERLAY X 3'R_RAIN07'R_TAVG07*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT07
OVERLAY X 3'R_RAIN08'R_TAVG08*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT08
OVERLAY X 3'R_RAIN09'R_TAVG09*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT09
OVERLAY X 3'R_RAIN10'R_TAVG10*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT10
OVERLAY X 3'R_RAIN11'R_TAVG11*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT11
OVERLAY X 3'R_RAIN12'R_TAVG12*TEMP
OVERLAY X 3*TEMP*FRST_MSK*SUIT12
```

```
REM calculate reverse suitabilities
RECLASS X I'SUIT01'R_SUIT01*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT02'R_SUIT02*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT03'R_SUIT03*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT04'R_SUIT04*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT05'R_SUIT05*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT06'R_SUIT06*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT07'R_SUIT07*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT08'R_SUIT08*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT09'R_SUIT09*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT10'R_SUIT10*2*0*1*2*1*0*1*-9999
RECLASS X I'SUIT11'R_SUIT11*2*0*1*2*1*0*1*-9999
```

RECLASS X I'SUIT12*R_SUIT12*2*0*1*2*1*0*1*-9999

REM Calculate 1 month break in transmission
OVERLAY X 3*SUIT01*R_SUIT02*TEMP
OVERLAY X 3*TEMP*SUIT03*C_SUIT02
OVERLAY X 3*SUIT02*R_SUIT03*TEMP
OVERLAY X 3*TEMP*SUIT04*C_SUIT03
OVERLAY X 3*SUIT03*R_SUIT04*TEMP
OVERLAY X 3*TEMP*SUIT05*C_SUIT04
OVERLAY X 3*SUIT04*R_SUIT05*TEMP
OVERLAY X 3*TEMP*SUIT06*C_SUIT05
OVERLAY X 3*SUIT05*R_SUIT06*TEMP
OVERLAY X 3*TEMP*SUIT07*C_SUIT06
OVERLAY X 3*SUIT06*R_SUIT07*TEMP
OVERLAY X 3*TEMP*SUIT08*C_SUIT07
OVERLAY X 3*SUIT07*R_SUIT08*TEMP
OVERLAY X 3*TEMP*SUIT09*C_SUIT08
OVERLAY X 3*SUIT08*R_SUIT09*TEMP
OVERLAY X 3*TEMP*SUIT10*C_SUIT09
OVERLAY X 3*SUIT09*R_SUIT10*TEMP
OVERLAY X 3*TEMP*SUIT11*C_SUIT10
OVERLAY X 3*SUIT10*R_SUIT11*TEMP
OVERLAY X 3*TEMP*SUIT12*C_SUIT11
OVERLAY X 3*SUIT11*R_SUIT12*TEMP
OVERLAY X 3*TEMP*SUIT01*C_SUIT12
OVERLAY X 3*SUIT12*R_SUIT01*TEMP
OVERLAY X 3*TEMP*SUIT02*C_SUIT01

REM assign the 1 month break, transmission status
OVERLAY X 9*SUIT01*C_SUIT01*TEMP
COPY X TEMP.RST*SUIT01.RST
COPY X TEMP.RDC*SUIT01.RDC
OVERLAY X 9*SUIT02*C_SUIT02*TEMP
COPY X TEMP.RST*SUIT02.RST
COPY X TEMP.RDC*SUIT02.RDC
OVERLAY X 9*SUIT03*C_SUIT03*TEMP
COPY X TEMP.RST*SUIT03.RST
COPY X TEMP.RDC*SUIT03.RDC
OVERLAY X 9*SUIT04*C_SUIT04*TEMP
COPY X TEMP.RST*SUIT04.RST
COPY X TEMP.RDC*SUIT04.RDC
OVERLAY X 9*SUIT05*C_SUIT05*TEMP
COPY X TEMP.RST*SUIT05.RST
COPY X TEMP.RDC*SUIT05.RDC
OVERLAY X 9*SUIT06*C_SUIT06*TEMP
COPY X TEMP.RST*SUIT06.RST
COPY X TEMP.RDC*SUIT06.RDC
OVERLAY X 9*SUIT07*C_SUIT07*TEMP
COPY X TEMP.RST*SUIT07.RST
COPY X TEMP.RDC*SUIT07.RDC
OVERLAY X 9*SUIT08*C_SUIT08*TEMP
COPY X TEMP.RST*SUIT08.RST
COPY X TEMP.RDC*SUIT08.RDC
OVERLAY X 9*SUIT09*C_SUIT09*TEMP
COPY X TEMP.RST*SUIT09.RST
COPY X TEMP.RDC*SUIT09.RDC
OVERLAY X 9*SUIT10*C_SUIT10*TEMP
COPY X TEMP.RST*SUIT10.RST
COPY X TEMP.RDC*SUIT10.RDC
OVERLAY X 9*SUIT11*C_SUIT11*TEMP
COPY X TEMP.RST*SUIT11.RST
COPY X TEMP.RDC*SUIT11.RDC
OVERLAY X 9*SUIT12*C_SUIT12*TEMP
COPY X TEMP.RST*SUIT12.RST
COPY X TEMP.RDC*SUIT12.RDC

REM calculate months of risk
OVERLAY X 1*SUIT01*SUIT02*TEMP
OVERLAY X 1*SUIT03*TEMP*TEMP1
OVERLAY X 1*SUIT04*TEMP1*TEMP
OVERLAY X 1*SUIT05*TEMP*TEMP1
OVERLAY X 1*SUIT06*TEMP1*TEMP
OVERLAY X 1*SUIT07*TEMP*TEMP1
OVERLAY X 1*SUIT08*TEMP1*TEMP
OVERLAY X 1*SUIT09*TEMP*TEMP1
OVERLAY X 1*SUIT10*TEMP1*TEMP
OVERLAY X 1*SUIT11*TEMP*TEMP1
OVERLAY X 1*SUIT12*TEMP1*MON_RISK

RECLASS X I'MON_RISK*MSK_RSK*2*1*1*20*-9999

rem suitability images changed to month values
copy X SUIT01.rst*month01.rst
copy x suit01.rdc*month01.rdc
ASSIGN X SUIT02*MONTH02*02*3
ASSIGN X SUIT03*MONTH03*03*3
ASSIGN X SUIT04*MONTH04*04*3
ASSIGN X SUIT05*MONTH05*05*3
ASSIGN X SUIT06*MONTH06*06*3
ASSIGN X SUIT07*MONTH07*07*3
ASSIGN X SUIT08*MONTH08*08*3
ASSIGN X SUIT09*MONTH09*09*3
ASSIGN X SUIT10*MONTH10*10*3
ASSIGN X SUIT11*MONTH11*11*3
ASSIGN X SUIT12*MONTH12*12*3

```

REM produce reverse suitability images 0 = 1 1= 0
RECLASS X I\SUIT01\R_SUIT01*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT02\R_SUIT02*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT03\R_SUIT03*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT04\R_SUIT04*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT05\R_SUIT05*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT06\R_SUIT06*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT07\R_SUIT07*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT08\R_SUIT08*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT09\R_SUIT09*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT10\R_SUIT10*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT11\R_SUIT11*2*0*1*2*1*0*1*-9999
RECLASS X I\SUIT12\R_SUIT12*2*0*1*2*1*0*1*-9999

```

```

REM produce starting months
OVERLAY X 3*SUIT01\R_SUIT12*TEMP
OVERLAY X 3*TEMP*MONTH01*START01
OVERLAY X 3*SUIT02\R_SUIT01*TEMP
OVERLAY X 3*TEMP*MONTH02*START02
OVERLAY X 3*SUIT03\R_SUIT02*TEMP
OVERLAY X 3*TEMP*MONTH03*START03
OVERLAY X 3*SUIT04\R_SUIT03*TEMP
OVERLAY X 3*TEMP*MONTH04*START04
OVERLAY X 3*SUIT05\R_SUIT04*TEMP
OVERLAY X 3*TEMP*MONTH05*START05
OVERLAY X 3*SUIT06\R_SUIT05*TEMP
OVERLAY X 3*TEMP*MONTH06*START06
OVERLAY X 3*SUIT07\R_SUIT06*TEMP
OVERLAY X 3*TEMP*MONTH07*START07
OVERLAY X 3*SUIT08\R_SUIT07*TEMP
OVERLAY X 3*TEMP*MONTH08*START08
OVERLAY X 3*SUIT09\R_SUIT08*TEMP
OVERLAY X 3*TEMP*MONTH09*START09
OVERLAY X 3*SUIT10\R_SUIT09*TEMP
OVERLAY X 3*TEMP*MONTH10*START10
OVERLAY X 3*SUIT11\R_SUIT10*TEMP
OVERLAY X 3*TEMP*MONTH11*START11
OVERLAY X 3*SUIT12\R_SUIT11*TEMP
OVERLAY X 3*TEMP*MONTH12*START12

```

```

REM produce ending months
OVERLAY X 3*SUIT01\R_SUIT02*TEMP
OVERLAY X 3*TEMP*MONTH01*END01
OVERLAY X 3*SUIT02\R_SUIT03*TEMP
OVERLAY X 3*TEMP*MONTH02*END02
OVERLAY X 3*SUIT03\R_SUIT04*TEMP
OVERLAY X 3*TEMP*MONTH03*END03
OVERLAY X 3*SUIT04\R_SUIT05*TEMP
OVERLAY X 3*TEMP*MONTH04*END04
OVERLAY X 3*SUIT05\R_SUIT06*TEMP
OVERLAY X 3*TEMP*MONTH05*END05
OVERLAY X 3*SUIT06\R_SUIT07*TEMP
OVERLAY X 3*TEMP*MONTH06*END06
OVERLAY X 3*SUIT07\R_SUIT08*TEMP
OVERLAY X 3*TEMP*MONTH07*END07
OVERLAY X 3*SUIT08\R_SUIT09*TEMP
OVERLAY X 3*TEMP*MONTH08*END08
OVERLAY X 3*SUIT09\R_SUIT10*TEMP
OVERLAY X 3*TEMP*MONTH09*END09
OVERLAY X 3*SUIT10\R_SUIT11*TEMP
OVERLAY X 3*TEMP*MONTH10*END10
OVERLAY X 3*SUIT11\R_SUIT12*TEMP
OVERLAY X 3*TEMP*MONTH11*END11
OVERLAY X 3*SUIT12\R_SUIT01*TEMP
OVERLAY X 3*TEMP*MONTH12*END12

```

```

REM produce 2nd season starting month
OVERLAY X 9*START01*START02*TEMP
OVERLAY X 9*START03*TEMP*TEMP1
OVERLAY X 9*START04*TEMP1*TEMP
OVERLAY X 9*START05*TEMP*TEMP1
OVERLAY X 9*START06*TEMP1*TEMP
OVERLAY X 9*START07*TEMP*TEMP1
OVERLAY X 9*START08*TEMP1*TEMP
OVERLAY X 9*START09*TEMP*TEMP1
OVERLAY X 9*START10*TEMP1*TEMP
OVERLAY X 9*START11*TEMP*TEMP1
OVERLAY X 9*START12*TEMP1*2_START

```

```

REM produce 2nd season ending month
OVERLAY X 9*END01*END02*TEMP
OVERLAY X 9*END03*TEMP*TEMP1
OVERLAY X 9*END04*TEMP1*TEMP
OVERLAY X 9*END05*TEMP*TEMP1
OVERLAY X 9*END06*TEMP1*TEMP
OVERLAY X 9*END07*TEMP*TEMP1
OVERLAY X 9*END08*TEMP1*TEMP
OVERLAY X 9*END09*TEMP*TEMP1
OVERLAY X 9*END10*TEMP1*TEMP
OVERLAY X 9*END11*TEMP*TEMP1
OVERLAY X 9*END12*TEMP1*2_END

```

```

REM assign 13-->0 start and end
ASSIGN X START01*TEMP*13*3
COPY X TEMP.RST*START01.RST

```



```

COPY X TEMP.RDC*START01.RDC
ASSIGN X START02*TEMP*13*3
COPY X TEMP.RST*START02.RST
COPY X TEMP.RDC*START02.RDC
ASSIGN X START03*TEMP*13*3
COPY X TEMP.RST*START03.RST
COPY X TEMP.RDC*START03.RDC
ASSIGN X START04*TEMP*13*3
COPY X TEMP.RST*START04.RST
COPY X TEMP.RDC*START04.RDC
ASSIGN X START05*TEMP*13*3
COPY X TEMP.RST*START05.RST
COPY X TEMP.RDC*START05.RDC
ASSIGN X START06*TEMP*13*3
COPY X TEMP.RST*START06.RST
COPY X TEMP.RDC*START06.RDC
ASSIGN X START07*TEMP*13*3
COPY X TEMP.RST*START07.RST
COPY X TEMP.RDC*START07.RDC
ASSIGN X START08*TEMP*13*3
COPY X TEMP.RST*START08.RST
COPY X TEMP.RDC*START08.RDC
ASSIGN X START09*TEMP*13*3
COPY X TEMP.RST*START09.RST
COPY X TEMP.RDC*START09.RDC
ASSIGN X START10*TEMP*13*3
COPY X TEMP.RST*START10.RST
COPY X TEMP.RDC*START10.RDC
ASSIGN X START11*TEMP*13*3
COPY X TEMP.RST*START11.RST
COPY X TEMP.RDC*START11.RDC
ASSIGN X START12*TEMP*13*3
COPY X TEMP.RST*START12.RST
COPY X TEMP.RDC*START12.RDC

```

```

ASSIGN X END01*TEMP*13*3
COPY X TEMP.RST*END01.RST
COPY X TEMP.RDC*END01.RDC
ASSIGN X END02*TEMP*13*3
COPY X TEMP.RST*END02.RST
COPY X TEMP.RDC*END02.RDC
ASSIGN X END03*TEMP*13*3
COPY X TEMP.RST*END03.RST
COPY X TEMP.RDC*END03.RDC
ASSIGN X END04*TEMP*13*3
COPY X TEMP.RST*END04.RST
COPY X TEMP.RDC*END04.RDC
ASSIGN X END05*TEMP*13*3
COPY X TEMP.RST*END05.RST
COPY X TEMP.RDC*END05.RDC
ASSIGN X END06*TEMP*13*3
COPY X TEMP.RST*END06.RST
COPY X TEMP.RDC*END06.RDC
ASSIGN X END07*TEMP*13*3
COPY X TEMP.RST*END07.RST
COPY X TEMP.RDC*END07.RDC
ASSIGN X END08*TEMP*13*3
COPY X TEMP.RST*END08.RST
COPY X TEMP.RDC*END08.RDC
ASSIGN X END09*TEMP*13*3
COPY X TEMP.RST*END09.RST
COPY X TEMP.RDC*END09.RDC
ASSIGN X END10*TEMP*13*3
COPY X TEMP.RST*END10.RST
COPY X TEMP.RDC*END10.RDC
ASSIGN X END11*TEMP*13*3
COPY X TEMP.RST*END11.RST
COPY X TEMP.RDC*END11.RDC
ASSIGN X END12*TEMP*13*3
COPY X TEMP.RST*END12.RST
COPY X TEMP.RDC*END12.RDC

```

```

REM produce 1st season starting month
OVERLAY X 8*START01*START02*TEMP
OVERLAY X 8*START03*TEMP*TEMP1
OVERLAY X 8*START04*TEMP1*TEMP
OVERLAY X 8*START05*TEMP*TEMP1
OVERLAY X 8*START06*TEMP1*TEMP
OVERLAY X 8*START07*TEMP*TEMP1
OVERLAY X 8*START08*TEMP1*TEMP
OVERLAY X 8*START09*TEMP*TEMP1
OVERLAY X 8*START10*TEMP1*TEMP
OVERLAY X 8*START11*TEMP*TEMP1
OVERLAY X 8*START12*TEMP1*1_START

```

```

OVERLAY X 3*1_START*MSK_RSK*TEMP
COPY X TEMP.RST*1_START.RST
COPY X TEMP.RDC*1_START.RDC

```

```

REM produce 1st season ending months
OVERLAY X 8*END01*END02*TEMP
OVERLAY X 8*END03*TEMP*TEMP1
OVERLAY X 8*END04*TEMP1*TEMP
OVERLAY X 8*END05*TEMP*TEMP1
OVERLAY X 8*END06*TEMP1*TEMP
OVERLAY X 8*END07*TEMP*TEMP1

```

```

OVERLAY X 8*END08*TEMP1*TEMP
OVERLAY X 8*END09*TEMP*TEMP
OVERLAY X 8*END10*TEMP1*TEMP
OVERLAY X 8*END11*TEMP*TEMP
OVERLAY X 8*END12*TEMP1*1_END

OVERLAY X 3*1_END*MSK_RSK*TEMP
COPY X TEMP.RST*1_END.RST
COPY X TEMP.RDC*1_END.RDC

REM mask out 1_season months from 2_season
OVERLAY X 2*2_END*1_END*TEMP
RECLASS X 1*TEMP*2_MASK*2*0*-15*-12*0*1*1*13*0*13*20*-9999
OVERLAY X 3*2_MASK*2_START*TEMP
COPY X TEMP.RST*2_START.RST
COPY X TEMP.RDC*2_START.RDC
OVERLAY X 3*2_MASK*2_END*TEMP
COPY X TEMP.RST*2_END.RST
COPY X TEMP.RDC*2_END.RDC

REM reverse 1_end and 2_end of pixels where end<start in both seasons
OVERLAY X 2*1_END*1_START*TEMP
RECLASS X 1*TEMP*1_REV*2*1*-5000*0*0*0*5000*-9999
OVERLAY X 2*2_END*2_START*TEMP
RECLASS X 1*TEMP*2_REV*2*1*-5000*0*0*0*5000*-9999
OVERLAY X 3*1_REV*2_REV*REV
OVERLAY X 3*REV*2_END*2_REV
OVERLAY X 3*REV*1_END*1_REV

OVERLAY X 7*2_REV*1_END*TEMP
COPY X TEMP.RST*1_END.RST
COPY X TEMP.RDC*1_END.RDC
OVERLAY X 7*1_REV*2_END*TEMP
COPY X TEMP.RST*2_END.RST
COPY X TEMP.RDC*2_END.RDC

REM calculate months of risk
OVERLAY X 1*SUIT01*SUIT02*TEMP
OVERLAY X 1*SUIT03*TEMP*TEMP1
OVERLAY X 1*SUIT04*TEMP1*TEMP
OVERLAY X 1*SUIT05*TEMP*TEMP1
OVERLAY X 1*SUIT06*TEMP1*TEMP
OVERLAY X 1*SUIT07*TEMP*TEMP1
OVERLAY X 1*SUIT08*TEMP1*TEMP
OVERLAY X 1*SUIT09*TEMP*TEMP1
OVERLAY X 1*SUIT10*TEMP1*TEMP
OVERLAY X 1*SUIT11*TEMP*TEMP1
OVERLAY X 1*SUIT12*TEMP1*SUIT

rem calculate catalyst rain mask
RECLASS X 1*m_rain01*R_RAIN01*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain02*R_RAIN02*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain03*R_RAIN03*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain04*R_RAIN04*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain05*R_RAIN05*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain06*R_RAIN06*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain07*R_RAIN07*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain08*R_RAIN08*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain09*R_RAIN09*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain10*R_RAIN10*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain11*R_RAIN11*2*0*0*80*1*80*9000*-9999
RECLASS X 1*m_rain12*R_RAIN12*2*0*0*80*1*80*9000*-9999
ndvicomp x 1*rain_msk*12*R_RAIN01*R_RAIN02*R_RAIN03*R_RAIN04*R_RAIN05*R_RAIN06*R_RAIN07*R_RAIN08*R_RAIN09*R_RAIN10*R_RAIN11*R_RAIN12

RECLASS X 1*SUIT*temp*2*1*1*20*-9999
overlay x 3*temp*rain_msk*con_msk

OVERLAY X 3*1_START*CON_MSK*1_STARTR
OVERLAY X 3*2_START*CON_MSK*2_STARTR
OVERLAY X 3*1_END*CON_MSK*1_END_R
OVERLAY X 3*1_END*CON_MSK*1_END_R
OVERLAY X 3*MON_RISK*CON_MSK*TEMP
COPY X TEMP.RST*MON_RISK.RST
COPY X TEMP.RDC*MON_RISK.RDC

RECLASS X 1*MON_RISK*MON_RSKR*2*1*1*4*2*4*7*3*7*20*-9999

```