An Investigation into using Textural Analysis and Change Detection Techniques on Medium and High Spatial Resolution Imagery for Monitoring Plantation Forestry Operations

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Preface

The work undertaken in this thesis was carried out at the School of Environmental Sciences, Faculty of Science and Agriculture, University of KwaZulu-Natal, Pietermaritzburg, in association with the Forestry and Forest Products Research Centre, a joint venture between the CSIR Natural Resources and the Environment Operating Unit and the University of KwaZulu-Natal.

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The duration of this study was from February 2002 to February 2006.

The contents of this work have not been submitted in any form to another University and, except where the work of others is acknowledged in the text, the results are the author's own investigation.

Mark Norris-Rogers
February 2006

We certify that the above statement is correct:

Dr. F.B. Ahmed | Prof. Dr. ir. P.R. Coppin | Dr. J. van Aardt

Dedication

I would like to dedicate this work to my wife, Anita, and children, Samuel and John, without whose support and sacrifice, I could not have undertaken this work.

He who finds a wife,
Finds what is good,
And receives favour from the Lord.

Proverbs 18:22

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Abstract

Plantation forestry involves the management of man-made industrial forests for the purpose of producing raw materials for the pulp and paper, saw milling and other related wood products industries. Management of these forests is based on the cycle of planting, tending and felling of forest stands such that a sustainable operation is maintained. The monitoring and reporting of these forestry operations is critical to the successful management of the forestry industry. The aim of this study was to test whether the forestry operations of clear-felling, re-establishment and weed control could be qualitatively and quantitatively monitored through the application of classification and change detection techniques to multi-temporal medium (15–30 m) and a combination of textural analysis and change detection techniques on high resolution (0.6-2.4 m) satellite imagery.

For the medium resolution imagery, four Landsat 7 multi-spectral images covering the period from March 2002 to April 2003 were obtained over the midlands of KwaZulu-Natal, South Africa, and a supervised classification, based on the Maximum Likelihood classifier, as well as two unsupervised classification routines were applied to each of these images. The supervised classification routine used 12 classes identified from ground-truthing data, while the unsupervised classification was done using 10 and 4 classes. NDVI was also calculated and used to estimate vegetation status. Three change detection techniques were applied to the unsupervised classification images, in order to determine where clear-felling, planting and weed control operations had occurred. An Assisted "Classified" Image change detection technique was applied to the Ten-Class Unsupervised Classification images, while an Assisted "Quantified Classified" change detection technique was applied to the Four-Class Unsupervised Classification images. An Image differencing technique was applied to the NDVI images. For the high resolution imagery, a series of QuickBird images of a plantation forestry site were used and a combination of textural analysis and change detection techniques was tested to quantify weed development in replanted forest stands less than 24 months old. This was achieved by doing an unsupervised classification on the multi-spectral bands, and an edge-enhancement on the panchromatic band. Both the resultant datasets were then vectorised, unioned and a matrix derived to determine areas of high weed.

It was found that clear-felling operations could be identified with accuracy in excess of 95%. However, using medium resolution imagery, newly planted areas and the weed status of forest stands were not definitively identified as the spatial resolution was too coarse to separate weed growth from tree stands. Planted stands younger than one year tended to be classified in the same class as bare ground or ground covered with dead branches and leaves, even if weeds were present. Stands older than one year tended to be classified together in the same class as weedy stands, even where weeds were not present. The NDVI results indicated that further research into this aspect could provide more useful information regarding the identification of weed status in forest stands. Using the multi-spectral bands of the high resolution imagery it was possible to identify areas of strong vegetation, while crop rows were identifiable on the panchromatic band. By combining these two attributes, areas of high weed growth could be identified. By applying a post-classification change detection technique on the high weed growth classes, it was possible to identify and quantify areas of weed increase or decrease between consecutive images. A theoretical canopy model was also derived to test whether it could identify thresholds from which weed infestations could be determined.

The conclusions of this study indicated that medium resolution imagery was successful in accurately identifying clear-felled stands, but the high resolution imagery was required to identify replanted stands, and the weed status of those stands. However, in addition to identifying the status of these stands, it was also possible to quantify the level of weed infestation. Only wattle (*Acacia mearnsii*) stands were tested in this manner but it was recommended that in addition to applying these procedures to wattle stands, they also are tested in *Eucalyptus* and *Pinus* stands. The combination of textural analysis on the panchromatic band and classification of multi-spectral bands was found to be a suitable process to achieve the aims of this study, and as such were recommended as standard procedures that could be applied in an operational plantation forest monitoring environment.

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Abbreviations

.gmd	File extension of Erdas Imagine Modeler tool
.imd	File extension of parameter file supplied with QuickBird imagery
°	Degrees
%	Percentage
°C	Degrees Centigrade
µm	Micrometer
amsl	Above mean sea level
AOI	Area of interest
APO	Annual plan of operations
AVHRR	Advanced very high-resolution radiometer
CD	Change detection
cm	Centimetres
CSIR	Council for Scientific and Industrial Research
CVA	Change vector analysis
DN	Digital number
DTM	Digital terrain model
ERTS	Earth Resources Technology Satellite
ESRI	Environmental Systems Research Institute, Inc.
ETM+	Enhanced Thematic Mapper Plus
FMS	Forest Management System database
GCP	Ground control point
GIS	Geographic information systems
GLM	Generalised linear model
GPS	Global Positioning System
ha	Hectares

ICFR	Institute for Commercial Forestry Research
km	Kilometre
km^2	Square kilometre
LIDAR	Light Detection and Ranging
LSU	Linear spectral unmixing
MAP	Mean annual precipitation
m	Metres
m^2	Square metres
mm	Millimetre
MSS	Multi-spectral Scanner
NDVI	Normalised difference vegetation index
NIR	Near infrared
nm	Nanometre
NOAA	National Oceanographic and Atmospheric Administration
PCA	Principal Components Analysis
®	Registered mark
RADAR	Radio Detection and Ranging
RGB	Red; Green; Blue
RMS(E)	Root mean square (error)
SAC	Satellite Applications Centre
SMA	Spectral mixture analysis
SPOT	Systeme Probatoire d'Observation de la Terra
SQL	Structured Query Language
™	Registered trade mark
TM	Thematic Mapper
TNDVI	Transformed normalised difference vegetation index
WRC	Water Research Commission

An Investigation into using Textural Analysis and Change Detection Techniques on Medium and High Spatial Resolution Imagery for Monitoring Plantation Forestry Operations

Chapter 1: Introduction

1.1 Background

Plantation forestry (see glossary, p.181) involves the management of man-made industrial forests (as opposed to natural or indigenous forests) for the purpose of producing wood fibre for the pulp and paper industry, saw logs for the saw milling industry and other related wood products. Management of these forests is based on the cycle of planting, tending and felling of forest stands (compartments in plantation forestry – *see glossary*) such that a sustainable operation is maintained.

The monitoring and reporting of these forestry operations is critical to the successful management of the forestry industry. This reporting is also one that introduces a substantial risk of data corruption of any forest management database due to incorrect or late reporting of operations. Examples of this include reporting incorrect compartment numbers where operations were carried out, forgetting to report an operation or reporting an operation as completed, when it has not been completed. These actions can have detrimental effects on the decision-making capability, especially for the long term planning scenarios such as yield regulation and volume determinations.

Monitoring and detecting such data errors is a very labour intensive exercise, especially for forestry companies with large land holdings spread over a wide geographic area. Manual audits go some way to detecting and controlling this problem, but are not always an optimal solution.

Technological developments in Geographic Information Systems (GIS) as well as recent developments in medium and high spatial resolution remote sensing technology offer the possibility of a more effective solution to this problem. However, research is required in order to develop suitable methodologies and applications of the remote sensing technologies available, especially for monitoring plantation forestry operations.

Plantation forestry in the Midlands of KwaZulu-Natal, South Africa utilises three main genera, *Eucalyptus*, *Pinus* and *Acacia* (see 3.1.2.6 Land Use, for details on the species). The cultivation of these forest stands is undertaken at an intensive scale in terms of its planning and management. This requires a high level of information that is both current and accurate, but which is also constantly changing. The type of data required includes details of the actual forest stands such as the area, species and age class (i.e. the date of planting), as well as details of what operations were undertaken and when; what quantity of materials such as seedlings, fertiliser and weed control chemicals were used, how many man-days were used for each operation and other such data. Considerable effort and cost is required to obtain, capture and store this data. It also requires sophisticated systems to manipulate and interrogate this data in order to provide data that can be used to report on current operations and plan future ones. Extensive use is made of digital databases, which are then accessed using commercial relational database management systems and Geographic Information Systems (Kätsch and Bredenkamp, 1997).

In order to ensure the validity of the data in these databases, manual audits involving visual inspections during field visits and other audit activities are undertaken. Because of time, cost and other practical constraints, these audits are only done on a small subset of the total data set, and therefore only cover small portions of widely spread landholdings. This is especially true for the major forestry companies that have a large geographic spread of forestry land holdings.

There is a critical set of operations that are most likely to affect the accuracy of the data in these databases. These are operations that change the status of the compartments and are generally understood to be the clear-felling, planting and thinning operations. Therefore, if these operations can be closely monitored, the risk of data corruption is greatly reduced.

The data maintained in these forestry databases are used to derive long term strategic plans such as yield regulation plans and sustainability levels (covering up to 30 years), medium term tactical plans including harvesting and planting scheduling, weed control plans, and roads maintenance plans (covering three to five year periods) and short term operational plans such as the annual plans of operations (APO), felling plans, budgetary and other financial forecast plans (covering the current year) of operation. This data is also used in the decision-making process regarding the establishment of processing plants such as pulp and sawmills, the costs of which can run into billions of Rand. Therefore, it is obvious that any errors in the data could have a serious impact on their effective execution.

Literature reviews show that remote sensing technology has been repeatedly used to detect changes in forestry environments. Considerable work has been done using remote sensing to successfully monitor the transformation of forest land cover. This has involved both coniferous and tropical forestry, but generally on a regional to global scale (Boyd *et al.*, 2002; Sader *et al.*, 2001; Castelli *et al.*, 1999; Cohen and Fiorella, 1999; Yuan *et al.*, 1999; Zhan *et al.*, 1998).

Other applications have included the determination of land-use cover types (Hallum, 1993), the mapping of forest mortality (Collins and Woodcock, 1994), the measurement of stand height and basal area in conifer plantations (Puhr and Donoghue, 2000), and volumetric estimates in *Eucalyptus* plantations (Kätsch and Van Laar, 2002). Häme *et al.* (1998), describe the successful detection of clear-felled areas in Finnish boreal forest, whose findings are also supported by Varjo (1997). Other publications such as Leckie (1985), Sohlberg (1985), Hildebrandt (1985) and Kätsch and Vogt (1999) describe the use of satellite-based remote sensing techniques being applied to forest enumerations and forest mapping.

Most of these studies have been applied in Northern Hemisphere boreal and other natural forests, but there is paucity of literature on the application of remote sensing being applied to the management of **plantation forestry**. The focus of this research is aimed at providing answers to the application of remote sensing to enhance plantation forest management, with a specific focus on monitoring the operations of clear-felling, planting and weed control. These operations are the most critical in terms of cost and importance in the management cycle of plantation forestry, hence this focus. It should be noted that all references to medium or high resolution refer to the *spatial* resolution, unless otherwise stated.

1.2 Hypothesis and Corollaries

This study hypothesises that the interaction of solar radiation with vegetation in plantation forests, as captured by space-borne optical sensors, provides information that is useful for monitoring plantation forestry operations. Two corollaries that stem from this hypothesis are:

1. The forestry operations of clear-felling, replanting and weed control, in the Midlands of KwaZulu-Natal, could be qualitatively monitored through the application of change detection techniques applied to multi-temporal, medium spatial resolution (15–30 m) satellite imagery, in conjunction with GIS technology.

2. The status of vegetation cover in re-established stands less than two years old could be quantitatively determined by the application of textural analysis and change detection techniques to multi-temporal, high spatial resolution (0.6-2.4 m) satellite imagery, where the level of discrimination is between crop and weed (see glossary).

1.3 Aim and Objectives

1.3.1 Aim

The aim of this research was to validate the above hypothesis, by applying selected change detection techniques to multi-temporal imagery of operational forests in the Midlands of KwaZulu-Natal, utilising the repeatability and scale of coverage of medium resolution satellite imagery (e.g. Landsat 7), and the high definition of high resolution satellite imagery (e.g. QuickBird 2). The purpose of this was to monitor the integrity of the data captured during the normal reporting of forestry operations, and to use exception reporting to highlight any possible database inaccuracies. The study aimed to provide a cost-effective and practical solution to the problem of monitoring and auditing these critical operations.

1.3.2 Objectives

The specific objectives of the study were:

1. To determine whether supervised and unsupervised classifications, as well as NDVI value estimations, on repeat imagery obtained from a medium resolution sensor (Landsat 7 ETM+), could be used to detect clear-felling, planting and weed status of plantation forestry stands.

2. To determine whether change detection analyses and NDVI estimates on the classified medium resolution imagery could be used to detect clear-felling, planting and weed status of plantation forestry stands.

3. To determine the accuracy of the classification and change detection results by comparing with ground-truthed data.

4. To compare the spectral classes of the classified imagery, and the change detection results, with the status of compartments reflected in the forestry database.

5. To determine whether unsupervised classification of the multi-spectral and panchromatic bands, as well as image segmentation techniques of textural analysis on the panchromatic band of high resolution QuickBird imagery could quantify vegetation cover in terms of crop versus weed, the density and spatial distribution of this cover by type (crop versus weed).

6. To determine whether change detection analyses on the classified high resolution imagery can detect changes in weed status.

7. To determine the accuracy of the classification and change detection results by comparing with ground-truthed data.

8. To compare the spectral classes of the classified imagery, and the change detection results, with the status of compartments reflected in the forestry database.

9. To test the feasibility of a canopy cover model as a means of creating a threshold for the identification of weed infestation from high resolution imagery.

1.4 Structure of thesis

Chapter 2 reviews the literature relevant to the study topic and provides a framework for this study in terms of remote sensing research. In Chapter 3 a detailed description of the study sites is given. This leads into Chapter 4, where the focus is on the research undertaken on the medium resolution imagery. This includes details of the materials and methods, and a presentation and discussion of the results and conclusions of the medium resolution imagery research. Chapter 5 details the research on the high resolution imagery, with descriptions of the methods and materials, and discussion of these results and conclusions. Chapter 6 presents a synthesis of the overall study by providing a general discussion, conclusions and recommendations of the findings. A glossary of terms is given at the end of the thesis, together with a list of references and relevant appendices.

Chapter 2: Literature Review

2.1 Introduction

Remote sensing has experienced significant developments since cameras were first taken up into the air. This is especially true for satellite remote sensing, which developed out of the early space flights of the 1960s and 1970s. It was during this time that multi-spectral techniques came to the fore, in place of the optical camera technology (Lillesand and Kiefer, 2000). From the introduction, in 1972, of the first purpose built remote sensing satellite, ERTS 1 (later renamed Landsat 1) to the current Landsat 7, SPOT 5, and similar multi-spectral/panchromatic sensors, the range of technologies has broadened to include RADAR, LIDAR and hyperspectral technologies. The latest developments have been in the area of spatial resolution, with order-of-magnitude increases being achieved in the Ikonos and QuickBird series of sensors, which have panchromatic resolutions of one metre or better (Donoghue, 1999). Directly related to these developments has been the exponential progress in computing technology (both hardware and software) which has made remote sensing technology and data available to a wider variety of different professional and technical disciplines. This has, in turn, expanded the application of remote sensing technology to many different fields.

The literature reviewed below covers topics that include the range of forestry applications that have made use of satellite imagery, the sensors and platforms most suitable for applications in plantation forestry, based on such factors as spatial and spectral resolutions, geometric and radiometric corrections and geo-referencing processes, repeat coverage cycles and other such procedures that are involved in the application of remote sensing techniques. Reference to methodology, classification and change detection techniques and procedures, in a GIS environment, are of particular interest.

2.2 The Application of Remote Sensing in Monitoring Forest Operations

By nature, commercial forestry, especially at an industrial scale as practiced by large forestry companies, is geographically very extensive. This creates a particular set of constraints when the monitoring of operations is required. Because of the large coverage obtained by remote sensing satellites (especially the medium spatial resolution sensors such as Landsat and SPOT), such satellites are particularly suitable for forest management applications.

2.2.1 Forestry Operations

Certain forestry operations have the greatest potential impact on database accuracy. Their impact is because they cause the most significant amount of change in the status of a compartment (e.g. changing from standing to felled) or major cost implications are involved. These are primarily the harvesting and re-establishment operations. They must be reflected in the database, and this in turn can affect long-term planning outcomes such as sustainability, yield regulation and volume production. Together with weed control, harvesting and replanting operations also contribute to the bulk of the costs relating to the forestry operation as a whole (Grobbelaar, 2000).

2.2.1.1 Harvesting Operations

Many studies have applied remote sensing techniques to the detection of harvesting operations (Lillesand and Kiefer, 2000; Puhr and Donoghue, 2000; Häme *et al.*, 1998; Jeanjean and Achard, 1997; Singh, 1989; Leckie, 1985; Sohlberg, 1985). Varjo (1997) refers to several references that show that clear-felling operations cause one of the largest spectral changes in Finnish operational forestry. Sader *et al.* (2001) were able to detect forest-clearing operations with 86.5% accuracy over several time periods, producing a kappa co-efficient of agreement of 0.82.

2.2.1.2 Re-Establishment Operations

Another major operation that causes a significant change in the status of a compartment is that of planting or re-establishment. Under normal plantation conditions in the KwaZulu-Natal Midlands, trees are planted on a grid pattern with an espacement varying from 3 m x 1.5 m (for *Acacia* species), 3 m x 2 m (for *Eucalyptus* species) to 3 m x 3 m (for *Pinus* species). At the time of planting, the seedlings have a crown diameter of less than 20 cm. However, after the first year of growth, provided the correct silvicultural treatments (especially weed control) have been applied, the canopies of the faster growing species (*Eucalyptus* and *Acacia*) are between 1.5 m and 2.0 m in diameter. Being slower growing, Pine canopy diameters are between 1.0 m and 1.5 m. Landsat 7 imagery has a fairly coarse spatial resolution of 30 m. This implies that the smallest detectable unit covers an area of 900 m² (0.09 ha). Based on the standard planting espacements listed above, there should be between 200, 150 and 99 trees (for *Acacia, Eucalyptus* and *Pinus* respectively) within a single pixel, and so individual tree counts are not feasible. Literature shows that even with the very high spatial resolutions of aerial photography and Light Detection and Ranging (LIDAR) technology, which have sub-metre pixel sizes, stem counts are still only in the experimental stage (Jacobs and Mthembu, 2001). Research done by Wulder *et al.* (2000) showed that with one-metre spatial resolution imagery, a minimum tree crown radius of 1.5 m was required for reliable tree location identification.

2.2.1.3 Weed Control Operations

Forest stands that are re-established generally have a range of vegetative cover which can vary from a pure stand of newly planted seedlings surrounded by bare soil to seedlings totally surrounded by weed vegetation. These various stages of vegetative cover affect the reflectance characteristics of the imagery, and the possibility of identifying whether this range of vegetation cover can be accurately detected has important implications for the monitoring of critical weed control operations (Datt, 1999). However, Nilson *et al.* (2001) found difficulty in quantitatively describing the effects on reflectance caused by the successional changes in ground and field-layer vegetation. Even with very high 0.5 m resolution airborne imagery, detection of weeds has varying success rates, depending on the type of weed and the age of the weed. Gray *et al.* (2004) obtained classification accuracies ranging from 49% to 96% for weeds in soybean fields, with the higher accuracies being in fields with fewer weed types present.

2.3 The Role of Geographic Information Systems (GIS) in Forestry and its Integration with Remote Sensing

By definition forest management involves the capture, interrogation, update and analysis of forest data that has spatial, as well as attribute components. In addition, this data is not only of considerable volume, but also very complex. This complexity and volume can only be handled effectively through the use of suitable technologies, and Geographic Information Systems (GIS) are ideal tools to meet this need (Von Gadow and Bredenkamp, 1992, Levinsohn and Brown, 1991). In addition to this complexity, plantation forestry data is categorical in nature (e.g. compartments, roads, rivers, dams, contours etc.) and best represented by a vector format, making

GIS the most appropriate tool to manage such data. Another key reason for using GIS is its capacity to integrate data from different sources and types (Lunetta, 1999; Dunningham and Thompson, 1989). Remote sensing data is of a continuous nature (as opposed to a categorical nature), and utilises a raster format. Such data requires some form of classification in order to extract useful information. Once classified, this information is available to aid decision-making processes, and this is best achieved by its integration into GIS (Lillesand and Kiefer, 2000; Eastman, *et al.*, 1995).

There is an increasing merging of remote sensing image processing software and GIS software (e.g. ERDAS Imagine™ (ERDAS, 2003), ArcGIS™ (ESRI, 2000), IDRISI™ (IDRISI, 2003), GeoMedia™ (Intergraph, 2003)), due to the extensive overlap between these software types. Image processing software is increasingly developing GIS-type functionalities, while GIS software is increasingly adding raster and image processing capabilities. This is also reflected in the fact that there are an increasing number of research projects that are integrating remote sensing techniques and GIS technology as a core part of their methodology (Xue, *et al.*, 2002; Yang and Lo, 2002; Smith and Fuller, 2001; Weng, 2001; Luque, 2000).

2.4 Factors affecting the use of Remote Sensing in Forestry

Remote sensing technology, in various forms, has been applied in forestry since the early part of the 20th Century. Aerial photography was applied in German forestry in the 1920's (Kätsch and Vogt, 1999; Hildebrandt, 1985). Wide use of aerial photography has been applied in the Nordic countries since the 1950's (Sohlberg, 1985). Satellite remote sensing applications began in earnest with the launch of the original ERTS 1 (later called Landsat 1) in the early seventies, mainly due to its multi-spectral scanner (MSS) technology. In 1981, a national forest cover project was undertaken in South Africa, using Landsat data (Kätsch and Vogt, 1999).

Generally, most of the work undertaken using remote sensing technologies for forestry have been for forest management, mapping and planning, damage assessment and inventory (Kätsch and Van Laar, 2002; Hildebrandt, 1985; Leckie, 1985; Sohlberg, 1985;), and in terms of forestry remote sensing research, the bulk of the literature falls into one or more of these categories.

It should be noted that the vast majority of this research has been carried out in Northern Hemisphere natural forests (which tend to be uneven-aged, mixed species stands, and usually of a great geographical extent). These are somewhat different from Southern Hemisphere plantation forests, which are even aged, single species (and even single clone) stands that cover relatively small areas, compared to natural forests.

Remote sensing imagery derives its usefulness from the information content that can be extracted from it. However, the application of remote sensing data in forest management applications has been slow due to high cost and the limited classification accuracies achieved to date (<80%) (Heyman, *et al.* 2003). This accuracy is dependent on such factors as the spatial, temporal, spectral and radiometric resolutions, the spatial scale of imaged features, the radiometric contrast between different features of interest, and the end purpose for which the imagery is required (Narayanan, *et al.* 2002). For remote sensing technology to be applied in forestry, several factors have to be considered, including the technical limitations of the sensors, the cost and availability of imagery and the purpose for which the technology is to be applied. These factors determine what sensor is to be used for a specific application.

With respect to the technical limitations, the most important aspects to be considered are the spatial, spectral and radiometric resolutions (Varjo, 1997). For change detection purposes, the temporal resolution of the imaging system must also be considered (Pouncey *et al.*, 1999).

2.4.1 Spatial Resolution

The minimum spatial resolution required is determined by the smallest feature that requires identification on an image (Varjo, 1997). The basic feature that is the focus of this study is the forest stand or compartment, which varies from about 0.5 hectare to 50 hectares in size, but which is, on average, 12 hectares. Ideally, one would want to be able to measure variation within these compartments, a practical size of which is about 500 m^2. Therefore, to detect this, the spatial resolution (or pixel size) of a suitable medium resolution sensor equates to a pixel size of 22.3 m x 22.3 m. Varjo (1997), quotes figures of 4–5 m as the best spatial resolution to monitor forest canopy, which would require the application of high spatial resolution sensors.

An essential element in deciding on a suitable spatial resolution is what the minimum mapping unit needs to be. Usually, this is defined as the pixel size of the chosen sensor, because most classification processes are pixel based. However it can be a larger unit, and in the case of forestry, is often the forest stand or compartment. Varjo (1997) and Varjo and Folving (1997), both support this. However, this can also present other problems where the delineation of stands is an issue (Varjo, 1997).

Concerning medium resolution sensor types, Landsat 7 multi-spectral bands have a pixel size of 30 m, while the panchromatic band has a 15 m spatial resolution. (At the time of undertaking the medium resolution study it was readily available and affordable. However, it has subsequently developed fundamental problems, in terms of the Scan Line Corrector failure, which will have a negative impact on its usefulness). SPOT 4 and 5 imagery is available as well, but is less affordable, as it is currently about three times the price of Landsat imagery. The swath width is only 60 km, compared to 185 km for Landsat 7, which makes it even more costly (Janssen, 2000). The spatial resolution of SPOT is 20 m in the multi-spectral bands, and 10 m in the panchromatic band. However, it has a lower spectral resolution than the Landsat 7 sensor, which reduces the spatial resolution advantage (Varjo, 1997). Narayanan *et al.* (2002) found that while Landsat TM imagery had higher information content than the Shuttle Imaging Radar–C at smaller pixel sizes, the reverse was true for larger pixel sizes, with the transition occurring at a pixel size of about 720 m. While radar technology is outside of the scope of this study, it does illustrate how one needs to understand the sensors' limitations and potential when choosing a suitable sensor for a project.

High resolution sensors such as the QuickBird and Ikonos sensors have a much finer spatial resolution (QuickBird: 2.4 m multi-spectral; 0.6 m panchromatic; Ikonos: 4 m multi-spectral; 1 m panchromatic) but are not readily available and are extremely expensive. This is compounded by the fact that having a higher spatial resolution means that the swath width is much smaller than lower resolution satellites such as Landsat, and therefore more images are required to cover the same area, which further increases the cost. However, they are effective for applications requiring high detail over small areas, although Heyman *et al.* (2003) observed that when using traditional per-pixel classifiers, increased spatial resolution increases the information content of the imagery but classification accuracy can decrease due to an increase in variability within each class.

2.4.2 Temporal Resolution

A fundamental principle of change detection is the application of multi-temporal imagery (Pouncey *et al.*, 1999). This introduces another parameter into the process, that of the required temporal resolution, i.e. how many images are required, and at what time interval? These requirements are project-specific, but certain aspects are generic.

Image availability can be a constraint, particularly due to weather conditions such as cloud cover hindering the acquisition of clear images at the required times. Other constraints in terms of temporal resolution can be the revisit cycle of the required sensor (for instance, the revisit cycle of Landsat 7 is 16 days, SPOT 4 is 26 days, while Ikonos has a 14-day cycle), (Janssen, 2000). Some coarse resolution sensors (e.g. NOAA AVHRR) have daily repeat cycles, but these are considered to have far too coarse a spatial resolution for change detection on a local as opposed to a regional or global scale.

Varjo and Folving (1997) found that change detection results were more accurate the shorter the interval between images. The ranges in this quoted study varied between one and three years, with change detection accuracies of 93.1% to 87.6%, respectively. However, this study was conducted in Scandinavian boreal forests (with slow growth rates), while South African sub-tropical/temperate plantations experience much faster growth rates. This latter factor might well play a significant role in the temporal resolution requirements.

2.4.3 Radiometric Resolution

Radiometric resolution determines the number of possible spectral values measured, and thus the degree of separability of small changes in spectral intensity (Varjo, 1997), in other words, the level of spectral differences that can be detected.

An associated problem is that of mixed pixels or mixels, which are caused by more than one feature, each of which has its own unique spectral reflectance value, being present within the same pixel. In other words, it is a function of the spatial resolution, such that the individual features are smaller than the pixel size.

Various procedures have been tried in an attempt to extract this information from within the pixel, e.g. McGovern *et al.* (2002) developed a radiometric normalisation technique using linear transformation functions that included the application of a thresholding process on sub-pixel scale elements to extract reference data from a land cover class. RMS errors for this technique ranged from 0.8 – 2.5 DN.

2.4.4 Spectral Resolution

Spectral resolution refers to the part of the Electromagnetic Spectrum that is being measured (Janssen, 2000), i.e. what wavelengths (or range of wavelengths) are captured into "bins", for which response is integrated. This is a function of the sensor selected for a project, and therefore the only control one has over this aspect is to understand what the specifications and limitations of each sensor are, and to select the most suitable one.

2.5 Rectification Requirements and Procedures

2.5.1 Geometric Referencing

Accurate spatial registration of the various images used is an essential feature in change detection (Lillesand and Kiefer, 2000; Singh, 1989). This is due to the fact that the basis of change detection relies on identifying changes in spectral reflectance between pixels of identical spatial location. Registration and rectification errors can lead to inaccurate results being produced during a change detection procedure due to mismatching of the overlaying pixels. This is a serious disadvantage of using pixel level analyses. Igbokwe (1999) describes a method of geometrical rectification and image registration with two-dimensional image correlation that produced image registration accuracies of 0.28 pixel. This methodology was tested on Landsat MSS and TM data. Toutin (2004) provides a very comprehensive review of the geometric processing issues involved in ortho-rectifying remote sensing imagery.

2.5.2 Atmospheric Correction

Atmospheric conditions can play a major role in the quality of electromagnetic radiation recorded by satellite sensors due to the scattering and absorption of various wavelengths by atmospheric gases and aerosols (Janssen, 2000; Song *et al.*, 2001). Calibration of images is designed to allow several images or difference images to be radiometrically comparable, as well as enabling the phenomena of interest to be more separable or identifiable (Varjo, 1997).

The fundamental principle on which the decision to undertake atmospheric correction or not is whether qualitative or quantitative results are required. Where qualitative results are the objective (e.g. such as determining thematic classes, or Boolean logic such as "Has change occurred – yes or no"), atmospheric correction is optional. However where any quantitative analysis is required (e.g. calculating areas of change, or degrees of change), atmospheric correction is important in order to ensure that the results are radiometrically comparable.

Song *et al.* (2001) compared seven absolute and one relative atmospheric correction algorithms, and concluded that simple dark object subtraction, with or without the Rayleigh atmosphere correction or relative atmospheric correction is recommended for classification and change detection applications. This correction is required where terrestrial surfaces are monitored over time, due to the necessity of putting multi-temporal data on the same radiometric scale. The work of Puhr and Donoghue (2000) also supports the need for atmospheric correction when comparing the results obtained from different images.

However, in an interesting paper describing a change detection methodology, Häme *et al.* (1998) differentiate between short term monitoring and long term monitoring of change. The former is used to detect disturbance changes, while the latter is used to detect trends. Due to this difference, there is a difference in the requirement for calibration between images, of which atmospheric correction is one element. According to Häme *et al.* (1998) short term monitoring can be based on the comparison of intensities from different parts within an image, where the greatest proportion of the image includes only vegetative succession. In such cases, images do not have to be calibrated into absolute reflectance values (unlike long term monitoring where trends need to be determined). Häme *et al.* (1998) also point out that where two independent image classifications are compared in order to highlight change, absolute calibration is also not required, provided that the change is very striking, or a large amount of ground-truth data is available. A problem does occur though, where there are errors in the classification, due to the uncertainty created in determining whether change has occurred or whether the difference is due to errors in the classification.

2.5.3 Radiometric Calibration

Where a supervised classification methodology is applied, and training data sets are available for every image pair (or where the image pairs are spectrally similar enough), radiometric calibration can be omitted (Varjo, 2003;Varjo, 1997).

An advantage of radiometric calibration being applied in change detection procedures is that non-change spectral variances (due to sensor anomalies, differing atmospheric conditions or variations in viewing or solar angles) can be detected and removed prior to any change detection being applied (Varjo, 1997). Chen *et al.* (2005) describe a simple radiometric correction method, called the Temporally Invariant Cluster (TIC) method, which created radiometrically comparable data sets in order to improve landscape change detection results.

2.6 The Use of Textural Analysis in Forestry Classification Applications

2.6.1 Introduction

The purpose of image classification is to characterise every pixel in an image into meaningful classes in order to extract meaning from the image. This is achieved either by utilising the relationship of spectral (or radiance) properties to one another, or the spatial relationships of the pixels, such as texture, shape, size or context (Lillesand and Kiefer, 2000). A third means is based on the temporal relationships between pixels, where the time element is used to distinguish classes, and it is this factor on which change detection is based.

2.6.2 Principles of Textural Analysis

While standard optical remote sensing classification techniques are based on the spectral characteristics inherent in imagery, incorporating ancillary information such as texture, context and structural characteristics has been shown to improve classification results (Ouma *et al.*, 2006; Tso and Mather, 2001; Coppin, 1991; Fung and LeDrew, 1987). It is interesting to note that these characteristics preceded the development of spectral analysis techniques, as they form the basis of the original manual image interpretation techniques utilised in extracting information from aerial photography (Tso and Mather, 2001; Janssen, 2000; Coppin, 1991), and are now of increasing importance due to their role in object-orientated segmentation and classification procedures.

Texture refers to the visual roughness or smoothness of features across an image, due to the spatial variability of tonal values, which result in a repetition of patterns across the image (Tso and Mather, 2001). This concept deals with the structure of the object itself, based on the tonal variation within itself (i.e. the "within object" variance, also referred to as the microstructure (Jonckheere, 2000)).

Tso and Mather (2001) define context as the probability of occurrence a group of pixels will have, based on the pixel nature across the whole scene. Context describes the relationship between an object and the rest of the scene (i.e. the "between objects" variance, also referred to as the macrostructure (Jonckheere, 2000)). It is usually applied through a statistical technique such as a majority filter window, which is used to refine a classification.

It should be noted that spectral and textural features are inter-related, and complement, rather than duplicate, information derived from both sources (Coppin, 1991). Both properties are always present in an image (Haralick *et al.*, 1973), but the degree to which one is dominant over the other is a factor of the resolution of the one compared to the other. Where spatial resolution is high in relation to the scale of tonal variation, texture can improve class discrimination in a classification. The converse is also true where homogenous areas within an image are small, as texture is a feature of an area rather than a point (Tso and Mather, 2001).

Textural analysis can be applied using four different theoretical approaches. These are the frequency domain theory (Jensen, 1996); a statistical approach (Jonckheere, 2000); joint grey-level probability density, after Haralick *et al.* (1973); and fractal theory (Tso and Mather, 2001). All of these methods involve the quantification of texture patterns. Of these four theories, two were considered to be applicable in this study; these being the frequency domain and the statistical approach, and detailed descriptions of these procedures are given in Chapter 5.1.3, Methods. A Fourier Transform technique, used to measure elements in the frequency domain and several statistical procedures, utilising convolution filter masks, as well as the variance and skewness functions were tested.

2.6.3 Statistical Approach

When using a statistical approach for the determination of textural characteristics, a fundamental principle on which this is based is that of spatial autocorrelation, i.e. things closer together are more likely to be similar than things further apart (Meisel and Turner, 1998). The basis on which this is measured is determined by the size of the convolution window applied. Therefore it is imperative that the optimal window size is determined prior to any analyses being undertaken. This can be done using semivariograms (Tso and Mather, 2001; Jonckheere, 2000; St-Onge and Cavayas, 1997).

2.6.3.1 Semivariograms

The semivariogram is a mathematical function that correlates the dissimilarity, or semivariance, of points within a data set to the distance between them, and when viewed graphically, describes the spatial correlation between all data points in the data set (Johnston *et al.*, 2001). It is a dissimilarity function because the variance of the difference increases with distance.

Mathematically, the semivariance function is defined as follows:

$$\lambda(h) = ½N(h)\sum_{i=1}^{N(h)}(x_i - y_i)^2 \quad \text{(Equation 2.1)}$$

where: $\lambda(h)$= semivariance at lag distance h;

$N(h)$ = number of data point pairs separated by h;

x_i = value at the start of the pair;

y_i = value at the end of the pair.

(Meisel and Turner, 1998)

Graphically, a typical semivariogram (a plot of the semivariances $\lambda(h)$) is as follows (Figure 2.1):

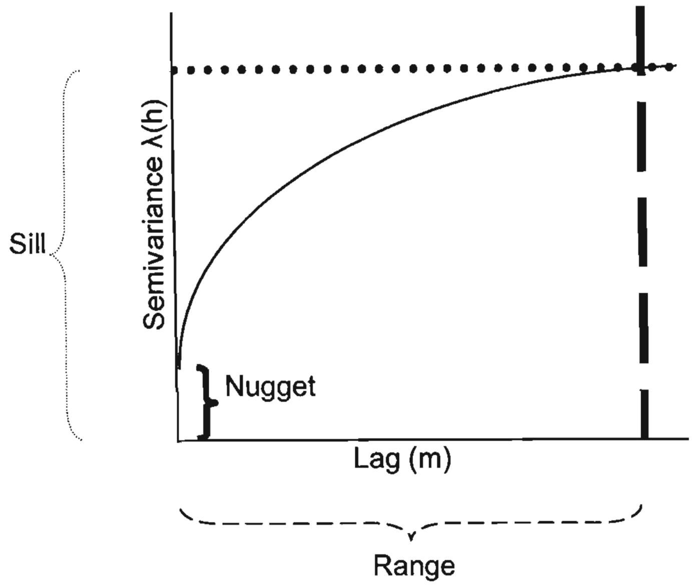


Figure 2.1 Illustration of a Typical Semivariogram

from which four critical measures, Lag; Sill; Range; and Nugget, are derived.

By fitting a recognised model (e.g. spherical; linear; circular or exponential) to the discrete points of the semivariogram a continuous line can be obtained, from which the range, sill and nugget can then be measured (Johnston *et al.*, 2001; Meisel and Turner, 1998).

The Lag is the distance between the data point pairs. To reduce the large number of possible combinations, these are usually grouped into distance classes, in a process called "binning".

The Sill is the maximum value of the semivariance $\lambda(h)$, i.e. where the graph reaches a plateau.

The Range is the lag distance at which the graph levels off, and is usually set at the point where the sill reaches 95% of the semivariance $\lambda(h)$. Beyond this point there is little or no autocorrelation between the variables. It is this factor that provides the means to determine the optimal window size (Tso and Mather, 2001).

The Nugget is the measurement or independent error parameter, and is the distance from the origin to where the graph intercepts the semivariance $\lambda(h)$.

(Johnston *et al.*, 2001; Jonckheere, 2000)

Two assumptions on which semivariance analyses are based are those of stationarity (i.e. any variation is due to separation distance alone) and anisotropy (i.e. no directional trends occur in the data). However, these are not always met when working with natural phenomena (Johnston *et al.*, 2001; Meisel and Turner, 1998). An advantage of using semivariance is that it tends to be insensitive to variations in contrast across consecutive images (St-Onge and Cavayas, 1997), which is an important consideration in a study such as this one, which is based on repeat images.

Various authors have applied semivariance analyses in studies of forest stands and attributes. Woodcock *et al.* (1988) calculated variograms for aerial photography and TM imagery of forest stands. Cohen *et al.* (1990) applied variograms in their studies on forest canopies. Other forestry applications of semivariance analyses have been done by Wulder *et al.* (2000); St-Onge and Cavayas (1997) and Hyppanen (1996).

2.6.4 Frequency Domain Approach

Textural analyses may also be carried out using techniques that have their theoretical bases in the frequency domain. In image processing, this is usually achieved through the application of a Fourier Transform. Fourier analysis is the mathematical technique of transforming an image's spatial components into its frequency components (Jensen, 1996). The frequency spectrum is called the magnitude of the Fourier Transform, and is displayed as a two-dimensional image. This image represents the magnitude and direction of the different frequency components of the input spatial image (Jensen, 1996), and is symmetrical about its centre. These images are in the form of a disc, with low frequency information close to the centre of the disc, i.e. the co-ordinate origin, and high frequency information further out to the extremity of the image (Fisher *et al.*, 2003; Tso and Mather, 2001). The square of the amplitude spectrum is known as the Fourier power spectrum, and the angular distribution of the power spectrum values is sensitive to structural directionality present in the spatial domain (Tso and Mather, 2001).

If there are many edges or strong linearity at a specific angle in the spatial input image, the power spectrum image will display high values concentrated around a direction perpendicular to the angle in the spatial domain. They appear as bright dots, and a line connecting these dots to the centre of the image is always orthogonal to the orientation of these lines in the input image. Thus the frequency and orientation of the lines can be determined (Jensen, 1996). This phenomenon was of particular interest to this study. However, these bright dots could also be the result of other features such as noise, and a filtering operation has to be done in order to separate noise and other linear features from the particular linear features of interest. Textural roughness can also be extracted using the power spectrum functionality, as the radial distribution of the power spectrum values is sensitive to this roughness or smoothness (Tso and Mather, 2001). Smooth structures produce high power spectrum values away from the origin, while coarse structures produce high values close to the power spectrum origin.

The filtering of power spectrum images is generally done using wedge or ring filters, where the angle and radius values of these filters control the width of the filter's effective area (Tso and Mather, 2001). Wedge filters are used to highlight directionality, while ring filters highlight textural roughness (Jonckheere, 2000).

While textural analyses can be done using the features of the frequency domain, for general image processing applications spatial domain filtering is more cost effective (Jensen, 1996), and it is certainly less complicated. Fourier methods become more appropriate when the filter functions required to perform the image processing become very large. There are also some specialised filter functions that are better done using Fourier techniques than spatial domain techniques (Jensen, 1996).

Textural analysis is generally done using a single band (Coppin, 1991; Fung and LeDrew, 1987), but Coburn and Roberts (2004) describe an alternative multiscale methodology using several bands of textural information with different window sizes, which resulted in a 40% improvement in the classification of forest stands.

2.7 The Use of Change Detection in Satellite Image Analyses

Singh (1989) defines change detection as "the process of identifying differences in the state of an object or phenomenon by observing it at different times". Eastman *et al.* (1995) distinguish between change detection and time series analysis as being two distinct processes, the analytical methods of which are often very different.

Change detection involves either the determination of differences in surface characteristics between two dates, or defining differences that are uncharacteristic of normal variation within a specified period. Time series analyses, on the other hand, involves detecting trends of change over a sequence of more than two images, and includes a description of characteristic values and an abstraction of anomalies (Eastman *et al.*, 1995). Change detection is a bi-temporal process, where the same site is compared at two different dates, while time-series analysis a more comprehensive process where the same area is compared over a longer interval with multiple images, also called temporal trajectory analysis. This process requires composite images built up from daily images obtained by such sensors as the NOAA AVHRR, SPOT VEGETATION or MODIS. Unfortunately all these sensors have a fairly coarse resolution, which limits their application in change detection (Coppin *et al.*, 2004). From these composite images, seasonal development curves are derived, against which the change detection processes are run. When applied to larger scale processes, such as across regional or global scales, trends rather than change events are analysed (Coppin *et al.*, 2004).

Irrespective of which process is used, there are several criteria that should be met when undertaking either of these procedures. These include the following:

- Data should be acquired from the same (or very similar) sensors,
- The same spatial, spectral and radiometric resolutions should be applied,
- The same viewing geometry and time of day should be used (anniversary dates can be used, as they minimise sun angle and seasonal differences).
- Accurate spatial registration between the images, preferably to within half a pixel, is also generally required. (Donoghue, 1999; Lillesand and Kiefer, 2000)

The type of data used in change analysis also has an effect on the process. There are two types of data used: quantitative (refers to difference in degree, e.g. temperature change) or qualitative (referring to difference in kind, e.g. a land use change). The analysis technique used will differ depending on the data type, and whether simple change (pair-wise) or multiple (time series) comparisons are being made (Eastman *et al.,* 1995). Another issue with change detection is the ability to detect incremental change (for instance, growth in young stands over time), as opposed to abrupt change (such as harvesting operations), which tends to be fairly easy to detect (Coppin *et al.*, 2004).

The net result of the above criteria is that the selection of a change detection procedure is dependent on the application and the data sets involved (Donoghue, 1999). Change detection and time series analyses are two processes that have uniquely benefited from remote sensing technology, and it is in this field that the greatest advances have been made (Eastman *et al.*, 1995). The next major step in the development of change analysis is to move from simply identifying historic change to predicting future change using various modelling algorithms. Authors such as Pontius *et al.* (2001) and Jensen *et al.* (1994) have researched this topic.

Despite all the advances made in the technology, digital change detection remains a difficult process, in part due to the classical remote sensing challenge: maximisation of the signal-to-noise ratio (Coppin *et al.*, 2004).

2.8 Change Detection Techniques

2.8.1 Introduction

By definition, change detection requires some form of classification procedure to be applied. Singh (1989) defines two classes of change detection techniques based either on any data transformation technique applied, or secondly on the analysis technique applied to delineate areas of change. Classic remote sensing principles have applied pixel level unsupervised and supervised classification techniques, as well as a combination of these two (Lillesand and Kiefer, 2000; Pouncey *et al.*, 1999; Mattila, 1998; Singh, 1989). However, a new development trend is now moving away from pixel based classification towards Object-orientated Classification, as applied in the *eCognition*® software (Mittelberg, 2002; Willhauck, 2000).

Varjo (1997) supports this, when he makes an interesting statement regarding the selection of change detection techniques, in which he suggests that for monitoring and updating purposes, none of the traditional methods are suitable. This would support the contention that new methods such as object-orientated processes, or the "Autochange Analysis" process (see 2.8.11) should be considered where such monitoring and reporting are of issue. The application of Nonparametric Discriminant Analysis has also been suggested as an alternative methodology (Varjo, 1997).

Varjo and Folving (1997) describe a methodology that applies an unsupervised clustering approach that combines a relative regression calibration with studentisation of the spectral difference features. By using forest stands as the classification units change detection accuracies of between 87.6% and 93.1% were achieved.

Coppin *et al.*, (2004), Häme *et al.* (1998) and Singh (1989) list several tested methods of change detection, including 1) thresholding of a single spectral feature; 2) direct classification of a multi-date data set; 3) change vector analysis; 4) decision tree classifiers; and 5) residual computation of a regression model between two images. Similarly, Jeanjean and Achard (1997) mention the use of simultaneous analysis of multi-temporal imagery or comparative analysis of independent single date classifications for change detection purposes, where the analysis techniques are derived from thresholding, supervised or unsupervised classification, or temporal analysis. Mas (1999) also tested several change detection methodologies for use with Landsat MSS imagery. These included image differencing, vegetative index differencing, Selective Principal Component Analysis, direct-multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison. A more detailed analysis of the various techniques is given below.

2.8.2 Post Classification Comparison

A comparison of independently classified images provides one of the simplest and most common means of detecting change. This method, called Post Classification Comparison, has several advantages, particularly because it does not require accurate registration of multi-date images, while also minimising the need to normalise for atmospheric and sensor differences (Coppin *et al.*, 2004; Singh, 1989).

This method has met with both success and failure, depending on the area of interest to which it was applied. Mas (1999) identified post-classification comparison as the most accurate procedure, with the added advantage of the change type being indicated. Spectral variations caused by differences in vegetation phenology and soil moisture variance resulted in image enhancement techniques producing poor results. These factors had less impact on the results from classification methods, and were also more efficient in handling imagery from different seasons. Other research found that because the accuracy of the change detection is totally dependent on the accuracies of the initial classifications, errors in classification are magnified with this method, which can lead to a large number of false change indications (Coppin *et al.*, 2004), and several studies have shown this method to be unreliable for use in detecting land cover and change analysis (Singh, 1989). An example of this is quoted by Singh (1989) where in one study this methodology identified six times more change than a change vector methodology applied to the same area.

However, Zukowskyj *et al.* (2001) describe the application of post-classification contextual filters to increase the overall accuracy of such classifications. A commonly applied such method is based on the use of a modal majority decision rule within a 3x3-kernel filter. These authors applied 221 different decision rules and kernel sizes in order to determine those that produced the greatest accuracy improvement, by quantifying the effects of decision rule changes, window size, shape and weighting, probability thresholding prior to filtering, edge effects and multiple pass filtering. For a set of imagery obtained from Landsat TM, the optimal filter proved to be a two-pass filter with both kernel sizes between 11x11 and 15x15 pixels, using a modal majority decision rule, with edge effects reduced. The resultant accuracy increased from 57.9% to 71.3%. It was concluded that simple filters were more effective than complex ones (Zukowskyj *et al.*, 2001).

2.8.3 Principal Component Analysis

A standard method of change detection involves the use of Principal Component Analysis (PCA), (Lillesand and Kiefer, 2000; Häme *et al.*, 1998; Eastman *et al.*, 1995; Singh, 1989). An interesting finding by Eastman *et al.* (1995) was that change detection was more identifiable in the minor (second and third) components, rather than the major (first) component, a fact also supported by the work of Fung and LeDrew (1987), as well as in Coppin *et al's.* (2004) review article. The latter authors found that statistics extracted from a subset of the data should not be used for land cover change detection due to the degree of variability and uncertainty of the unextracted part of the data. This is in contrast to the findings of Eastman *et al.* (1995), who found that improved results were obtained when only input data from the area of interest were analysed. Singh (1989) reported that the use of standardised variables (i.e. correlation matrix) produced significantly better results than applying non-standardised variables (i.e. a variance-covariance matrix). PCA does have a limitation due to the effect that this process has on the spatial structure and content of remotely sensed images, resulting in structural differences between the various principal components, as well as between them and the original image. Avena *et al.* (1999) discuss this issue in the light of their research and conclude that great care is necessary in the application of PCA to remote sensing, as well as in the interpretation of the results. Without a thorough understanding of the eigenstructure of the data and visual inspection of the resultant images it is difficult to interpret the actual nature of the principal components, and to avoid drawing incorrect conclusions, a thorough knowledge of the study area is required before using this methodology for change detection (Coppin *et al.*, 2004).

A variation of PCA can be applied where information on particular areas of interest is known. This system, known as Canonical Component Analysis, maximises the separability of the known classes, while simultaneously minimising intra-class variability (Lillesand and Kiefer, 2000). While the data reduction improves classification efficiency, the increased spectral separability improves classification accuracy.

2.8.4 Univariate Image Differencing Technique

Singh (1989) describes the univariate image differencing technique, where equivalent pixels of two co-registered images are subtracted from one another to derive a resultant change image. Coppin *et al.* (2004) found this methodology the most widely applied change detection algorithm. The actual changes are recorded in the tails of a histogram, with minimal to no change areas being around the mean. The success of this method is determined by how well the threshold values are set to distinguish change from no-change values in the histogram. Image subtraction and thresholding was at one stage the most common method to detect land-cover change due to its ability to accentuate spectral change (Lunetta, 1999). Various edge-effect enhancements have been tested to improve change detection results, but with mixed success (Singh, 1989).

2.8.5 Image Regression

Another method is Image Regression, based on the assumption that values of pixels at time t_1 are a linear function of the same pixels at time t_2. A least-squares regression is applied using these pixel values to derive a difference image. The size of the residuals indicates where change occurred. However, the critical step is the determination of the threshold values for the "no-change" pixel residuals (Coppin *et al.*, 2004). This methodology is reported to produce marginally better results than the univariate image differencing technique in detecting tropical forest cover changes (Singh, 1989).

2.8.6 Image Ratioing

Image Ratioing can also be applied to produce a difference image, having the advantage of producing a result rapidly. Two images of different dates are divided (t_1/ t_2) on a pixel-by-pixel basis, such that where there is a close similarity in reflectance values between the relevant pixels, the resultant ratio is close to 1, and no change is indicated (Coppin *et al.,* 2004). Values further away from 1 indicate possible change, but again, the successful application of this method depends on appropriate threshold values being applied (Singh, 1989).

2.8.7 Vegetation Indices Differencing

Vegetation Indices Differencing is a refinement of Image Ratioing, based on the use of particular bands (also called band ratioing). This method has the advantage that significant intensity differences in the spectral response curves are emphasized, while the ratioing effect also reduces the influence of topographic effects and normalised irradiance differences on multi-date images (Singh, 1989). As the name indicates, this methodology has found particular application in vegetation studies, chiefly due to the particular spectral characteristic that is inherent in vegetation, being strong absorbance in the red spectrum and strong reflectance in the near infrared spectrum (Lillesand and Kiefer, 2000). Various indices have been developed, but all are based on the use of Red and Near-Infrared (NIR) bands, which in the case of Landsat 7 sensors are Bands 3 and 4 respectively. Chen *et al.* (1999) give a comprehensive listing of these indices and their formulae.

The most commonly applied index is the Normalised Difference Vegetation Index (NDVI), which, for Landsat imagery, is calculated as: *(band 4 - band 3)/(band 4 + band 3)*. Regarding its application in change detection, Singh (1989) quotes several studies that have applied vegetation indices to detect changes in vegetation canopy. The results were such that it was not possible to draw definitive conclusions as to its efficacy. Nelson (1982), (in Singh, 1989), found that NDVI provided an accurate means of delineating forest canopy change. However, Singh (1989) also describes Banner and Lynham's (1981) findings that using a Transformed NDVI (TNDVI) were less accurate in delineating clear-felled areas than using a supervised classification technique.

In a variation of vegetation indices, Datt (1999) studied the remote sensing of chlorophyll content in *Eucalyptus* species using the visible/near infrared reflectance values and indices of specific wavelengths. The 710nm wavelength proved to have the most sensitivity to chlorophyll content, while the best performing indices was the ratio $(R_{850}-R_{710})/(R_{850}-R_{680})$. While chlorophyll content is beyond the scope of this study, there could be a potential application of this methodology in assisting in the determination of weed status as opposed to crop status.

2.8.8 Generalised Linear Models

In order to provide a quantitative approach to image-based change detection Morisette *et al.* (1999) applied Generalised Linear Models (GLMs) to enhance standard change detection techniques. Preliminary variogram analysis was applied to the image data to determine initial sampling considerations. A "joint-count" test was used to assess the independence of the binary response (change/no-change) data set derived from the reference data. A model error term was then checked using the empirical variogram of the residuals. The conclusion reached in this study was that GLMs could assist in the examination of different change metrics, while applying the resulting model across the whole image enabled a probability of change estimate to be calculated, as well as pixel-specific estimates of the variability of change estimate. However, the assumption of independent response data used for the modelling should be respected.

2.8.9 Change Vector Analysis

Another technique applied in change detection is the use of Change Vector Analysis (CVA). Eastman *et al.* (1995) and Lillesand and Kiefer (2000) describe its use in determining clear-felled and re-established areas. This procedure uses spectral and spatial data to perform a spatial-spectral clustering on two images taken at different times to define homogeneous areas. These areas are first defined for each image, after which a change vector is calculated between the area spectral means of the two images. The magnitude of the vector describes the intensity of change while the angle defines the type of change (Singh, 1989). Change detection and the classification of the change are thus separate operations, unlike multi-date classifications, which combine the two processes. A significant advantage of this method is its ability to analyse change concurrently in all bands as opposed to selected bands (Coppin *et al.*, 2004). However, a problem reported with this method is that it is parameter sensitive, but there is no clear procedure on defining these parameters (Häme *et al.*, 1998). Singh (1989) quotes several studies where this methodology was applied to forestry situations.

Zhan *et al.* (1998) discuss the use of this technique when applied using the Red and Near-Infrared (NIR) reflectance space. The technique is based on the change phenomenon represented by the rapid change in brightness and greenness associated with deforestation (or clear-felling in plantation situations). In other words, the brightness-greenness space signatures of a location recorded at different dates can indicate whether change has occurred, as well as an indication as to the type of change occurrence. Greenness is related to the difference between the NIR and the red bands (NIR – Red), while brightness is related to the mean of NIR and red ([NIR+Red]/2). Thus, a change vector in the NIR/Red space is equivalent to the change vector in the greenness/brightness space, indicating a change event. When the reflectance difference is calculated between images of two separate dates, this produces a Delta image (i.e. the amount of change between the two images), represented as a Delta-Brightness or a Delta-Greenness image. The Delta- Red and the Delta-NIR space are overlain on the Delta-Brightness and Delta-Greenness space and used to interpret the change vectors (Zhan *et al.*, 1998).

Nackaerts *et al.* (2005) describe the performance of a modified change vector analysis (mCVA) process applied to forest change detection. This methodology overcomes a disadvantage of the standard change vector analysis, i.e. the need for reference data to interpret the change vectors, by preserving the information held in the change vector's magnitude and direction as continuous data, for *n* change indicator input bands. These can be subjected to statistical change feature extraction, and the feature extraction phase is the only time training data are required. In standard CVA, reference data are required for the "*change-no change*" thresholding in the magnitude domain, and again for the angle grouping.

2.8.10 Delta Transformation Technique

A technique related to CVA is the Delta Transformation Technique developed by Walkey (1997) (in Lillesand and Kiefer, 2000). Using 2D scatter-plots to graph change versus no change axes, change occurrences are represented as data concentrations above or below the axis of stable spectra (i.e. area of no change).

2.8.11 Autochange Analysis

Häme *et al.* (1998) describe a change detection and classification methodology, called "Autochange" Analysis, that is similar in some respects to Change Vector Analysis, but uses, as an input, two images acquired on different dates, and a parameter list given by the user. Change detection and classification are performed as separate processes, with the output being a five-channel image estimating the degree of change and classifies the changed and unchanged areas. The method carries out the change analysis using homogeneous areas selected from the images and only in the last step is the whole image classified. Changes are detected and identified using a *k*-clustering algorithm in two phases. First, clustering is performed on the two images to form "primary clusters". Second, clustering is then performed within the primary clusters of the later image to produce the "secondary clusters". Then change magnitude and change type are obtained by comparing the primary clusters in the earlier image to the secondary clusters in the later image.

2.9 Enhancements to Classification and Change Detection Techniques

Although the use of supervised and unsupervised classification procedures, in various forms and versions, is still fundamental to the science of change detection (Lillesand and Kiefer, 2000; Janssen, 2000), ongoing research has resulted in a constant stream of new techniques and processes being developed to enhance the effectiveness of these classification techniques. Successful change detection is totally dependent on an accurate classification of an image and all of the enhancements are aimed at increasing the accuracy of the classification process such that clear distinctions between the various classes or items of interest can be separated in the image.

2.9.1 Artificial Neural Networks

Conventional classification techniques generally have a statistical basis from which they work. Alternative approaches have been developed using non-statistical bases, in the form of Artificial Neural Networks (ANN) and Knowledge-based methods such as Decision Trees (Qiu and Jensen, 2004; Tso and Mather, 2001). An ANN consists of an input layer, a hidden layer and output layer. In each layer, nodes called neurones are present. Every neurone is connected to every other neurone in the adjacent layer. Each neurone has a weight and value associated with it, based on the sum of the product of the weights and values of the previous computational layer (Tso and Mather , 2001). A process, called a learning strategy, provides an initial set of weights and controls how these weights and neurones should be updated to improve performance. The concept of multiple nodes or neurones provides a robustness to the classification process, as it reduces the potential impact of problematic data unduly skewing results. Qiu and Jensen (2004) describe a method that combines neural networks with fuzzy systems, whereby the learning algorithms of the neural network automate the creation of the fuzzy set parameters for the fuzzy "if-then" rules in the expert system. This resulted in superior classification accuracies compared to the back-propagation based ANN and the maximum likelihood classifier.

Boyd *et al.* (2002) compared the accuracy of vegetation indices, regression analysis and neural networks in estimating coniferous forest cover in the U.S. Pacific Northwest. While results of all three methodologies were very similar, the neural network technique offered advantages through its ability to analyse complex datasets without assumptions being required, a good tolerance to spectral 'noise', the ability to integrate multi-source data, and the possibility to weight the significance of the discriminating variables used.

Bruzzone and Serpico (2000) describe a methodology to enhance feature selection in multi-class (i.e. more than two land-cover classes) classification, whereby an upper bound is set to the error probability of the Bayes' classifier. The main advantage with this technique is that it allows one to select features by taking into account their effects on classification errors.

2.9.2 Clustering Techniques

Another preparatory method for classification involves some form of clustering technique that enables an image to be segmented into regions with similar radiometric properties. This clustering process is usually an automated process using a *k*-means or dynamic clustering method. This latter method is limited by being very slow and does not work well on large datasets such as coarse-scale remote sensing images (Viovy, 2000). In addition, it is necessary to define the number of clusters prior to executing the programme, but this is seldom a known quantity. In order for an automated clustering process to be of maximum benefit, it is desirable that the number of clusters be automatically determined so that a good indication of similar spectral groupings is obtained. This then gives a good idea of how many classes can be extracted during a classification process. From this preliminary process, further classification can then occur to refine the final groupings required. Viovy (2000) describes a methodology that achieved an automated clustering, based on hierarchical and dynamic clustering principles, which was very fast, and did not result in any degradation on large imagery. Duda and Canty (2002) compared several clustering algorithms used in unsupervised classification systems, and found that fuzzy clustering performed the best compared to a reference scene of Landsat 5 imagery. The clustering techniques tested were the *k*-means, Extended *k*-means, Fuzzy *k*-means, Fuzzy Maximum Likelihood, and Agglomerative Hierarchical algorithms.

2.9.3 Spectral Unmixing Techniques

Spectral unmixing, also known as spectral mixture analysis (SMA); linear spectral unmixing (LSU) or spectral mixture modelling (Adams *et al.*, 1986), is a technique that aims to extract additional information from within pixels. It is based on the assumption that a pixel is made up of a linear combination of pure components, known as endmembers (Adams *et al.*, 1986). However, multiple scattering by vegetation surfaces can cause significant non-linear mixing, and the failure of SMA to account for this is an acknowledged limitation of this procedure (Dennison and Roberts, 2003). These end-member components could be water, soil, shadow, vegetation etc. The signal received by the sensor depends on the proportion of these individual components within the pixel, and this technique can be used to find the proportions (or abundance) of these endmembers within a pixel, as well as a number of endmember spectra of known composition (Van der Meer, 1999). This process produces a fraction image of the endmember.

It can be modelled in the following way:

$$b_i = \sum_{e=1}^{N} a_{e,i} x_i + \varepsilon_\lambda \sum_{e=1}^{N} x_e = 1 \quad \text{(Equation 2.8.1)}$$

where: b_i is the reflectance of mixed pixel spectra in Band i;

$a_{e,i}$ is the reflectance of the component in Band i;

x_i indicates the proportion of pixel area covered by the ground cover type $_e$; and

ε_λ is the residual error (Dennison and Roberts, 2003; Shakoor, 2003).

Model residuals, ε_λ, or the root mean squared error (RMSE) are used to assess the model fit, according to the following equation:

$$RMSE = \sqrt{\frac{\sum_{\lambda=1}^{M}(\varepsilon_\lambda)^2}{M}} \quad \text{(Equation 2.8.2)}$$

where: M is the number of bands (Dennison and Roberts, 2003).

The spectral unmixing process produces a series of "fraction images" for each endmember, with data values lying between 0 and 1 (ideally) (Neville *et al.*, 1997), and a root mean square (RMS) error estimate representing the difference between the observed mixed spectrum and the calculated mixed spectrum. Values of 0 represent pixels that have no endmember of interest present, while values of 1 in a fraction image represent a complete presence of the endmember of interest (Farrand, 2002).

Van der Meer (1999) derived an iterative spectral unmixing (ISU) process by applying optimisation techniques to run the iterations. These techniques include the minimisation of the following criteria: average RMS; the spread of RMS values; the spatial structure of the RMS image; the spatial anisotropy of the RMS values; and the local variance.

The selection of endmembers can be undertaken in a number of ways. The normal way is to select pixels that are known to be pure representations of each endmember based on ground-truthed data. Another method is to select pixels from within an image. The success of this method is dependent on proper endmembers being selected and that the image endmember pixel spatial resolution is smaller than the physical features being modelled (Peddle and Johnson, 2000). Dennison and Roberts (2003) describe several methods of endmember selection including the use of Principal Components Analysis; determination of a simplex that fits the image data; the application of a Pixel Purity Index; and the use of "virtual" endmembers selected to minimise RMSE within user-specified constraints. Which ever method is selected, the key principle is that the success of any SMA application depends of the success of endmember identification.

Spectral matching algorithms, such as Multiple Endmember Spectral Mixture Analysis (MESMA) and Spectral Angle Mapping (SAM), are used to identify unknown spectra based on the degree of similarity to one or more known spectra. Dennison *et al.* (2004) reported that these two methods produced similar results in a vegetation study, but that the selection of error constraints had a greater impact on the number of spectral matches than which algorithm was applied. Another point of interest is noted by Farrand (2002) in his discussion on Spectral Feature Fitting, where it was stressed that analysis should be done using only those channels that cover the absorption band of interest.

2.9.4 Tasselled Cap Technique

When using multi-band imagery, such as Landsat or SPOT, there are various options that assist in being able to extract and view features of interest. One of these is the Tasseled Cap transformation (Pouncey *et al.*, 1999), which provides a means to optimize data viewing for vegetation studies. This information is displayed as three data structure axes defined as:

• Brightness—a weighted sum of all bands, defined in the direction of the principal variation in soil reflectance.

• Greenness—orthogonal to brightness, a contrast between the near-infrared and visible bands. Strongly related to the amount of green vegetation in the scene.

• Wetness—relates to canopy and soil moisture.

2.9.5 Hybrid Techniques

The separation of live green material from brown senescent or dead vegetation is often a required result of a classification process. Datt (2000) reports on a procedure that can be used to separate these two classes with 100% accuracy. This process involves the application of a cross-correlogram spectral matching technique, based on the finding of a diagnostic absorption feature near 1730 nm for dry vegetation and a chlorophyll absorption feature near 680 nm for green vegetation. A calculation of the cross correlation between a reference spectrum and test spectra at different match positions in these two spectral regions enabled this separation to be identified.

Barandela and Juarez (2002) describe an interesting procedure in which a supervised classification system that has an ongoing learning capability has been developed. Using a Nearest Neighbour rule as the central classifier, additional procedures have been added to reduce the risk of noise being added into the training sample. This methodology could have application in an operational system, as it would allow for an automated process to be put in place to classify the regular repeat images required for such a system.

Where there are only a few classes required from a classification, a technique of potential application is a partially supervised process (as opposed to the normal supervised classification technique) that allows for the efficient mapping of a specific land-cover class, or a few land-cover classes (Fernandez-Prieto, 2002). Based on the combined use of a Radial Basis Function network (which models the image data distribution) and a Markov Random Field approach (which uses the spatial-contextual data), only training data sets from the specific classes of interest are used, instead of a fully supervised classification approach (Fernandez-Prieto, 2002). The advantage with this method is that a classification accuracy comparable with that of fully supervised classifiers is obtained, but with less effort.

Huang *et al.* (2002) developed a modified version of this transformation for use on Landsat 7 data, while Collins and Woodcock (1994) applied a similar methodology called the Gramm-Schmidt Transformation to detect change in forest mortality. The results of this technique produce components that are multi-temporal analogues of the three major Tasseled Cap dimensions (brightness, greenness, wetness), as well as a component measuring change. The advantage that this technique holds over other change detection techniques lies in the relationship between the scene characteristics and the transformed components, which allows the extraction of information not available with other change detection methodologies (Collins and Woodcock, 1994). Coppin *et al.* (2004) describe several variations of the tasseled cap procedure that have been tested for their effectiveness as change detection agents by various researchers.

More theoretical research is currently being done on the use of multi-fractal dimension indices as textural descriptors of remotely sensed data. Parrinello and Vaughn (2002) describe the use of a multi-fractal index, called *Spectrum Range*, which can substitute or complement classical textural descriptors by calculating the multi-fractal spectrum of pixels inside images such that multi-fractal indices can be used as textural feature descriptors. However, this methodology does not appear to be suitable for feature extraction at an operational level at this stage. It will no doubt offer potential benefits for improved feature extraction in the future.

In addition to simple enhancements of the classification process, attempts have also been made to model future changes based on observed patterns identified through change detection. An example of this is given by Petit *et al.* (2001) that modelled land cover change using a Markov chain process. While this type of application holds promise for the future, it lies outside the scope of this study. It does, however, illustrate the use of change detection beyond the simple application of highlighting change.

The use of machine learning systems such as Support Vector Machines (SVM) has been tested by Pal and Mather (2005), and improved classification accuracies compared to neural networks or maximum likelihood classifiers are reported.

2.10 Threshold Determination

The use of threshold techniques is a key element in change detection, but determining the values of these threshold levels is critical to the successful application of this technique (Eastman *et al.*, 1995; Singh, 1989). As noted by Singh (1989) virtually all methods of change detection rely on some sort of thresholding criteria to identify true change from no change or "noise" effects. Rosin and Ioannidis (2003) describe and evaluate several image thresholding algorithms which can be applied in order to derive the thresholds required.

Lillesand and Kiefer (2000) refer to the use of a *"change-versus-no change binary mask"* as part of the process to establish threshold levels, while Singh (1989) describes a method for applying multiple threshold levels using density slicing, where objects represented by several different pixel value groupings are categorised into several pre-defined slices. However, selection of the best threshold levels is usually based on *apriori* knowledge of the scene characteristics (Singh, 1989). Bruzzone and Fernandez-Prieto (2000) developed an automatic threshold technique, for use in unsupervised change detection that assists in the determination of decision thresholds by taking into account the various costs that may be associated with commission and omission errors. This method minimises the overall change detection cost, such that the more critical kinds of error are reduced according to end-user requirements.

2.11 Accuracy Assessment Techniques

The results of any classification process need to be verified as to their accuracy in correctly defining features into categories of interest. Although this can be a difficult process, it is generally done using certain statistical tests and models. Remote sensing literature gives several examples of these methodologies (Janssen, 2000; Lillesand and Kiefer, 2000; Biging *et al.*, 1999) while Khorram, *et al.*, (1999) devote a whole publication to addressing this topic, specifically on land-cover change detection accuracy assessment.

When change detection procedures are involved, the issue of accuracy assessment becomes even more complex, but not addressing them can lead to failure in achieving the goals of change detection (Biging *et al.*, 1999).

Lowell (2001) describes an area-based accuracy assessment technique using 500-pixel by 500-pixel areal sample units. A subjective assessment of the amount of change was then made using image enhancement techniques on each sample unit in order to obtain an independent assessment of change. Confidence intervals were then calculated on the basis of these independent estimates of change.

A review of the literature revealed a wide range of classification accuracies were achieved, and appeared to be independent of the classification procedure (i.e. supervised or unsupervised). Varjo and Folving (1997) quoted accuracies of between 87.6% and 93.1%; Zukowskyj *et al.* (2001) achieved accuracies of 71.3% and Rowlinson *et al.* (1999) reported accuracies of 52.5%. Singh (1989) gives a comprehensive listing of accuracies achieved using a wide variety of different change detection techniques, which ranged from 51.4% to 74.4%. All of these studies utilised Landsat TM imagery. Heyman *et al.* (2003) quote a range of achieved accuracies from 42% to 75% from several different studies.

2.12 Review Summary

Based on this review of the literature it is evident that much work has been done in monitoring general land cover/land use change (Hostert *et al.*, 2003; Chen, 2002; Yang and Lo,2002; Petit *et al.*, 2001; Pontius *et al.*, 2001; Smith and Fuller, 2001; Luque, 2000; Castelli *et al.*, 1999; Chen *et al.*, 1999; Mas, 1999; Morisette *et al.*, 1999; Yuan *et al.*, 1999; Zhan *et al.*, 1998; Hallum, 1993), as well as a good deal of research focussing specifically on forest land cover/land use change monitoring (Chen *et al.*, 2005; Nackaerts *et al.*, 2005; Heyman *et al.*, 2003; Boyd *et al.*, 2002; Kayitakire *et al.*, 2002; Jacobs and Mthembu, 2001; Nilson *et al.*, 2001; Sader *et al.*, 2001; Puhr and Donoghue, 2000; Cohen and Fiorella, 1999; Häme *et al.*, 1998; Jeanjean and Achard, 1997; Varjo, 1997; Varjo and Folving, 1997; Hypannen,1996; Coppin, 1991). In terms of the application of remote sensing to forest management, literature shows that there has been a wide range of applications in this field, including considerable use of change detection techniques for various forest management purposes. In particular, the detection of clear-felled stands is a well-researched application (Cohen and Fiorella, 1999; Häme *et al.*, 1998; Varjo, 1997; Coppin, 1991).

However, apart from one paper which examined plantation forest inventory data in the United Kingdom (Puhr and Donoghue, 2000) all other work was based on studies done in the Northern Hemisphere boreal and mixed forests (covering North America, Scandinavia and Russia) or tropical rain forest or savannah. Kätsch and Vogt (1999) describe remote sensing applications for mapping, mensuration and disease/stress assessment in Southern African plantation forestry, while Kätsch and Van Laar (2002) discuss the estimation of growing stock of eucalypt plantation forests. No other published work was found that specifically addressed the monitoring of plantation forest operations. Häme *et al.* (1998) and Coppin (1991) describe the monitoring of clear-felling, thinning, soil preparation and regeneration operations, but again these are in Northern Hemisphere boreal and mixed forests. Two works (Gray *et al.*, 2004; Shaw, 2004) that discussed the use of remote sensing for monitoring of weed growth in crop lands were located, but both were based on agricultural applications, rather than forestry ones. It would appear that limited work has been done in this specific field of interest.

Thus, there is a distinct gap in the literature regarding remote sensing applications in plantation forestry in general, and certainly a dearth of literature covering the monitoring of plantation forestry operations in Southern Africa. This study seeks to address these gaps by investigating whether the application of proven remote sensing techniques can be used to monitor specific forestry operations, namely clear-felling, replanting and weed control, in South African plantation conditions.

Another aspect that this literature review highlighted is that while there have been several studies done on identifying individual tree crowns (e.g. Jacobs and Mthembu, 2001; Wulder *et al.*, 2000), this review did not find any studies that had used tree rows as a means of separating crop and weed in a manner similar to that applied in the high resolution portion of this study. This is another unique contribution that this study attempts to add to the body of remote sensing knowledge.

As the focus of this study was to test the application of proven remote sensing techniques for monitoring plantation forestry operations, it was necessary to select the most appropriate techniques. Image differencing, change vector analysis (CVA) and composite analysis appear to be the preferred choices in forest change detection applications (Cohen and Fiorella, 1999), although Coppin *et al.* (2004) found that Univariate Image Differencing was the most widely applied change detection algorithm. However, post-classification techniques have also proved to be suitable and popular for land cover change detection (Lunetta, 1999). Variations on the CVA technique, such as the Tasselled Cap Transformation and Autochange Analysis, have also proved successful (Cohen and Fiorella, 1999; Häme *et al.*, 1998; Collins and Woodcock, 1994). Other methodologies such as vegetation indices (NDVI, TNDVI), Principal Component Analysis (PCA) and non-parametric Kernel methods have also been successfully applied (Varjo, 1997), as have various clustering or segmentation techniques (Kätsch, 2003; Pekkarinen, 2002; Viovy, 1997). Based on these findings from the literature, as well as practical considerations such as the availability of software, post-classification change detection was selected as the most appropriate technique for the change detection process. In addition, a segmentation process using textural analysis techniques was selected to improve the high resolution imagery classification results.

While there is plenty of literature on thresholding (Rosin and Ioannidis, 2003; Bruzzone and Fernandez-Prieto, 2000; Lillesand and Kiefer, 2000; Eastman *et al.*, 1995; Singh, 1989 to list a few), no specific thresholding techniques that might be applicable to plantation forest monitoring have been reported. It was therefore decided to test the feasibility of utilising the canopy characteristics to derive suitable thresholds to separate crop from weed.

An important process that requires attention in any of the techniques applied is that of accuracy assessment, due to the fact that none of these techniques is absolute in its application. The basis of classification and change detection is that these processes are an estimation of reality, based on indirect measurement of certain criteria. Therefore, some form of accuracy assessment is required in order to establish levels of confidence in the output results of any change detection procedure. Accuracy needs to be assessed at two points, the first being an evaluation of the classification accuracy, and the second being an assessment of the change detection procedure (Biging *et al.*, 1999, Khorram, *et al.*, 1999).

Having established a framework in terms of published research on the subject matter of this study, it was then necessary to select a suitable study area in which to test the hypotheses. An area of appropriate forestry activity was identified in the KwaZulu-Natal Midlands, the details of which are discussed in the next chapter.

Chapter 3: The Study Area

3.1 Introduction

The study area is located in the Province of KwaZulu-Natal, Republic of South Africa, in an area known generically as the Midlands, where commercial plantation forestry is a primary economic activity. The medium resolution imagery study sites consisted of 162 compartments located on 20 plantations north of Pietermaritzburg, being concentrated around the town of Greytown, as well as in an area to the north of the town of Howick (see Figure 3.1.1). They were all within plantations falling under the management of the Midlands District of Mondi Business Paper SA – Forest Operations. The NE corner co-ordinates of the study site were 28° 55' 29"S; 31° 01' 19"E, and SW corner co-ordinates were 29° 34' 58" S; 30° 13' 25" E.

Compartments that could be considered for the medium resolution study sites had to meet certain criteria. These were as follows:

- They needed to be representative in terms of plantation forestry in the KwaZulu-Natal Midlands.
- They needed to cover the range of genera (*Eucalyptus; Pinus* and *Acacia*) that make up the most important commercial forestry species planted in the KwaZulu-Natal Midlands.
- The full range of operations from clear-felling, planting and weed control through to canopy closure was required to be present within the study site. Each of these operations should also be present in each image acquired, in order to account for any seasonal variation. While it would have been useful to have the full range of operations occur within the same compartments within the duration of the study, this was not considered critical, as each image was considered as independent of the other images, with regard to these criteria.

Study sites for the high resolution imagery were based on a subset of the medium resolution imagery compartments, due to the smaller extent covered by the high resolution imagery. Seventeen compartments from two adjacent plantations, known as Mistley and Canema, were initially selected for the high resolution study sites, although these were later reduced to twelve as a result of some compartments not meeting the requirements of the high resolution research (see Figure 3.1.2).

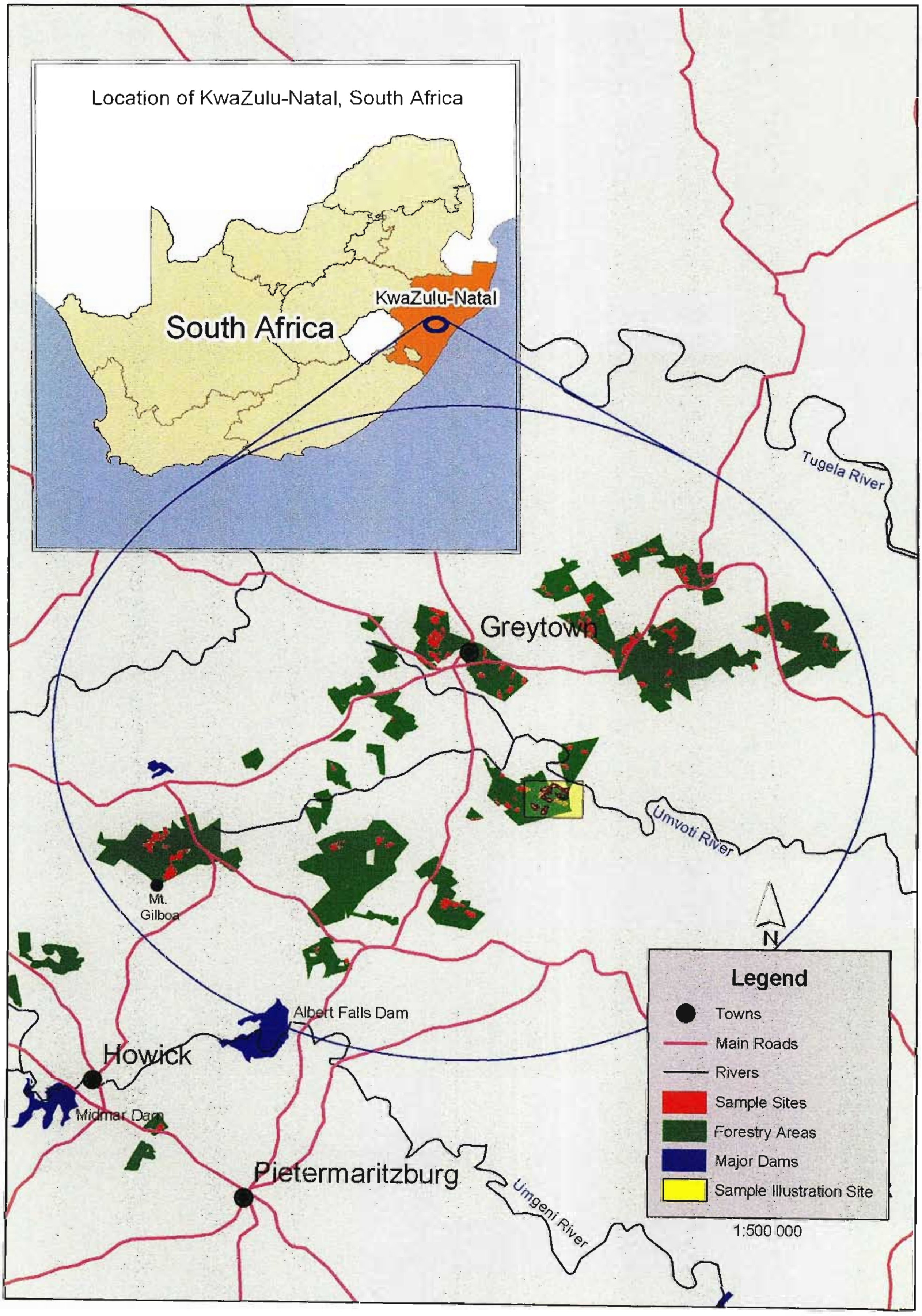


Figure 3.1.1 Location of Medium Resolution study sites in the KwaZulu-Natal Midlands

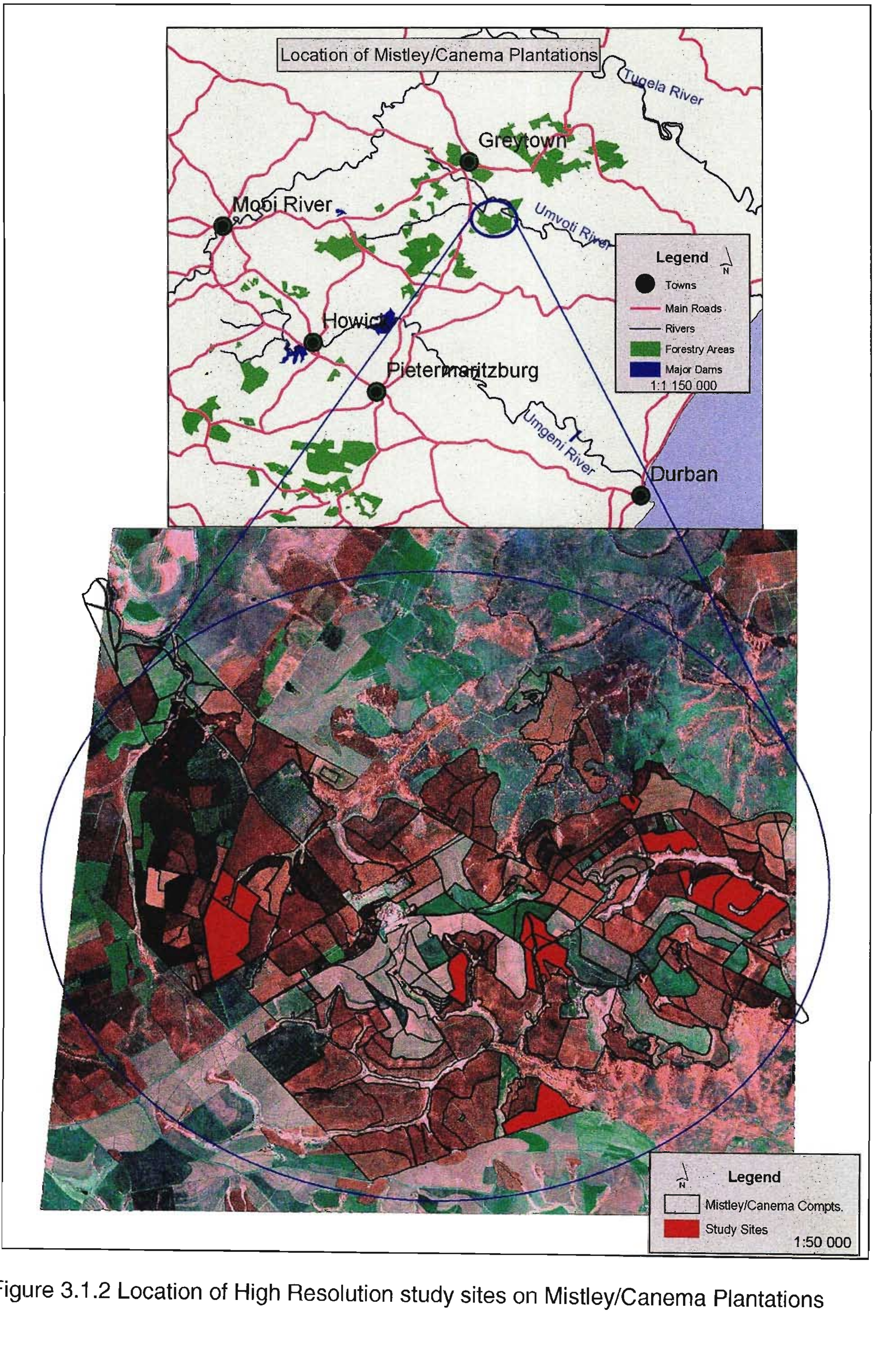


Figure 3.1.2 Location of High Resolution study sites on Mistley/Canema Plantations

For the high resolution study sites, the requirements were much more focussed on the re-establishment phase, rather than the whole rotation. For this reason the following criteria were required:

- They had to have been re-established (either planted or coppiced) within the early phase of the high resolution project. This was the main reason why some of the compartments initially selected were later discarded, as they had not been re-established in time to provide a result.

- Although it would have been preferable that the study sites covered the range of genera (pine, gum and wattle) that make up the most important commercial forestry species planted in the KwaZulu-Natal Midland, no replanted gum compartments were available within the study area, and only one gum coppiced compartment was present. However, a good selection of replanted wattle compartments was available.

While the study area is characterised by a unique set of climatic and topographic conditions, within the area there is a range of climatic, geological and physiographic variations. Being a well-established forestry area meant that the plantations were in rotation, with all three genera, *Eucalyptus*, *Pinus* and *Acacia,* represented and so all operations would be available for study. The necessity of visiting specific sites for ground-truthing purposes was catered for by the sites being close enough to Pietermaritzburg, the base of operations.

3.2 Biophysical Description of Study Area

3.1.2.1 Climate

The study area falls in the summer rainfall region of South Africa, with the resultant characteristic warm, wet summers and cold, dry winters. Figures 3.2.1 and 3.2.2 provide the detailed distribution of temperature and rainfall. Mean annual rainfall varies from 800 mm to 1200 mm, which is either associated with frontal weather patterns or summer thundershowers. With thunderstorms being a primary summer weather phenomenon, a lightening flash density of 7 to 8 flashes/km^2 *per annum* is experienced. Winter precipitation events are sometimes associated with snow in the higher lying areas in the Howick area (Snyman, 2002).

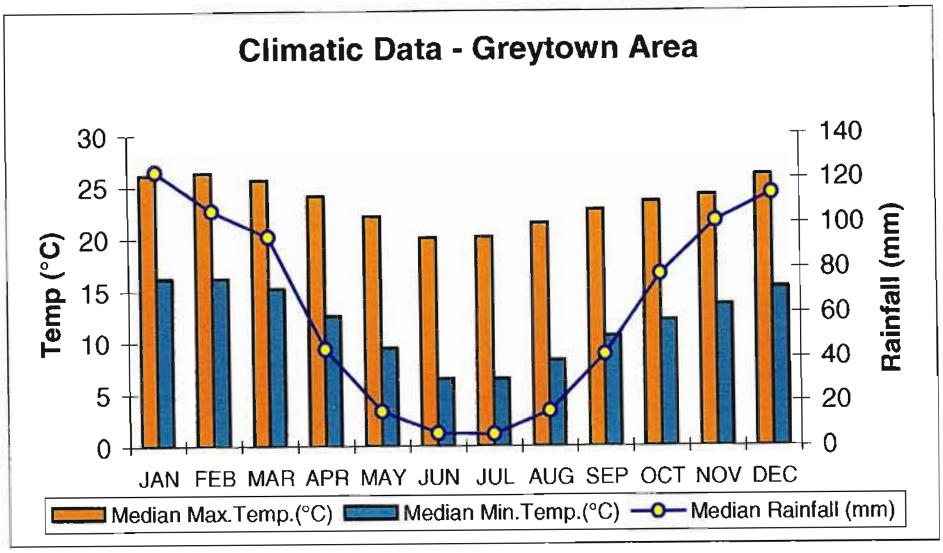


Figure 3.2.1 Climatic Data – Greytown area. (Snyman, 2002)

Temperatures range between 24°C to 26°C in summer but drop to between 11°C and 14°C in winter for most areas (see Figures 3.2.1 and 3.2.2). Frost is a regular occurrence, apart from the low-lying easterly areas.

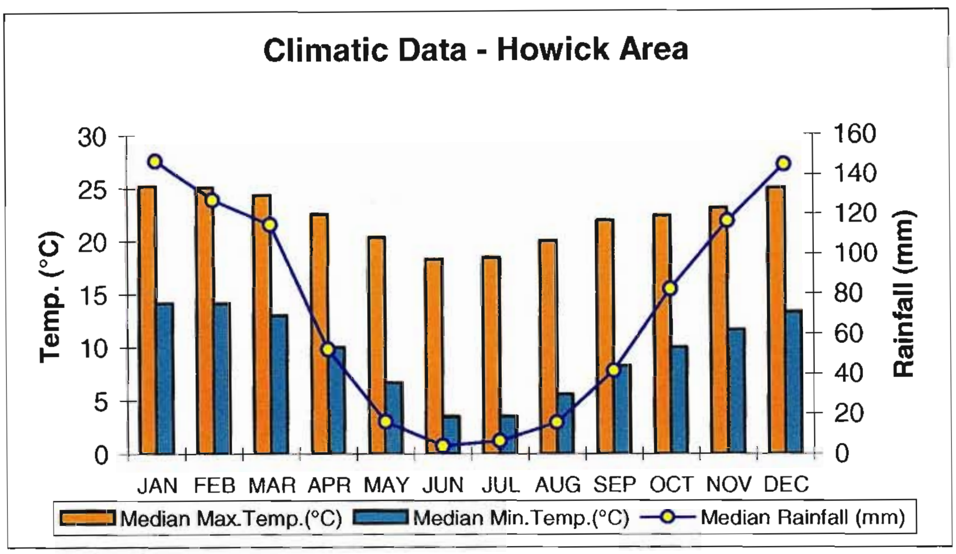


Figure 3.2.2 Climatic Data – Howick area. (Snyman, 2002)

3.1.2.2 Geology and Soils

The Greytown area straddles two major geological zones, with the eastern section underlain by intercalated arenaceous (sandstone) and argillaceous (clay) strata. An assemblage of tillites and shales underlies the western section. Dolerite outcrops also occur (WRC, 1995).

Argillaceous (clay) strata dominate the geology of the Howick area, with the outer areas having intercalated arenaceous (sandstone) and argillaceous (clay) strata

(WRC, 1995). Dolerite sills and dykes are common, in association with areas of the "red" Hutton and Inanda soil forms.

Soils in the Greytown area are generally well-weathered fine-sandy-clay-loam humic topsoils, underlain by yellow or red apedal subsoils, with the dominant soil forms being the Sweetwater, Inanda, Kranskop and Magwa forms. Hutton, Clovelly and Oakleaf forms occur in the lower lying areas, and the drier northern slopes. High (>1.8%) topsoil carbon contents are common, while clay contents vary between 25% and 35% in topsoil horizons, but reach levels of up to 55% in deeper subsoils.

Mispah and Glenrosa forms (lithosols) commonly occur on steep slopes, particularly in the drier, warmer areas towards the Tugela River. Hydromorphic soils of the Tukulu form generally occur along riparian areas (Snyman, 2002).

In the Howick area, fine-sandy-clay humic topsoils, underlain by yellow or red apedal subsoils, characterise the soils. Dominant soil forms are Inanda and Magwa, with Hutton being the subdominant soil form. Topsoil horizon clay contents vary from 34% to 35%, reaching levels of 60% in deeper subsoils. Hydromorphic soil forms, such as Tukulu and Katspruit, occur along riparian zones, with peat soils such as the Champagne form and organic variants of the Katspruit and Westleigh forms occurring in wetlands, especially in the upper reaches of the Umvoti River (Snyman, 2002).

3.1.2.3 Topography

The Greytown area is characterised by an undulating plateau with moderate to steep slopes in places. The eastern and northern boundaries of the area are characterised by steeply incised river valleys (such as the Tugela River) leading into more rugged terrain below the plateau area. Altitude varies from 750 m to 1570 m above mean sea level (amsl).

In the Howick area, the topography is more varied, ranging from undulating terrain interspersed with prominent hills having moderate to steep slopes, to the Gilboa area, which forms a high plateau, dominated by Mount Gilboa. Steep scarps are present along the perimeter of this plateau. Altitudes in the Howick area vary from 750 m to the peak of Mount Gilboa at 1768 m amsl.

3.1.2.4 Hydrology

The study area within the Greytown area is part of the U primary drainage basin, falling mainly into the U40 and U20 secondary catchments (i.e. the hydrological catchment areas defined by the Water Research Commission (WRC, 1995)). The mean annual precipitation (MAP) is 860 mm, with a median annual simulated run-off of 126 mm. The average groundwater depth is 25 m, with an annual recharge rate of 60 mm. The main river draining through the area is the Umvoti River (WRC, 1995).

The Howick area falls within the U and V primary drainage basins, with the secondary catchments being U20 and V20, and is an important catchment for the major river of the area, the Umgeni River. MAP is 980 mm, and a median annual simulated run-off of 144 mm. The average depth to groundwater is less than 20 m, with an annual groundwater recharge rate of 75 mm (WRC, 1995).

3.1.2.5 Natural Vegetation

In both study areas the predominant natural vegetation type is a grassland biome, associated with the Short Mistbelt vegetation type in the Greytown area, and Moist Upland Grassland vegetation type in the Howick area (Low and Rebelo, 1996).

The main type in the Greytown area is the Natal Mist Belt 'Ngongoni Veld (Acocks veld type 45, (Acocks, 1988)). This occurs as a transitional stage between the Highveld Sourveld of the higher lying plateau regions and the 'Ngongoni Veld proper (Acocks veld type 5) of the lower lying regions. These grasslands are Sourveld, with the main species being *Themeda triandra* where the sward is relatively undisturbed, with significant communities of *Monocymbium ceresiiforme*, *Trachypogon spicatus* and *Tristachya leucothrix*. Where intensive agriculture, especially overgrazing has occurred, there is a marked increase in *Aristida junciformis* (Camp, 1997).

Patches of indigenous forest and thickets occur in the more sheltered river valleys, with dominant species being *Rapanea melanophloeos*, *Cryptocarya woodii* and *Syzygium gerrardii*. Other species present include shrubs and climbers such as *Dalbergia obovata* and *Uvaria caffra.*

In the Howick area, the main natural vegetation ranges between Southern Tall Grassveld (Acocks veld type 65) and Natal Mist Belt 'Ngongoni Veld (Acocks veld type 44). Grassland areas are classified as sourveld, with *Themeda triandra, Heteropogon contortus, Tristachya leucothrix, Eragrostis curvula* and *Elionurus muticus* being the main species. *Hyparrhenia hirta* (thatch grass) is also characteristic of these areas. Much of the area's grassland is in a poor condition, and exists as a secondary vegetation status. Incorrect grazing management has led to an increase in unpalatable species and the intrusion of herbaceous weeds (Camp, 1997).

In sheltered sites and rocky outcrops, woodland and thickets occur, with the dominant tree species being *Maytenus heterophylla, Zanthozylem capense, Ziziphus mucronata, Rhus rehmanniana* and *Acacia sieberana.* Forest pioneer species such as *Rapanea melanophloeos,* and Fynbos species such as the *Cliffortia* species occur in areas protected from fires (Camp, 1997).

Both of these areas fall predominantly into the Bioresource Group 5, Moist Midlands Mistbelt, as defined by Camp (1997).

3.1.2.6 Land Use

By definition, the study area was located in a commercial plantation forestry area. However, the predominant land use throughout the study area is commercial forestry, together with sugar cane and arable cropping (generally maize) as well as some beef and sheep farming activities. Plantation forestry activities are undertaken by large forestry companies (e.g. Mondi, Sappi), and many private farmers in this area.

The plantation forests consist of exotic hardwood and softwood species that are grown primarily for the production of pulp and paper, although there is a smaller market handling saw timber for the furniture and construction industries. Softwood species are of the genus *Pinus*, and consist predominantly of three species, *P. patula, P. taeda* and *P. elliottii.* Hardwood species are of the genera *Eucalytpus* (commonly called Gum) and *Acacia* (generally known as Wattle). There is only one species of *Acacia* widely cultivated, *A. mearnsii,* which is utilised for the production of tannin extract from its bark, as well as the timber being used in the pulp and cellulose industries.

The *Eucalytpus* species fall into two categories, defined by their wood density. These are called soft (or sub-tropical) gums, grown in the warmer areas, and hard (or cold-tolerant) gums, grown in the higher lying, more temperate areas. The hard gums have a higher wood density than the soft gums. Main species in the soft gums are *E. grandis* and *E. saligna*, while the main species of hard gums include *E. macarthurii, E. dunnii, E. nitens* and *E. smithii.* A great deal of afforestation is now done using clonal hybrids of these species (e.g. *E. grandis x E. nitens*).

For the pulp and paper industry, gum and wattle are grown on short rotations of 8 to 10 years, while pines are grown for 15 years. The forest industry is run on the principle of the European Normality Model (Von Gadow and Bredenkamp, 1992). This model allows for sustainable use, whereby the forest areas are managed on a rotational basis, such that all felled areas are replanted, and the area felled at any one time is equivalent to the total afforested area divided by the rotation length (e.g. if 100 ha is afforested on a 10 year felling cycle, or rotation, only 10 ha is felled and replanted annually, thus creating a continual production cycle).

Having found sites suitable for this study, the chosen methodologies could then be applied as the next step in this research. The materials, methods and results of applying classification, textural analyses and change detection techniques to medium and high resolution imagery for monitoring plantation forestry operations are described in detail in the next two chapters.

Chapter 4: Monitoring Forest Operations using Medium Resolution (30 m) Imagery

4.0 Introduction

The scale of coverage that can be obtained from medium resolution satellite imagery lends itself to forest monitoring applications, particularly in areas where these operations have a wide geographic dispersion. Also, such imagery tends to be cheaper than high resolution imagery, and so can provide a broad-scale "first-look" product cost-effectively (Lillesand and Kiefer, 2000). These factors provided the rationale for its application in this study.

4.1 Materials and Methods

4.1.1 Introduction

The materials and methods utilised in this study were based on proven remote sensing image classification and change detection techniques, but with the aim of detecting change in, and monitoring of vegetation state, within a commercial plantation forest environment. This requirement meant that the repeat cycle was a matter of months, rather than the years that are normally reported in literature.

4.1.2 Materials

Materials used in this research project were primarily data sets in various digital formats. Three different types of base data sets were utilised for this study, which involved the integration of these data sets, a process that was made possible through the use of GIS.

4.1.2.1 Suitable Study Sites

Suitable sites were located by a process that included overlaying Landsat 7 path/row grids on a data set of the forestry landholdings that fell within a radius of 100 km of Pietermaritzburg. This distance was chosen as being practical for travelling to ground-truthing sites. Also overlain were data sets that showed where harvesting and planting operations were planned to occur over the next year (2002/2003), as these were the critical operations that had to be monitored as part of the objectives of this study. A supplementary data set of the physiographic regions was also included to try and include some of the main site factors, such as geology, soil and climate, in the study sites. This process was undertaken using ArcGIS 8® (ESRI, 2000), and resulted in suitable compartments being identified to form the study area.

A set of 162 compartments in 20 plantations were identified from which ground-truthing sites were selected. For display purposes only 15 of these compartments are shown (see Sample Illustration Site – Figure 3.1.1).

4.1.2.2 Satellite Imagery Data

The satellite imagery applied in this study was standard Landsat 7 multi-spectral imagery purchased from the Satellite Applications Centre (SAC) of the CSIR. The selection of the Landsat 7 sensor was based primarily on a cost/benefit basis, and was a balance between obtaining imagery with a resolution small enough to detect the critical spectral information required, and being available at a reasonable cost. Another factor to be considered was the repeat cycle, especially as this study required imagery at a much closer interval than is normally the case for change detection processes. The revisit cycle of sixteen days for Landsat 7 was suitable, especially over periods of high cloud cover, as it allowed a greater chance of obtaining a cloud-free image.

The specific Landsat images used in this study were selected on the basis of the following criteria:

1. Imagery with a maximum amount of cloud-free coverage over the areas of interest.
2. Imagery covering as much of the seasonal variation as practically possible, but with at least a mid-winter and mid summer image, together with an inter-seasonal image. As many of the forestry operations that were to be monitored as part of this study reach a peak in mid to late summer (January to May), this was a particular period of interest.
3. Imagery that covered all the areas of interest within the study site in a single image.

The images were obtained from SAC as geo-referenced to Transverse Mercator, Lo 31°, Clark 1880 spheroid, Cape Datum (i.e. equivalent to USGS L1G processing level). They were supplied on compact disc in ERDAS Imagine® .IMG format.

A total of four images were purchased, covering the period from March 2002 to April 2003. Technical specifications of the sensor are provided in Appendix 1, together with a sample of a raw image.

The four images obtained for this study were captured on the following dates:

First image – 30.03.2002 (referred to as the March image in the text).

Second image – 18.06.2002 (referred to as the June image in the text).

Third image – 28.01.2003 (referred to as the January image in the text).

Fourth image – 02.04.2003 (referred to as the April image in the text).

Details of the images are summarised in Table 4.1 below.

Table 4.1 Summary of Landsat 7 images used in study

Image	Date Acquired	Time Acquired (GMT)	Frame Details: Path/Row	Cloud Cover	Sun Azimuth	Sun Elevation
March	30.03.2002	07:39:33	K-J 168/080	0000	52.11°	42.89°
June	18.06.2002	07:39:16	K-J 168/080	0000	36.19°	28.00°
January	28.01.2003	07:39:16	K-J 168/080	0000	81.27°	54.15°
April	02.04.2003	07:39:29	K-J 168/080	0000	50.94°	42.24°

Source: SAC, 2003.

These images were standard Landsat 7 (ETM+) images, including the seven multi-spectral bands (i.e. Bands 1 to 7), with a 30 m spatial resolution, plus a panchromatic band image with a 15 m resolution. The panchromatic images were not utilised in this study. For analysis purpose, all multi-spectral bands (excluding the thermal infrared (TIR) band) were used. However, for display purposes, an RGB composite image was used comprising Bands 4, 3, and 2.

4.1.2.3 Forest Management Attribute Data

The forest management information is recorded on a monthly basis by the field staff and captured into an Informix relational database called the Forest Management System (FMS). All operational information is captured into this database, which is linked to the GIS using key fields. Reports can be drawn from FMS, either using the standard menu system, or using SQL.

Specific information that is required by the GIS on a regular basis is available through the creation of standard "views" or query tables in FMS. These include the compartment register, which lists all the base information for every compartment, and certain planning information such as felling or planting plans.

A record is kept of all operations that have an operation code, for the lifespan of a compartment, including some information if a compartment is merged with another compartment. If the compartment is deleted however, the history is deleted as well. This historical aspect of the database has a key role to play when it comes to comparing the data derived from the satellite imagery with the database data.

Compartment data, both as base data and historical operational data, were extracted from FMS and used in this study to compare with the data classified by the imagery, in order to test the hypothesis proposed for this study. Specific compartment information extracted from FMS included species, felling dates, planting and coppice (see glossary) dates and growth cycle. Historical information extracted included when burning, planting and other establishment operations had occurred, as well as when weed control operations had been done. This information was queried on a compartment basis.

4.1.2.4 Geographic Information System (GIS) Data

In addition to the forest management information, a complete set of digital spatial data for all forestry landholdings in the study area was maintained through the application of GIS technology. This information included the legal cadastral information, compartment (commercial and non-commercial) information, roads, rivers, contours, buildings, dams and a considerable amount of derived information such as slope classes, climatic data and other such information.

The cadastral information provided a means to enable the image processing functions to be focussed on the specific areas of interest. This reduced the processing time as well as reducing the disk space requirements, although these still proved to be very intensive. The compartment information provided the units of observation on which the image processing and analysis were based. This data also provided the link in terms of integrating the image analysis results with the FMS data and in so doing enabled a comparison reporting process to be devised.

4.1.3 Methods

As stated earlier, the fundamental principle on which this study was based is that of image classification and change detection techniques being applied to satellite imagery. The aim was to then integrate the classified imagery with operational data extracted from the FMS database to provide exception reports that highlighted possible discrepancies between the operational data recorded in the database and what actually the case in the field was.

4.1.3.1 Image Rectification and Atmospheric Correction

As the base GIS data was projected to Transverse Mercator, Clarke 1880 (Cape datum) on Lo31°, the imagery was ordered with these projection parameters.

The only exception was the March image, which had already been purchased with the datum being in WGS 1984. This image then had to be reprojected to match the other images. This was done using the image rectification tools in ERDAS Imagine® (ERDAS, 1999), with the image being geo-rectified to the January 2003 image. Apart from the data being supplied in a projected state, according to the above parameters, no other geo-rectification was considered necessary, as the images all matched to within one to one and half pixels. As the unit of observation was the compartment, and analyses were based on compartments, rather than pixels, it was felt that this error was well within acceptable limits. This was reinforced by the mixed pixel effect experienced along the edges of compartments.

4.1.3.2 Classification Ground-Truth Data

A key factor in defining the best analytical method to adopt was to select which classification method would provide the greatest separation between classes, thereby producing the most accurate change detection analysis.

As part of the classification process, field trips were made close to the time of image acquisition (usually within two weeks) to ascertain the actual status of each compartment selected as a ground-truthing site. An exception was the March image, due to it having been acquired prior to the commencement of this project.

The ground-truthing assessment was based on confirming whether a compartment was standing or felled (including operations in-progress). For felled compartments, verification was made as to whether it had been burnt or not, and whether replanting or coppicing (for gum stands) had occurred. A visual estimate of ground cover, in terms of soil, slash (see glossary), crop and weed cover was also made, and if a crop was present, an estimate of its height was also made. A random check was made on the spatial location, using a GPS, to confirm that the compartment spatial data matched the ground location. A digital camera was also used in the January and April trips to photograph sites as visual references for each class.

4.1.3.3 Determination of Land-Cover Classification Classes

The aim of determining land-cover classes was to identify all possible vegetation classes that represented the status of each compartment on the ground. This ranged from bare soil through crop and/or weed cover to a closed canopy state.

Originally ten land-cover classes were decided on, but after the January image ground-truthing it was decided to split the canopy cover state into a younger canopy (or pre-canopy) as Class 9, and a mature (or closed) canopy state, Class 12. Class 11 was also added to cater for the slash/weed situation observed during the field trip. In both cases, these classes were added to test whether additional separation could be obtained.

The 12 classes were defined as follows, with photographs of typical sample sites being given in Appendix 9:

Class 1 Bare Soil (no crop)
Class 2: Slash (including senescent vegetation)
Class 3: Crop/Slash
Class 4: Crop/Soil
Class 5: Crop/Slash/Weed
Class 6: Crop/Soil/Weed
Class 7: Crop/Soil/Slash/Weed
Class 8: Crop/Weed
Class 9: Pre-canopy Closure
Class 10: Weed
Class 11: Slash/Weed
Class 12: Closed Canopy

4.1.3.4 Supervised Classification Procedure

It was initially decided to utilise a supervised classification procedure as the first step in the classification process due to it being well documented as a recognised method (Lillesand and Kiefer, 2000; Varjo, 1997; Janssen, 2000; Pouncey *et al.*, 1999). This method however, required the use of ground-truthed data to provide training data sets. The ground-truthed land-cover classes were used to define these training classes, with six to eight training sites being selected for each land-cover class, within each image. Using the standard functions available in ERDAS Imagine®, area of interest (AOI) polygons were digitised within ground-truthed compartments in areas known to represent the relevant land-cover class. These signatures were then evaluated for separability and contingency. The signature separability test was run on all eight bands within the raw image, with the transformed divergence algorithm being applied as the distance measure. The contingency parameters utilised the parallelepiped algorithm for the non-parametric rule, and parametric algorithms for the overlap and unclassified rules. The parametric rule used the maximum likelihood classifier.

Once the signature files had been finalised, a supervised classification was run on the image, utilising the maximum likelihood classifier. The classification was limited to areas of interest defined by a polygon layer of the cadastral boundaries of each farm within the study area. This was done to reduce the processing time, and the resultant output file size. It also allowed easier assessment of the results as only the areas of interest were shown in the classified image.

The results are discussed in detail in section 4.2.

4.1.3.5 Unsupervised Classification Procedure

A result similar to the supervised classification was also obtained with an unsupervised classification, using ten classes, i.e., the number of classes determined by the initial ground-truthing. As the additional two classes (i.e. Classes 8 and 11) applied to the supervised classification did not provide useful information, it was decided to apply the original ten-class grouping to the unsupervised classification process.

The first process was to undertake an unsupervised classification, based on ten classes. This was achieved by applying the standard ISODATA model in ERDAS Imagine®, running six to eight iterations to achieve a convergence level of 0.950. An area of interest (AOI) based on the farm cadastral boundaries was applied during the process to limit the analysis to only the areas within the required plantation boundaries. This was necessary in order to limit the classification process to only those areas of interest to this study (i.e. forest stands), and in so doing removing potential bias from pixel values of non-forestry objects within the images (Kätsch, 2003).

Distinct groupings were noted in the Ten Class Unsupervised Classifications, and so a second unsupervised classification was run on the raw image file, but this time specifying only four classes (see Figure 4.2.4). Apart from this, the same parameters were applied to the procedure as for the ten-class classification.

4.1.3.6 NDVI Value Estimation Procedure

An additional process was also run, using the Indices module in ERDAS Imagine® to produce standard NDVI values from each raw image.

It was possible at this stage to run a comparison with the database, either visually or by converting the classification data to a vector format and joining to an extract from the FMS database. However, it was shown that an improved classification resulted from completing the change detection process first and then using that data to run the comparison.

4.1.3.7 Change Detection Routines

The second major step in the analysis process was to undertake the change detection procedures. Following an intensive review of the literature on this subject (see section 2.8 above), together with discussions with the project Supervisors and Dr. Jari Varjo of the Finnish Forestry Research Institute, it was decided to adopt a post-classification approach, utilising the Assisted Change Detection model that is available from the ERDAS website and run as a model within ERDAS Imagine® (ERDAS, 2003). The actual change detection process was run in two stages (see Figure 4.1.3.1). It was hoped to apply some additional techniques reviewed in the

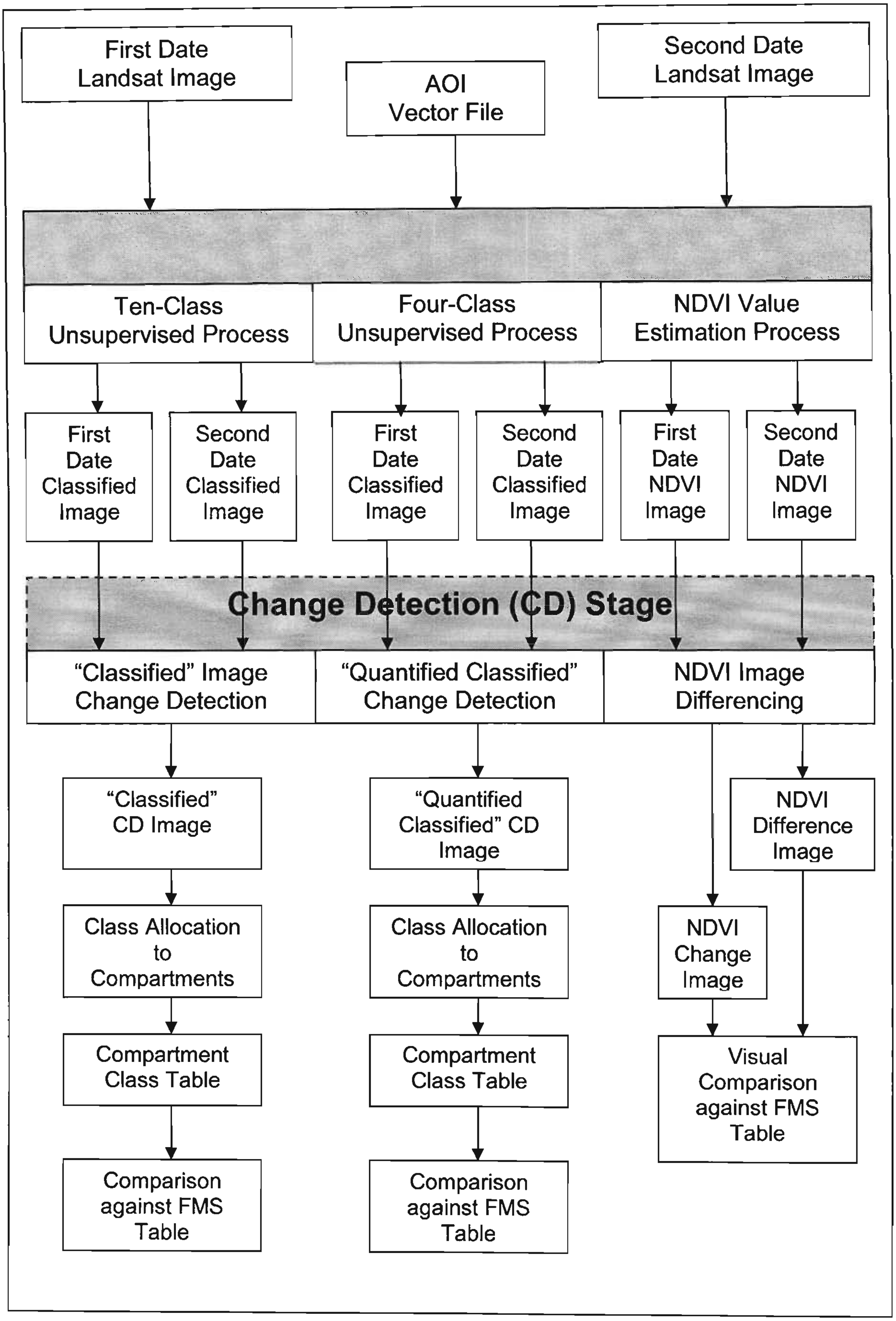


Figure 4.1.3.1 Diagram of the Image Analysis Process Flow applied in this study

literature, such Change Vector Analysis and segmentation, but some practical considerations, such as proprietary software or algorithms, prevented this.

4.1.3.8 “Classified” Image Change Detection Routine

The first stage was to run the Assisted Change Detection model’s “Classified Image” Module on the Ten-Class Unsupervised Classification data set, using the first-date classified image and the second-date classified image as the inputs to produce a difference image. This model works by testing to see if each pixel in image 1 is the same as the equivalent pixel in image 2, and if not, returns the Image 2 value (ERDAS, 2003). The resultant difference image displayed all change in terms of their state in second date image, i.e. if any class was displayed it meant that it had changed to that class. Unchanged data was represented by blank or white pixels (i.e. null data). This model did not indicate the class from which it changed, i.e. its original class.

4.1.3.9 “Quantified Classified” Change Detection Routine

The second stage in this change detection routine was to run the Four-Class Unsupervised Classification data set through the second module of the Assisted Change Detection model. This module, called the “Quantified Classified Change Detection” Module, produced a difference image that had a two-digit value for each cell. The first digit indicated the class to which it had changed, while the second digit identified the class from which it had changed, e.g. a 32 code indicated that the pixel had changed to class 3 from class 2 (ERDAS, 2003). A limitation with this module was that it could only handle a maximum of six classes.

Thus the Ten-Class Unsupervised Classification data set could not be analysed using this module. However, it provided very useful results with the Four-Class Unsupervised Classification data set.

4.1.3.10 NDVI Image Differencing Routines

A final set of change detection procedures was run on the NDVI images, using the Change Detection/Image Differencing model in ERDAS Imagine®. The two input files were the first date NDVI image and the second date NDVI image. The output files were two difference images, one being a standard image difference file (called an NDVI change image in this study), whose values reflected the amount of change between pixels, while the other image was a "highlight change" file (called an NDVI difference image), which indicated all change above a user-selected threshold level, using colour coding.

4.1.3.11 Acquisition of Repeat Images at Specified Time Intervals

The steps described above were applied to every image acquired for analyses.

4.1.3.12 Classification and Change Detection Accuracy Assessment

In order to assess the classification accuracy against the ground-truthed data, a standard error matrix (Khorram *et al.*, 1999), as well as a chi-square test, was run for every classification, whereby each sample compartment's ground-truthed class was tested against the equivalent class as determined by the image classification process. These tests were run on an Excel® spreadsheet add-in programme, EZAnalyze (EZAnalyze, 2005).

A review of the literature on accuracy assessment (see 2.11 above), described a wide range of accuracies, but did not set a limit as to what was accurate or not. Initial results from the signature separation and contingency matrices for the supervised classification training data indicated a general level of accuracy not lower than 80%, and so it was decided to set a threshold level of 85% as being an acceptable level of accuracy. Treitz and Howarth (2000) referred to an accuracy level of 67.6% being insufficient for operational classification and mapping.

The same procedure was used to test the classification accuracy of the change detection processes.

4.1.3.13 Comparison of Imagery Data with the Forestry Database

The final phase of the analytical process was to compare the resultant unsupervised Ten-Class and Four-Class classes, identified by the classification and change detection procedures, with the data recorded in the operational forestry database. Because of the format of the data in the forestry database, it was not possible to automate this process as part of this study, as it would have required additional routines to be written into the forestry database programme. However, a manual process was undertaken to create a summary table of the relevant data in the forestry database against which the imagery data could be compared. This was done by determining what operations had been recorded against all of the study compartments in the period between each image. A Ten-Class or a Four-Class Unsupervised Classification class was then allocated to each study compartment. The resultant table was then joined to the image data table described above and a standard query was then run to identify where there were discrepancies between the two data sets.

As an additional check, a visual comparison was also made between the NDVI difference images and a thematic GIS layer showing the compartment status as reflected by the operational forestry database.

4.2 Results and Discussion

4.2.1 Introduction

The results of this study are described below in terms of the outcomes of each stage of the classification and change detection process detailed in section 4.1.2 above.

For the purposes of clarity, a sample illustration site (see Figure 3.1.1), comprising 15 out of the 162 sample compartments, has been chosen from the study area to be used to illustrate the relevant results described and discussed below. This same area was used throughout this section to show the patterns of classification and change identified in this study. However, these descriptions and discussions apply to the results obtained over the whole study area. Where applicable, significant variations from these results are noted and discussed.

Figure 4.2.1 shows the sample illustration sites for all four images, based on an RGB composite image of bands 4, 3 and 2. The changes in spectral characteristics could be clearly seen (for example, see compartments E14 and E23), and illustrated the fundamental principle of identifiable change over time on which this study was based. Identifying what that change actually represented was the challenge of this (and any change detection) project.

4.2.2 Image Classification

4.2.2.1 Supervised Classification

Figure 4.2.2 shows the type of classification achieved using supervised classification. The classified imagery, signatures and classification accuracy are discussed below.

4.2.2.2 General Description of Classified Image

The overall impression gained from this classification is the range of classes that occur across the compartments, with no compartment consisting of only one class, where all pixels had the same value. Each compartment had two or more classes, although there tended to be a dominant class. Compartments with the least variation were those with either a closed canopy, or bare soil, i.e. the two extreme states of

Fig.a RGB Composite Landsat Image: March 2002

Fig.b RGB Composite Landsat Image: June 2002

Fig.c RGB Composite Landsat Image: January 2003

Fig.d RGB Composite Landsat Image: April 2003

Figure 4.2.1 RGB Composite Images (Bands 4:3:2) of Sample Illustration Sites

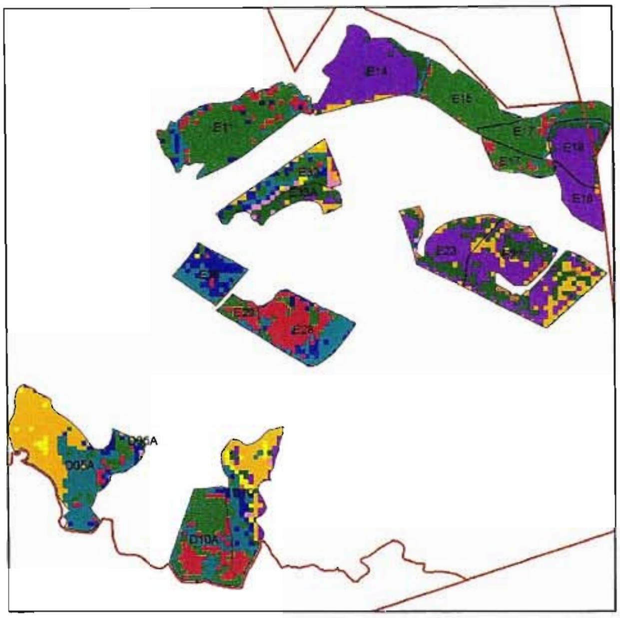


Fig.a Supervised Classification Image: March 2002

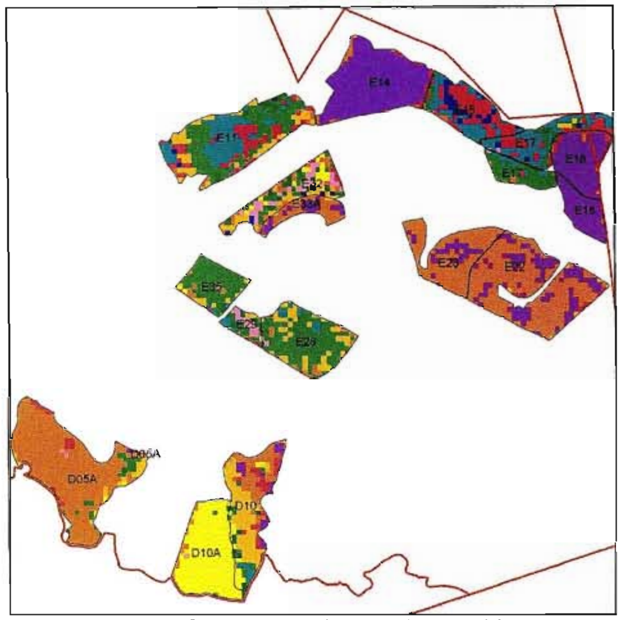


Fig.b Supervised Classification Image: June 2002

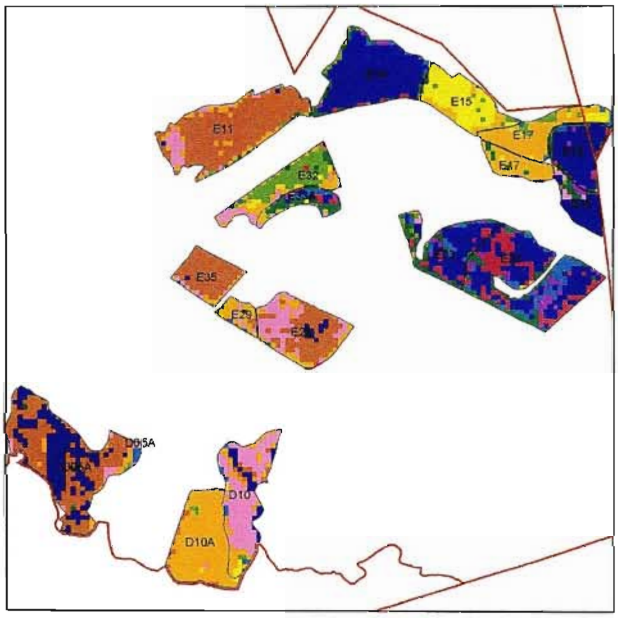


Fig.c Supervised Classification Image: January 2003

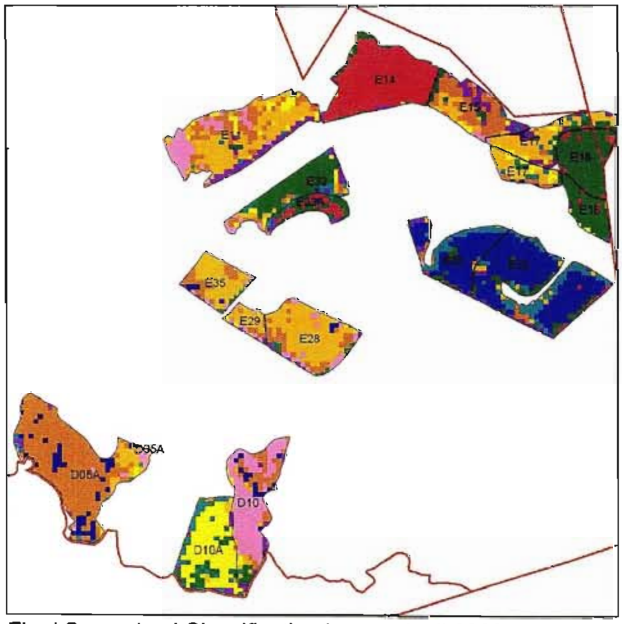


Fig.d Supervised Classification Image: April 2003

Figure 4.2.2 Supervised Classification Images

vegetation cover. The compartments with the greatest variation were those that had some measure of weed together with crop cover. There did not appear to be a seasonal effect, with a summer image having more variation than a winter one, as one might expect. It was this range of classes that prompted the move to an unsupervised classification, as less variation occurred with this classification method.

Another effect that was consistently noted throughout the study area was the mixed pixel effect along the edges of some compartments. For this reason, any edge pixels were disregarded when analysing an image.

4.2.2.3 Signature Separability and Contingency Matrices

Results from the signature separability and contingency matrices indicated that there was a clear separation between some of the classes. Examples of this included Class 2, slash and Class 12, closed canopy. There were however, exceptions, where the degree of separability was such that distinct classes could not be obtained (see Table 4.2.1).

Table 4.2.1 Signature Separability: April 2003 Image (Best Minimum Separability)

Class Pairs									
1: 2 **1997**	1: 3 **2000**	1: 4 1839	1: 5 **2000**	1: 7 **2000**	1: 8 **2000**	1: 9 **2000**	1: 10 **2000**	1:11 **2000**	1:12 **2000**
	2: 3 1755	2: 4 1795	2: 5 **1997**	2: 7 **1997**	2: 8 **1992**	2: 9 **1998**	2: 10 **2000**	2:11 **1958**	2:12 **2000**
		3: 4 1823	3: 5 1502	3: 7 1483	3: 8 1493	3: 9 1650	3: 10 1805	3:11 1291	3:12 **1999**
			4: 5 **1976**	4: 7 **1929**	4: 8 1862	4: 9 **1984**	4: 10 **1995**	4:11 **1929**	4:12 **2000**
				5: 7 1618	5: 8 1887	5: 9 1836	5: 10 **1910**	5:11 1759	5:12 **2000**
					7: 8 1520	7: 9 1802	7: 10 1562	7:11 1804	7:12 **1998**
						8: 9 1344	8: 10 1686	8:11 **1913**	8:12 **1983**
							9: 10 1285	9:11 1767	9:12 1775
								10:11 1893	10:12 **1995**
									11:12 **2000**

Class 1 Bare Soil
Class 2 Slash
Class 3 Crop/Slash
Class 4 Crop/Soil
Class 5 Crop/Slash/Weed
Class 6 Not present in image
Class 7 Crop/Soil/Slash/Weed
Class 8 Crop/Weed
Class 9 Pre-canopy closure
Class 10 Weed
Class 11 Slash/Weed
Class 12 Closed Canopy
BOLD = separable **(>1900)**

As an example, the separability between Class 1, bare soil and Class 4, crop/soil for the April image signature separability test produced a separability of 1839. However, overall separability was 1843 and a best minimum separability of 1285, well below the recommended limit of 1900 (Pouncey *et al.*, 1999). The equivalent results for the March image produced figures of 1914 and 909, respectively (see Table 4.2.2). The other images produced similar results.

Similar results were produced by the contingency matrices for the signatures, with Classes 8, 9 and 12 giving contingency results above 90%. However, the other class signatures produced figures in the low 80%s and 70%s.

Table 4.2.2 Signature Separability: March 2002 Image (Best Minimum Separability)

Class Pairs									
1:2 1568	1:3 **1996**	1:4 **1985**	1:5 **2000**	1:6 1204	1:7 **2000**	1:8 **2000**	1:9 **2000**	1:10 **2000**	1:12 **2000**
	2:3 **2000**	2:4 **1995**	2:5 **2000**	2:6 1724	2:7 **2000**	2:8 **2000**	2:9 **2000**	2:10 **2000**	2:12 **2000**
		3:4 1855	3:5 **1973**	3:6 **1996**	3:7 **1994**	3:8 **1997**	3:9 **2000**	3:10 **1997**	3:12 **2000**
			4:5 **1994**	4:6 1851	4:7 **1983**	4:8 **1990**	4:9 **2000**	4:10 **1997**	4:12 **2000**
				5:6 **2000**	5:7 1815	5:8 **1911**	5:9 1671	5:10 909	5:12 **2000**
					6:7 **2000**	6:8 **2000**	6:9 **2000**	6:10 **2000**	6:12 **2000**
						7:8 1858	7:9 1847	7:10 1729	7:12 **2000**
							8:9 **1917**	8:10 1815	8:12 **2000**
								9:10 1693	9:12 **1993**
									10:12 **2000**

Class 1 Bare Soil
Class 2 Slash
Class 3 Crop/Slash
Class 4 Crop/Soil
Class 5 Crop/Slash/ Weed
Class 6 Crop/Soil/ Weed
Class 7 Crop/Soil/Slash/ Weed
Class 8 Crop/Weed
Class 9 Pre-canopy closure
Class 10 Weed
Class 11 Not present in image
Class 12 Closed Canopy
***BOLD = separable* (>1900)**

4.2.2.4 Classification Accuracy

In setting up the accuracy assessment tests, a null hypothesis that the spectral classes detected by the image did not reflect the land-cover classes identified in the ground-truthing process was proposed. The results of the chi-square tests for every image produced overall probabilities of less than 0.05, thus suggesting that the null hypothesis be rejected (see Table 4.2.3 to Table 4.2.6). When the individual classes were examined on their own, differentiation between some classes was seen to be

Table 4.2.3 Error Matrix: Supervised Classification – March 2002 Image

Observed	Reference: Class 01	Class 02	Class 03	Class 04	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Class 12	Row Total	Incremental Chi Square	User Accuracy
Class 01	6	0	0	0	0	0	1	0	0	0	0	7	45.198	85.7%
expected	*0.700*	*0.500*	*0.400*	*0.300*	*0.400*	*0.700*	*1.300*	*0.400*	*0.700*	*0.300*	*1.300*			
Class 02	0	5	0	0	0	0	0	0	0	0	0	5	65.000	100.0%
expected	*0.500*	*0.357*	*0.286*	*0.214*	*0.286*	*0.500*	*0.929*	*0.286*	*0.500*	*0.214*	*0.929*			
Class 03	0	0	3	0	0	0	1	0	0	0	0	4	36.721	75.0%
expected	*0.400*	*0.286*	*0.229*	*0.171*	*0.229*	*0.400*	*0.743*	*0.229*	*0.400*	*0.171*	*0.743*			
Class 04	1	0	0	3	0	0	1	0	0	0	0	5	40.077	60.0%
expected	*0.500*	*0.357*	*0.286*	*0.214*	*0.286*	*0.500*	*0.929*	*0.286*	*0.500*	*0.214*	*0.929*			
Class 05	0	0	0	0	3	0	0	0	1	0	1	5	29.577	60.0%
expected	*0.500*	*0.357*	*0.286*	*0.214*	*0.286*	*0.500*	*0.929*	*0.286*	*0.500*	*0.214*	*0.929*			
Class 06	0	0	1	0	0	7	5	2	1	0	0	16	29.132	43.8%
expected	*1.600*	*1.143*	*0.914*	*0.686*	*0.914*	*1.600*	*2.971*	*0.914*	*1.600*	*0.686*	*2.971*			
Class 07	0	0	0	0	0	0	3	0	1	0	0	4	10.615	75.0%
expected	*0.400*	*0.286*	*0.229*	*0.171*	*0.229*	*0.400*	*0.743*	*0.229*	*0.400*	*0.171*	*0.743*			
Class 08	0	0	0	0	0	0	2	1	0	1	0	4	11.593	25.0%
expected	*0.400*	*0.286*	*0.229*	*0.171*	*0.229*	*0.400*	*0.743*	*0.229*	*0.400*	*0.171*	*0.743*			
Class 09	0	0	0	0	0	0	0	1	3	0	0	4	22.875	75.0%
expected	*0.400*	*0.286*	*0.229*	*0.171*	*0.229*	*0.400*	*0.743*	*0.229*	*0.400*	*0.171*	*0.743*			
Class 10	0	0	0	0	1	0	0	0	0	2	0	3	33.944	66.7%
expected	*0.300*	*0.214*	*0.171*	*0.129*	*0.171*	*0.300*	*0.557*	*0.171*	*0.300*	*0.129*	*0.557*			
Class 12	0	0	0	0	0	0	0	0	1	0	12	13	47.414	92.3%
expected	*1.300*	*0.929*	*0.743*	*0.557*	*0.743*	*1.300*	*2.414*	*0.743*	*1.300*	*0.557*	*2.414*			
Columns Total	7	5	4	3	4	7	13	4	7	3	13	70 *Grand Total*	372.147 *Chi Square Total*	68.6% *Overall Accuracy*
Producer Accuracy	85.7%	100.0%	75.0%	100.0%	75.0%	100.0%	23.1%	25.0%	42.9%	66.7%	92.3%			
Khat	0.631											**DF**	100	
												P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.4 Error Matrix: Supervised Classification – June 2002 Image

Observed	Reference: Class 02	Class 03	Class 04	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Class 11	Class 12	Row Total	Incremental Chi Square	User Accuracy
Class 02	3	0	0	0	0	0	0	0	0	0	0	3	11.625	100.0%
expected	*0.615*	*0.154*	*0.308*	*0.154*	*0.615*	*0.385*	*0.077*	*0.308*	*0.077*	*0.154*	*0.154*			
Class 03	1	2	0	0	0	0	0	0	0	0	0	3	24.625	66.7%
expected	*0.615*	*0.154*	*0.308*	*0.154*	*0.615*	*0.385*	*0.077*	*0.308*	*0.077*	*0.154*	*0.154*			
Class 04	1	0	3	0	1	0	0	0	0	0	0	5	14.500	60.0%
expected	*1.026*	*0.256*	*0.513*	*0.256*	*1.026*	*0.641*	*0.128*	*0.513*	*0.128*	*0.256*	*0.256*			
Class 05	0	0	0	2	0	0	0	0	0	0	0	2	37.000	100.0%
expected	*0.410*	*0.103*	*0.205*	*0.103*	*0.410*	*0.256*	*0.051*	*0.205*	*0.051*	*0.103*	*0.103*			
Class 06	0	0	0	0	6	3	0	0	0	0	0	9	18.300	66.7%
expected	*1.846*	*0.462*	*0.923*	*0.462*	*1.846*	*1.154*	*0.231*	*0.923*	*0.231*	*0.462*	*0.462*			
Class 07	0	0	0	0	0	1	0	0	0	0	0	1	6.800	100.0%
expected	*0.205*	*0.051*	*0.103*	*0.051*	*0.205*	*0.128*	*0.026*	*0.103*	*0.026*	*0.051*	*0.051*			
Class 08	1	0	0	0	0	0	1	0	0	0	0	2	19.938	50.0%
expected	*0.410*	*0.103*	*0.205*	*0.103*	*0.410*	*0.256*	*0.051*	*0.205*	*0.051*	*0.103*	*0.103*			
Class 09	0	0	0	0	0	1	0	4	0	0	0	5	27.760	80.0%
expected	*1.026*	*0.256*	*0.513*	*0.256*	*1.026*	*0.641*	*0.128*	*0.513*	*0.128*	*0.256*	*0.256*			
Class 10	1	0	0	0	0	0	0	0	1	0	0	2	19.938	50.0%
expected	*0.410*	*0.103*	*0.205*	*0.103*	*0.410*	*0.256*	*0.051*	*0.205*	*0.051*	*0.103*	*0.103*			
Class 11	1	0	1	0	1	0	0	0	0	2	0	5	14.500	40.0%
expected	*1.026*	*0.256*	*0.513*	*0.256*	*1.026*	*0.641*	*0.128*	*0.513*	*0.128*	*0.256*	*0.256*			
Class 12	0	0	0	0	0	0	0	0	0	0	2	2	37.000	100.0%
expected	*0.410*	*0.103*	*0.205*	*0.103*	*0.410*	*0.256*	*0.051*	*0.205*	*0.051*	*0.103*	*0.103*			
Columns Total	8	2	4	2	8	5	1	4	1	2	2	39 *Grand Total*	231.985 *Chi Square Total*	69.2% *Overall Accuracy*
Producer Accuracy	37.5%	100.0%	75.0%	100.0%	75.0%	20.0%	100.0%	100.0%	100.0%	100.0%	100.0%	**DF**	100	
Khat	0.652											**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.5 Error Matrix: Supervised Classification – Jan. 2003 Image

Observed	Reference: Class 01	Class 02	Class 03	Class 04	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Class 12	Row Total	Incremental Chi Square	User Accuracy
Class 01	5	0	0	0	0	0	0	0	0	0	0	5	28.333	100.0%
expected	*0.750*	*0.875*	*0.625*	*0.250*	*0.250*	*0.250*	*0.375*	*0.375*	*0.250*	*0.500*	*0.500*			
Class 02	0	7	0	0	0	0	0	0	0	0	0	7	33.000	100.0%
expected	*1.050*	*1.225*	*0.875*	*0.350*	*0.350*	*0.350*	*0.525*	*0.525*	*0.350*	*0.700*	*0.700*			
Class 03	0	0	5	0	0	0	0	0	0	1	0	6	29.000	83.3%
expected	*0.900*	*1.050*	*0.750*	*0.300*	*0.300*	*0.300*	*0.450*	*0.450*	*0.300*	*0.600*	*0.600*			
Class 04	1	0	0	2	0	0	0	0	0	1	0	4	20.167	50.0%
expected	*0.600*	*0.700*	*0.500*	*0.200*	*0.200*	*0.200*	*0.300*	*0.300*	*0.200*	*0.400*	*0.400*			
Class 05	0	0	0	0	2	0	0	0	0	0	0	2	38.000	100.0%
expected	*0.300*	*0.350*	*0.250*	*0.100*	*0.100*	*0.100*	*0.150*	*0.150*	*0.100*	*0.200*	*0.200*			
Class 06	0	0	0	0	0	2	0	0	0	0	0	2	38.000	100.0%
expected	*0.300*	*0.350*	*0.250*	*0.100*	*0.100*	*0.100*	*0.150*	*0.150*	*0.100*	*0.200*	*0.200*			
Class 07	0	0	0	0	0	0	3	0	0	0	0	3	37.000	100.0%
expected	*0.450*	*0.525*	*0.375*	*0.150*	*0.150*	*0.150*	*0.225*	*0.225*	*0.150*	*0.300*	*0.300*			
Class 08	0	0	0	0	0	0	0	3	0	0	0	3	37.000	100.0%
expected	*0.450*	*0.525*	*0.375*	*0.150*	*0.150*	*0.150*	*0.225*	*0.225*	*0.150*	*0.300*	*0.300*			
Class 09	0	0	0	0	0	0	0	0	0	2	0	2	18.000	0.0%
expected	*0.300*	*0.350*	*0.250*	*0.100*	*0.100*	*0.100*	*0.150*	*0.150*	*0.100*	*0.200*	*0.200*			
Class 10	0	0	0	0	0	0	0	0	2	0	0	2	38.000	0.0%
expected	*0.300*	*0.350*	*0.250*	*0.100*	*0.100*	*0.100*	*0.150*	*0.150*	*0.100*	*0.200*	*0.200*			
Class 12	0	0	0	0	0	0	0	0	0	0	4	4	36.000	100.0%
expected	*0.600*	*0.700*	*0.500*	*0.200*	*0.200*	*0.200*	*0.300*	*0.300*	*0.200*	*0.400*	*0.400*			
Columns Total	6	7	5	2	2	2	3	3	2	4	4	40 *Grand Total*	352.500 *Chi Square Total*	82.5% *Overall Accuracy*
Producer Accuracy	83.3%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	0.0%	0.0%	100.0%	DF	100	
Khat 0.801												P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.6 Error Matrix: Supervised Classification – April 2003 Image

Observed	Reference: Class 01	Class 02	Class 03	Class 04	Class 05	Class 07	Class 08	Class 09	Class 10	Class 11	Class 12	Row Total	Incremental Chi Square	User Accuracy
Class 01	2	0	0	0	0	0	0	0	0	0	0	2	15.500	100.0%
expected	*0.229*	*0.171*	*0.171*	*0.171*	*0.057*	*0.229*	*0.229*	*0.229*	*0.114*	*0.057*	*0.343*			
Class 02	0	2	0	0	0	0	0	0	0	0	0	2	21.333	100.0%
expected	*0.229*	*0.171*	*0.171*	*0.171*	*0.057*	*0.229*	*0.229*	*0.229*	*0.114*	*0.057*	*0.343*			
Class 03	0	0	2	0	0	0	0	0	0	0	0	2	21.333	100.0%
expected	*0.229*	*0.171*	*0.171*	*0.171*	*0.057*	*0.229*	*0.229*	*0.229*	*0.114*	*0.057*	*0.343*			
Class 04	2	0	0	3	0	0	0	0	0	0	0	5	23.000	60.0%
expected	*0.571*	*0.429*	*0.429*	*0.429*	*0.143*	*0.571*	*0.571*	*0.571*	*0.286*	*0.143*	*0.857*			
Class 05	0	0	1	0	1	0	0	0	0	0	0	2	21.333	50.0%
expected	*0.229*	*0.171*	*0.171*	*0.171*	*0.057*	*0.229*	*0.229*	*0.229*	*0.114*	*0.057*	*0.343*			
Class 07	0	0	0	0	0	3	0	0	0	0	0	3	23.250	100.0%
expected	*0.343*	*0.257*	*0.257*	*0.257*	*0.086*	*0.343*	*0.343*	*0.343*	*0.171*	*0.086*	*0.514*			
Class 08	0	0	0	0	0	0	4	2	0	0	0	6	23.167	66.7%
expected	*0.686*	*0.514*	*0.514*	*0.514*	*0.171*	*0.686*	*0.686*	*0.686*	*0.343*	*0.171*	*1.029*			
Class 09	0	1	0	0	0	1	0	2	0	0	2	6	7.125	33.3%
expected	*0.686*	*0.514*	*0.514*	*0.514*	*0.171*	*0.686*	*0.686*	*0.686*	*0.343*	*0.171*	*1.029*			
Class 10	0	0	0	0	0	0	0	0	2	0	0	2	33.000	100.0%
expected	*0.229*	*0.171*	*0.171*	*0.171*	*0.057*	*0.229*	*0.229*	*0.229*	*0.114*	*0.057*	*0.343*			
Class 11	0	0	0	0	0	0	0	0	0	1	0	1	34.000	100.0%
expected	*0.114*	*0.086*	*0.086*	*0.086*	*0.029*	*0.114*	*0.114*	*0.114*	*0.057*	*0.029*	*0.171*			
Class 12	0	0	0	0	0	0	0	0	0	0	4	4	19.333	100.0%
expected	*0.457*	*0.343*	*0.343*	*0.343*	*0.114*	*0.457*	*0.457*	*0.457*	*0.229*	*0.114*	*0.686*			
Columns Total	4	3	3	3	1	4	4	4	2	1	6	35 *Grand Total*	242.375 *Chi Square Total*	74.3% *Overall Accuracy*
Producer Accuracy	50.0%	66.7%	66.7%	100.0%	100.0%	75.0%	100.0%	50.0%	100.0%	100.0%	66.7%	DF	100	
Khat 0.714												P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

statistically valid (numbers in italics are individual chi-square values). Using the chosen threshold level of 85% (see section 4.1.3.12) a success rating was decided on as follows:

85 –100%: Acceptable classification

<85% : Unacceptable classification

The overall accuracy results reported in the error matrices were all below this threshold, resulting in unacceptable overall classification results. However, the classification of some individual classes recorded much higher user or producer accuracies (see Table 4.2.3 to 4.2.6).

When the supervised classifications were undertaken the classes tended to fall into three groups of signatures, defined by the extent of the classification accuracy. These groupings were as follows:

1). Compartments that ranged from being clear-felled to planted, weed-free stands younger than one year.

2). Planted stands older than one year or with significant weed growth, but not having reached a closed canopy stage (usually less than two years old).

3). Stands with a closed canopy.

The first and last groups represented either end of the classification spectrum, with the middle group tending to classify all the spectral ranges that were not sufficiently distinct to enable the classification results to produce distinct classes suitable for consistent determination of the status of a compartment.

Most clear-felled areas could be clearly identified. There was however, some cross-classification between Class 1, bare soil and Class 4, crop/soil. This was anticipated, as the contingency matrices indicated that there was not a clear distinction between these two classes. It would also account for the lack of distinction between felled stands and those planted, weed-free stands younger than a year. The error matrix results showed that whereas virtually all the ground-truthed Class 1 compartments (i.e. bare soil) were correctly classified, up to 50% of the Class 4 ground-truthed compartments were incorrectly classified as Class 1 (see Table 4.2.3 to Table 4.2.6).

When assessing the classified images visually (see Figure 4.2.2), compartment E18 in the January image displays a good example of a felling operation in progress, where the southern half of the compartment was classified as Class 12, closed canopy (i.e. unfelled) while the northern section was classified as Class 2, slash.

The ease with which incorrect classifications can occur, even within a fairly controlled environment such as a supervised classification, is illustrated by compartment E18 in the sample site (see Figure 4.2.2d, April image). The presence of an unburnt needle mat together with some wattle "lawn" regrowth of less than ten centimetres in height still caused it to be classified as a Class 4, crop/soil, rather than as Class 1 or 2, which in actual fact it was. Despite this anomaly, clear-felled areas can be identified with a high degree of accuracy, which could be expected in the light of the results from the contingency matrices.

At the other end of the classification spectrum, compartments with full canopy cover could also be clearly identified, and had a very uniform classification. Examples of this are seen in compartments E14 and E18 in the March (Figure 4.2.2a) and June (Figure 4.2.2b) images. However, other compartments, such as E22 and E23, were also full canopy, but were classified as Class 9, pre-canopy closure stage. When visually checked across the study site, this classification did not appear to be linked to species, although there was a greater tendency for pine and gum stands to be classified as Class 12, full canopy, while wattle tended to be classified more as Class 9, pre-canopy closure. The classification of closed canopy in the January (i.e. summer) image was much more consistent in terms of compartments being classified as Class 12, full canopy. This result was borne out by the error matrix results of the April image (Table 4.2.6), where 66.7% of the Class 12 ground-truthed compartments were correctly recorded as Class 12 in the image, but 33.3% were classified as Class 9. However, in the June and January images (Tables 4.2.4; 4.2.5 respectively), the error matrix results showed that all Class 12 ground-truthed compartments were correctly classified as Class 12. In the March image 92.3% of Class 12 compartments were classified correctly, but with one compartment (7.7%) being classified as Class 9 (see Table 4.2.3).

The cross-classification between Class 12, full canopy and Class 9, pre-canopy closure in the autumn and winter images is probably due to the nature of some species, especially wattle, to reduce leaf area during periods of moisture stress, either by shedding leaves/needles (gum/pine) or by the pinnules closing up (wattle).

This would have the effect of reducing canopy density, and so causing the shift in spectral reflectance towards pre-canopy closure state. This would also explain why wattle, with its greater canopy reduction, was much more likely to be classified as such, rather than pine or gum. This fact was reinforced by the January classification being much more consistent in classifying closed canopy as Class 12.

Although closed canopy and clear-felled states can be identified with reasonable accuracy, the young regrowth period (i.e. from time of planting to canopy closure – usually a period of about 2 years, depending on species, silvicultural management and site factors) becomes problematic for the classification process. Using visual assessment, this can be seen if one compares the classifications for E11, E15, E17, E28, E29 and E35 across all four images (see Figure 4.2.2). For example, E11 in the March image is classified as Class 1, bare soil, Class 4, crop/soil and Class 6, crop/soil/weed; in June, as Class 4, crop/soil and Class 6; in January as Class 10, total weed; and in April as Class 8, crop/weed, Class 9, pre-canopy closure, and Class 10, total weed. When ground-truthed in January it was classed as Class 9, pre-canopy closure, and was used as a training site for this class. However, it was not correctly classified during the classification process. Other examples of misclassification include compartments E28 and E35 in the January image, which were classified as Class 10, total weed, when in fact they were Class 8, crop/weed. In the June image they were classified as Class 9, pre-canopy closure, but were ground-truthed as being Class 6, crop/soil/weed. However, in the April image, both compartments were correctly classified.

It was noted that the error matrices for the March and June images (see Tables 4.2.3 and 4.2.4) reflected much more misclassification than the equivalent test for the January and April images (see Table 4.2.5 and Table 4.2.6). There was a much greater separation of classes in the latter two images, with many of the classes having a 100% correct classification. While there was no obvious reason for this difference, it is thought that because the ground-truthing for these images was much more intensive than for the first two images, it enabled better training sites to be established, which, in turn, produced a more accurate classification.

When considering the classification on compartments that were in the first two years of a re-establishment cycle (i.e. from planting to canopy closure), the density of vegetation appeared to be the most critical classification determinant, irrespective of whether it was crop or weed. Compartments that had been weed-free at the time of image acquisition were generally classified in one or more of the first 4 classes, depending on the density of the crop. Compartments with either a substantial crop cover or weed cover, or a combination of both tended to fall into the middle order classes (Class 5 to Class 8, including Class 10). There was, however, too much overlap between all of these classes to be able to successfully produce distinct groupings. There also appeared to be a seasonal effect, where the annual weeds died off in winter, and so produce a different spectral signature.

While it was clear that there were many cross-classifications within these groups of classes, the errors all occurred within the class range, rather than being misclassifications across the major class groupings, e.g. being classified as full canopy or clear-felled.

An interesting point that was observed in the March image was in compartment D05A, which was in the process of being weeded at the time of image acquisition. One can clearly see the weeded area, classified as Class 4, crop/soil, and the non-weeded portion, classified as Class 8, crop/weed. Unfortunately, this was the only compartment where such a process could be identified, but it could provide a basis from which it might be possible to highlight weeding operations more accurately, or locate areas of potential weed problems.

A general observation that should be made about the use of such imagery is that a significant amount of information can be gleaned through visual interpretation, especially if one has ancillary information about the compartments being observed. This would include knowing what species are planted, the age of the crops and something about what operations have been done on the compartments. One can identify areas of possible weed concentration within compartments; areas of either good growth, where canopy closure has been reached ahead of the rest of the compartment (e.g. see compartment D05A in the January image), or alternatively, areas of poor growth where there appears to be bare soil in a compartment that has otherwise reached a Class 9, pre-canopy closure stage.

4.2.2.5 Unsupervised Classification

When comparing the results of the supervised and unsupervised classifications it was found that the unsupervised classifications produced more consistent distinctions between the classes. In addition a reduction in the number of classes also gave greater separability. It was therefore concluded that an unsupervised classification provided the best separation between classes, and would be adopted as the main classification procedure. An additional advantage was that it was also a much simpler procedure to implement. The initial unsupervised classification was run using ten classes, based on the early ground-truthing identifying 10 possible classes.

It must be noted that the class numbers in the unsupervised classification bear NO relationship with the equivalent numbers in the supervised classification classes, and so should not be interpreted as being synonymous. Because of the *apriori* nature of the supervised classes, compared to the *post-priori* nature of the unsupervised classes, the differentiation between these classes was unrelated, and therefore direct comparison between these two methods was not possible. An example of this is seen in the fact that ten of the twelve supervised classes cover the first twelve month period after clear-felling, compared to only five of the ten unsupervised classes covering this same period.

4.2.2.6 Ten-Class Unsupervised Classification

The unsupervised classification process categorised the spectral values into ten classes, which were defined as follows:

Class 1 Excluded (classified features outside of the compartments)
Class 2: Closed Canopy (usually soft gum)
Class 3: Closed Canopy (usually hard gum; mature pine)
Class 4: Closed Canopy (usually young pine; wattle)
Class 5: Pre-canopy Closure
Class 6: Crop/Soil/Slash/Weed
Class 7: Weed
Class 8: Crop/Soil/Slash/Weed
Class 9: Planted/Coppiced (< 1 year old)
Class 10: Slash/Burnt (i.e. felled compartments)

Descriptive categories were allocated to these classes, based on ground-truthed data, from which it was found that these classes followed the general trend from dense vegetative cover to no vegetative cover. Classes 2, 3 and 4 formed a distinct grouping, as did Classes 9 and 10, with very minimal cross-classification between them as groups. Classes 6, 7 and 8 also formed a unique group. However, within these categories, classes could not be assigned definitive descriptive categories, as there was not a clear differentiation between many of them, especially between Classes 6, 7 and 8, which tended to cover a wide range of vegetation cover. Neither were the genera linked to Classes 2, 3 and 4 absolute, but were allocated on the basis of a general trend. Sample illustration sites of the Ten-Class Unsupervised Classifications are given in Figure 4.2.3.

As with the Supervised Classification error matrices, the results for this classification also produced overall probabilities of less than 0.05, showing that the classifications were statistically significant, and therefore valid (see tables 4.2.7 to 4.2.11). Regarding the closed canopy classes, mature pine and gum compartments were generally classified as Class 2 or 3 in the summer image, but as Class 3 or 4 in the winter image. Mature wattle canopy tended to be classified as Class 2 or 3 in the summer image, but as Class 4 or 5 in the autumn and winter images. Examples of this were seen in compartments E22, E23 and E33A in the March and June images (see Figure 4.2.3 a, b). The Producer Accuracies for Class 2 varied from 50% (however, there were two samples in this case, one of which was classified as Class 5) to 100%, with some cross-classification with Classes 3 and 4, where the accuracy was not 100% (refer to Tables 4.2.7 to 4.2.11). This was not unexpected given the proximity of these Class spectral values to Class 2.

Clear-felled areas, on the other hand, were classified as Class 10 fairly consistently across all images and independent of species. Compartments E14, E18, E22 and E23 in the January and April images illustrated this. Some portions of the clear-felled compartments tended to be classified as Class 9, but this was not all that common. These results were reflected in the error matrices as well, with the June, January and April images all having Producer Accuracies above 95% for Class 10 (see Tables 4.2.9 to 4.2.11). The March image Producer Accuracy dropped to 72% (Table 4.2.8).

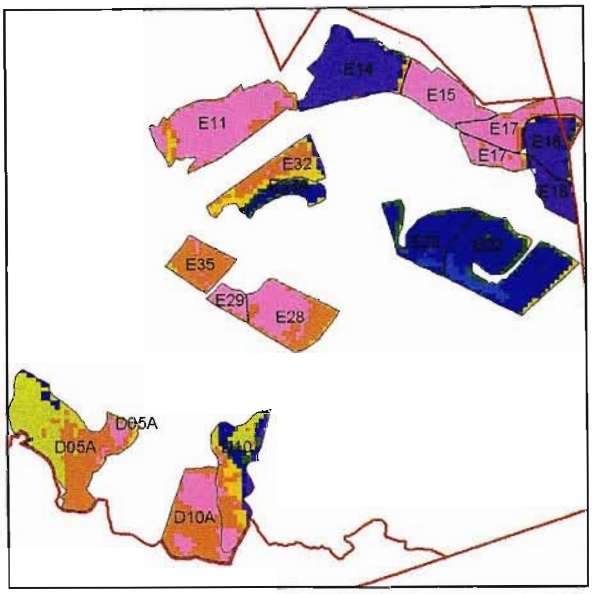


Fig.a Ten-Class Unsupervised Classification Image: March 2002

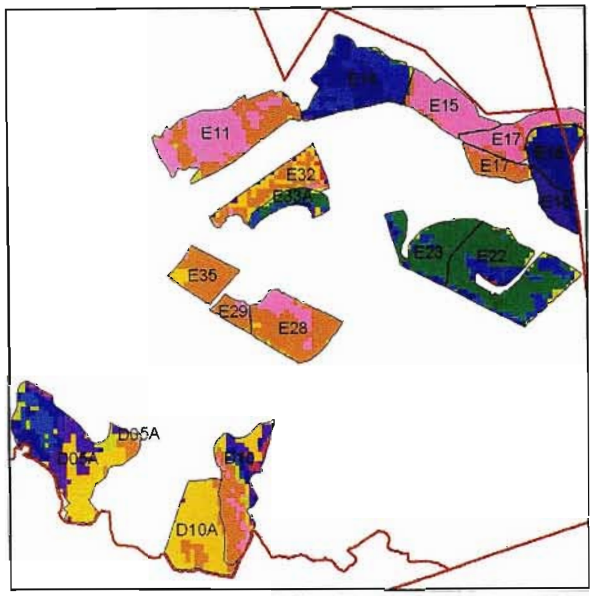


Fig.b Ten-Class Unsupervised Classification Image: June 2002

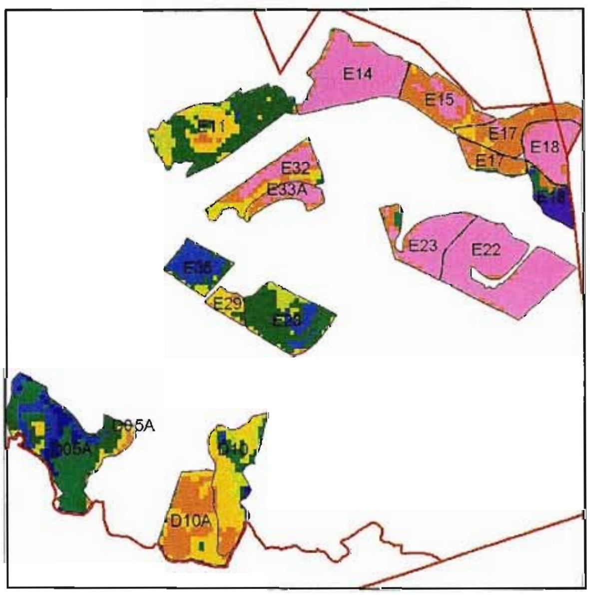


Fig.c Ten-Class Unsupervised Classification Image: January 2003

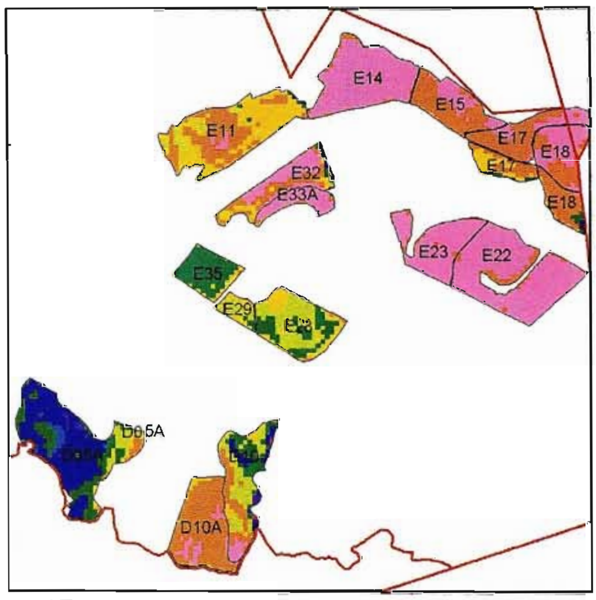


Fig.d Ten-Class Unsupervised Classification Image: April 2003

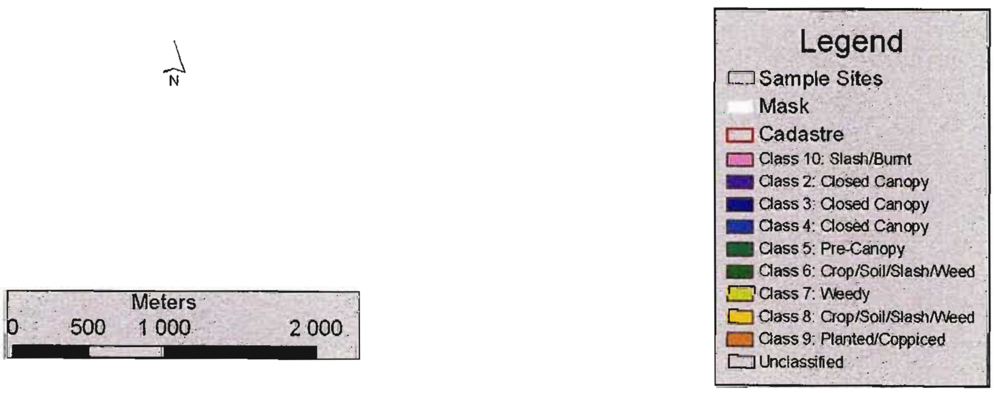


Figure 4.2.3 Ten-Class Unsupervised Classification Images

Table 4.2.7 Error Matrix: Ten-Class Unsupervised Classification – March 2002 to April 2003 Combined Image Data

Observed	Reference Class 02	Class 03	Class 04	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**12**	1	0	0	1	0	0	0	0	**14**	131.061	85.7%
expected	*1.021*	*0.438*	*0.656*	*0.438*	*0.583*	*0.802*	*1.750*	*3.135*	*5.177*			
Class 03	1	**3**	1	1	0	0	0	0	0	**6**	53.175	50.0%
expected	*0.438*	*0.188*	*0.281*	*0.188*	*0.250*	*0.344*	*0.750*	*1.344*	*2.219*			
Class 04	1	1	**6**	1	0	0	0	0	0	**9**	84.968	66.7%
expected	*0.656*	*0.281*	*0.422*	*0.281*	*0.375*	*0.516*	*1.125*	*2.016*	*3.328*			
Class 05	0	0	1	**3**	0	0	0	0	0	**4**	73.333	75.0%
expected	*0.292*	*0.125*	*0.188*	*0.125*	*0.167*	*0.229*	*0.500*	*0.896*	*1.479*			
Class 06	0	1	1	0	**7**	1	1	0	0	**11**	103.072	63.6%
expected	*0.802*	*0.344*	*0.516*	*0.344*	*0.458*	*0.630*	*1.375*	*2.464*	*4.068*			
Class 07	0	0	0	1	0	**5**	3	0	0	**9**	51.040	55.6%
expected	*0.656*	*0.281*	*0.422*	*0.281*	*0.375*	*0.516*	*1.125*	*2.016*	*3.328*			
Class 08	0	0	0	0	0	3	**8**	3	0	**14**	36.663	57.1%
expected	*1.021*	*0.438*	*0.656*	*0.438*	*0.583*	*0.802*	*1.750*	*3.135*	*5.177*			
Class 09	0	0	0	0	0	0	5	**33**	8	**46**	67.817	71.7%
expected	*3.354*	*1.438*	*2.156*	*1.438*	*1.917*	*2.635*	*5.750*	*10.302*	*17.010*			
Class 10	0	0	0	0	0	2	7	7	**63**	**79**	65.477	79.7%
expected	*5.760*	*2.469*	*3.703*	*2.469*	*3.292*	*4.526*	*9.875*	*17.693*	*29.214*			
Columns Total	**14**	**6**	**9**	**6**	**8**	**11**	**24**	**43**	**71**	**192** ***Grand Total***	666.606 ***Chi Square Total***	72.9% ***Overall Accuracy***
Producer Accuracy	85.7%	50.0%	66.7%	50.0%	87.5%	45.5%	33.3%	76.7%	88.7%	**DF**	64	
Khat 0.662										**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.8 Error Matrix: Ten-Class Unsupervised Classification –March 2002 Image

Observed	Reference Class 02	Class 03	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**10**	0	0	0	0	0	0	0	**10**	55.833	100.0%
expected	*1.519*	*0.380*	*0.253*	*0.759*	*1.013*	*1.266*	*1.646*	*3.165*			
Class 03	2	**2**	0	0	0	0	0	0	**4**	28.917	50.0%
expected	*0.608*	*0.152*	*0.101*	*0.304*	*0.405*	*0.506*	*0.658*	*1.266*			
Class 05	0	0	**2**	0	0	0	0	0	**2**	77.000	100.0%
expected	*0.304*	*0.076*	*0.051*	*0.152*	*0.203*	*0.253*	*0.329*	*0.633*			
Class 06	0	1	0	**6**	1	0	0	0	**8**	55.776	75.0%
expected	*1.215*	*0.304*	*0.203*	*0.608*	*0.810*	*1.013*	*1.316*	*2.532*			
Class 07	0	0	0	0	**4**	1	0	0	**5**	28.180	80.0%
expected	*0.759*	*0.190*	*0.127*	*0.380*	*0.506*	*0.633*	*0.823*	*1.582*			
Class 08	0	0	0	0	3	**1**	0	0	**4**	20.194	25.0%
expected	*0.608*	*0.152*	*0.101*	*0.304*	*0.405*	*0.506*	*0.658*	*1.266*			
Class 09	0	0	0	0	0	2	**11**	7	**20**	26.087	55.0%
expected	*3.038*	*0.759*	*0.506*	*1.519*	*2.025*	*2.532*	*3.291*	*6.329*			
Class 10	0	0	0	0	0	6	2	**18**	**26**	25.252	69.2%
expected	*3.949*	*0.987*	*0.658*	*1.975*	*2.633*	*3.291*	*4.278*	*8.228*			
Columns Total	**12**	**3**	**2**	**6**	**8**	**10**	**13**	**25**	**79** ***Grand Total***	317.239 ***Chi Square Total***	68.4% ***Overall Accuracy***
									DF	49	
									P	0.000	
Producer Accuracy	83.3%	66.7%	100.0%	100.0%	50.0%	10.0%	84.6%	72.0%			
Khat 0.610											

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.9 Error Matrix: Ten-Class Unsupervised Classification – June 2002 Image

Observed	Class 02	Class 04	Class 05	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**1**	0	0	1	0	0	2	20.750	50.0%
expected	*0.051*	*0.103*	*0.051*	*0.308*	*0.872*	*0.615*			
Class 04	0	**2**	0	0	0	0	2	37.000	100.0%
expected	*0.051*	*0.103*	*0.051*	*0.308*	*0.872*	*0.615*			
Class 05	0	0	**1**	0	0	0	1	38.000	100.0%
expected	*0.026*	*0.051*	*0.026*	*0.154*	*0.436*	*0.308*			
Class 08	0	0	0	**3**	2	0	5	8.535	60.0%
expected	*0.128*	*0.256*	*0.128*	*0.769*	*2.179*	*1.538*			
Class 09	0	0	0	1	**13**	0	14	14.158	92.9%
expected	*0.359*	*0.718*	*0.359*	*2.154*	*6.103*	*4.308*			
Class 10	0	0	0	1	2	**12**	15	17.245	80.0%
expected	*0.385*	*0.769*	*0.385*	*2.308*	*6.538*	*4.615*			
Columns Total	1	2	1	6	17	12	39 ***Grand Total***	135.688 ***Chi Square Total***	82.1% ***Overall Accuracy***
Producer Accuracy	100.0%	100.0%	100.0%	50.0%	76.5%	100.0%	**DF**	25	
Khat	0.773						**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.10 Error Matrix: Ten-Class Unsupervised Classification –January 2003 Image

	Reference									
Observed	**Class 03**	**Class 04**	**Class 05**	**Class 07**	**Class 08**	**Class 09**	**Class 10**	**Row Total**	**Incremental Chi Square**	**User Accuracy**
Class 03	**1**	1	0	0	0	0	0	2	17.500	50.0%
expected	*0.103*	*0.103*	*0.051*	*0.103*	*0.308*	*0.256*	*1.077*			
Class 04	0	**1**	1	0	0	0	0	2	27.250	50.0%
expected	*0.103*	*0.103*	*0.051*	*0.103*	*0.308*	*0.256*	*1.077*			
Class 05	1	0	**0**	0	0	0	0	1	18.500	0.0%
expected	*0.051*	*0.051*	*0.026*	*0.051*	*0.154*	*0.128*	*0.538*			
Class 07	0	0	0	**0**	1	0	0	1	5.500	0.0%
expected	*0.051*	*0.051*	*0.026*	*0.051*	*0.154*	*0.128*	*0.538*			
Class 08	0	0	0	0	**3**	0	0	3	16.500	100.0%
expected	*0.154*	*0.154*	*0.077*	*0.154*	*0.462*	*0.385*	*1.615*			
Class 09	0	0	0	0	2	**3**	1	6	10.343	50.0%
expected	*0.308*	*0.308*	*0.154*	*0.308*	*0.923*	*0.769*	*3.231*			
Class 10	0	0	0	2	0	2	**20**	24	11.502	83.3%
expected	*1.231*	*1.231*	*0.615*	*1.231*	*3.692*	*3.077*	*12.923*			
Columns Total	2	2	1	2	6	5	21	39 ***Grand Total***	107.095 ***Chi Square Total***	71.8% ***Overall Accuracy***
								DF	36	
								P	0.000	
Producer Accuracy	50.0%	50.0%	0.0%	0.0%	50.0%	60.0%	95.2%			
Khat	0.552									

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.11 Error Matrix: Ten-Class Unsupervised Classification –April 2003 Image

	Reference								Row	Incremental	User
Observed	**Class 02**	**Class 04**	**Class 05**	**Class 06**	**Class 07**	**Class 08**	**Class 09**	**Class 10**	**Total**	**Chi Square**	**Accuracy**
Class 02	**2**	0	1	0	0	0	0	0	**3**	26.167	66.7%
expected	*0.171*	*0.429*	*0.171*	*0.086*	*0.086*	*0.257*	*0.686*	*1.114*			
Class 04	0	**3**	0	0	0	0	0	0	**3**	18.000	100.0%
expected	*0.171*	*0.429*	*0.171*	*0.086*	*0.086*	*0.257*	*0.686*	*1.114*			
Class 05	0	1	**1**	0	0	0	0	0	**2**	10.250	50.0%
expected	*0.114*	*0.286*	*0.114*	*0.057*	*0.057*	*0.171*	*0.457*	*0.743*			
Class 06	0	1	0	**1**	0	0	0	0	**2**	19.000	50.0%
expected	*0.114*	*0.286*	*0.114*	*0.057*	*0.057*	*0.171*	*0.457*	*0.743*			
Class 07	0	0	0	0	**1**	2	0	0	**3**	24.222	33.3%
expected	*0.171*	*0.429*	*0.171*	*0.086*	*0.086*	*0.257*	*0.686*	*1.114*			
Class 08	0	0	0	0	0	**1**	1	0	**2**	6.021	50.0%
expected	*0.114*	*0.286*	*0.114*	*0.057*	*0.057*	*0.171*	*0.457*	*0.743*			
Class 09	0	0	0	0	0	0	**6**	0	**6**	20.250	100.0%
expected	*0.343*	*0.857*	*0.343*	*0.171*	*0.171*	*0.514*	*1.371*	*2.229*			
Class 10	0	0	0	0	0	0	1	**13**	**14**	18.813	92.9%
expected	*0.800*	*2.000*	*0.800*	*0.400*	*0.400*	*1.200*	*3.200*	*5.200*			
Columns Total	**2**	**5**	**2**	**1**	**1**	**3**	**8**	**13**	**35** ***Grand Total***	142.722 ***Chi Square Total***	80.0% ***Overall Accuracy***
Producer Accuracy	100.0%	60.0%	50.0%	100.0%	100.0%	33.3%	75.0%	100.0%	**DF**	49	
Khat	0.745								**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

As was noted in the supervised classification description, compartment E18 in the January image illustrates a felling operation in progress, with the northern section classified as Class 10, while the southern portion is classified as Class 2.

While the mature canopy and clear-felled areas were relatively accurately classified, the intermediate classes were less accurately classified. The density of ground cover, the season of acquisition and to some extent the species and its age all had an effect.

Areas of young plantings that were relatively weed-free were classified as Class 9 or Class 10 in all four images, i.e. independent of season. Classification of portions of these areas into Class 8 was also fairly frequent. Compartments E15 and E17 in the January image were examples of this. Compartments with young plantings, but with weed infestations tended to be classified into Classes 6, 7 and 8, usually in combination with each other. This was also reflected by the error matrices, which usually had a spread of values across these classes (see tables 4.2.7 to 4.2.11).

However, irrespective of the season, compartments with a noticeable presence of Class 7 indicated a strong possibility that weeds were a problem in those compartments. This class often tended to appear in patches within the compartment, rather than being the dominant class. This was reinforced by the fact that the unplantable, open areas frequently had this class as a predominant class, especially in the summer months. Attempts were made to have this class as a class on its own, but its presence was very seldom dominant enough for it to produce a noticeable classified group. However, it should be observed and noted where it does appear, as it could serve as a useful warning of potential weed problems. Compartments D10, E11, E28 and E29 illustrated this class well.

The seasonal variation that occurred in the mature canopy classification was illustrative of a phenomenon noted with the unsupervised classification process, which was that species played a role in how compartments were classified, in addition to the actual ground cover and season of acquisition. This tended to complicate the interpretation of the results somewhat. The reason for this variation in classification is likely to be the seasonal variation in canopy density, as explained in the supervised classification discussion (see section 4.2.1.1 above), where the winter canopy was less contiguous due to a reduction in leaf cover.

The cross-classifications displayed in the winter images were mainly due to the fact that weed growth had to a large extent ceased, and what weed was present was usually senescent and brown in colour. The spectral effect of this was to reduce its signature to that close to bare soil, hence the classification into Class 9 or 10. Therefore this classification did not always mean that a site was weed-free.

Careful analysis of all the classes in the Ten-Class Unsupervised Classification across all the images, together with a detailed inspection of the history records of all operations that had occurred in the observed compartments during this same period, enabled a classification flow diagram to be developed. This flow is documented in Figure 4.2.4, and provided a key to understand and interpret the classification results. It was from this diagram that the Four-Class Unsupervised Classification process was devised, and implemented.

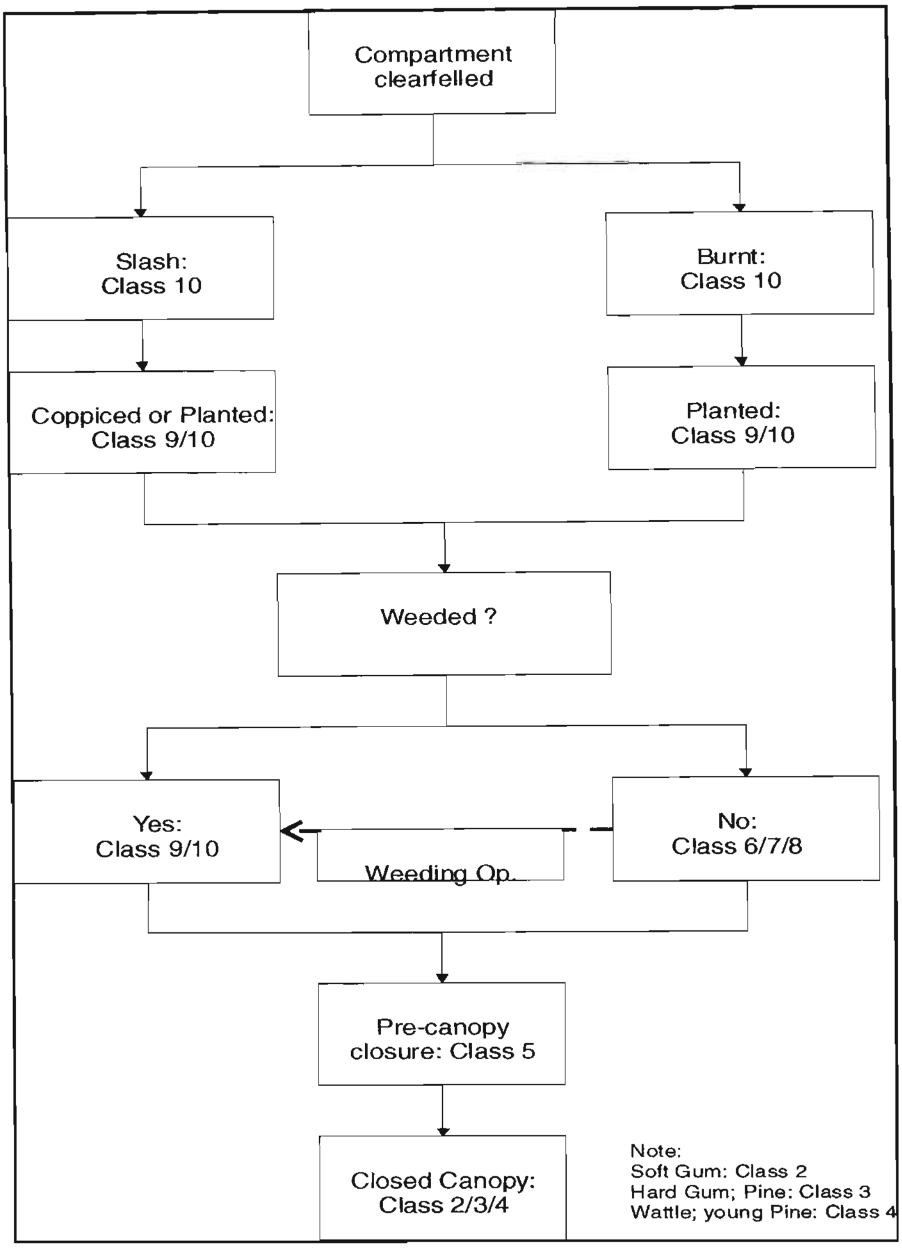


Figure 4.2.4 Process Flow of Class Allocation by Unsupervised Classification Model.

The process flow started with a compartment being clear-felled, where it was classified as Class 10. Although there are two different treatment methods, depending on whether the slash (or harvesting residue – see glossary) is burnt or not, there was no differentiation between these two states at this stage. This continued to be the case through the re-establishment phase, with no differentiation between coppiced or planted crops. The first differentiation occurred once substantial weed growth had occurred, with weedy compartments falling into Classes 6, 7 or 8. Weed-free compartments, on the other hand, remained as Class 9 or 10. Weeded compartments also returned to this class, once weeding operations had occurred. The final differentiation occurred with the closure of canopy cover (Class 2, 3 or 4), with an intermediary step where the canopy was less dense, but approaching full closure (Class 5). As was noted above, there was some movement between these two states over the course of the year due to seasonal effects and species characteristics.

Bruzzone and Serpico (2000), support the logic behind this process in stating that a more effective classification is achieved by reducing the number of features available when defining a feature set as an input to the classifier.

4.2.2.7 Four-Class Unsupervised Classification

As the initial supervised classification analyses gave a strong indication that it would be necessary to group signatures and classes, several alternative groupings were tested, including five, four and three classes, by running the classifications and visually comparing how a chosen set of compartments were classified, particularly in terms of the process flow described in Figure 4.2.4. After these comparisons were run between the various groupings it was found that the four-class classification gave the clearest information. The main aim of the Four-Class Unsupervised Classification was to attempt to improve the classification of compartments to determine whether they were likely to be weed-free, or have a potential weed problem. Figure 4.2.5 illustrates the Four-Class Unsupervised Classification. The class descriptions for Four Class classification differs from the other classifications, and is as follows:

Class 1 Closed Canopy (Dense Canopy) – *equivalent to Ten-Class Unsupervised Classes 2-4*

Class 2 Pre-Canopy (Open Canopy) – *equivalent to Ten-Class Unsupervised Class 5*

Class 3 Weedy – *equivalent to Ten-Class Unsupervised Classes 6-8*

Class 4 Weed-free (Also equivalent to clear-felled) – *equivalent to Ten-Class Unsupervised Classes 9-10* *(see Section 4.2.2.6).*

This classification produced mixed results, with only very general indications being given as to whether there were weed problems or not, although the error matrices again gave overall probabilities of less than 0.05 (see Tables 4.2.12 to 4.2.16). However, the separation between standing and clear-felled was again very clear, as is illustrated by compartments E14, E18, E22 and E23 when comparing the June and January images (see Figure 4.2.5 b, c).

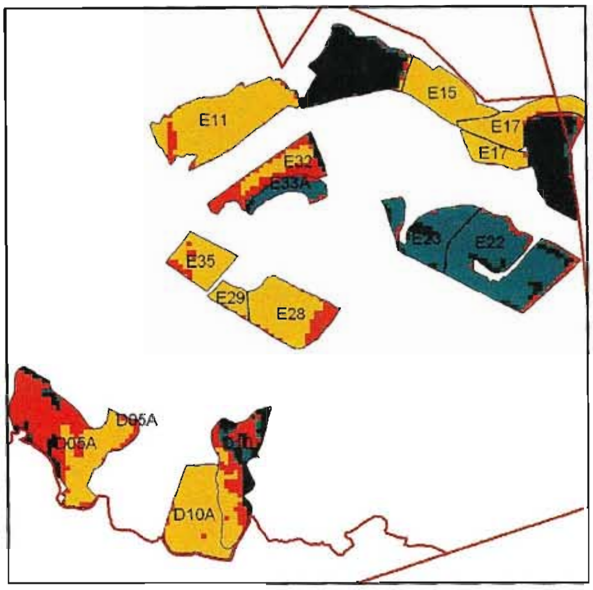


Fig.a Four-Class Unsupervised Classification Image: March 2002

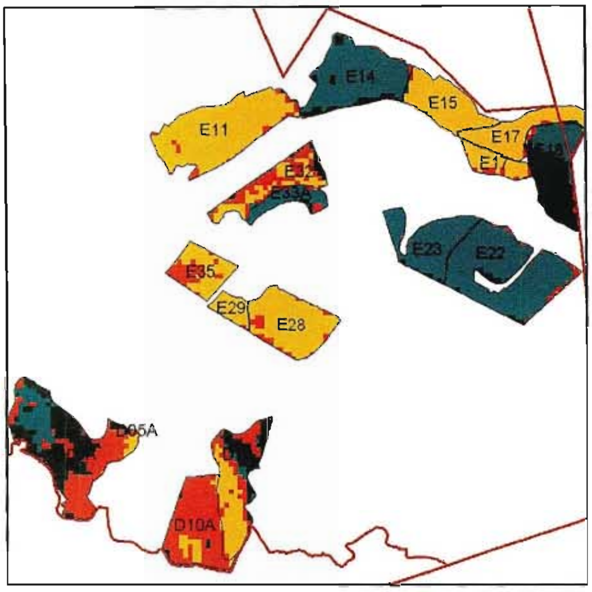


Fig.b Four-Class Unsupervised Classification Image: June 2002

Fig.c Four-Class Unsupervised Classification Image: January 2003

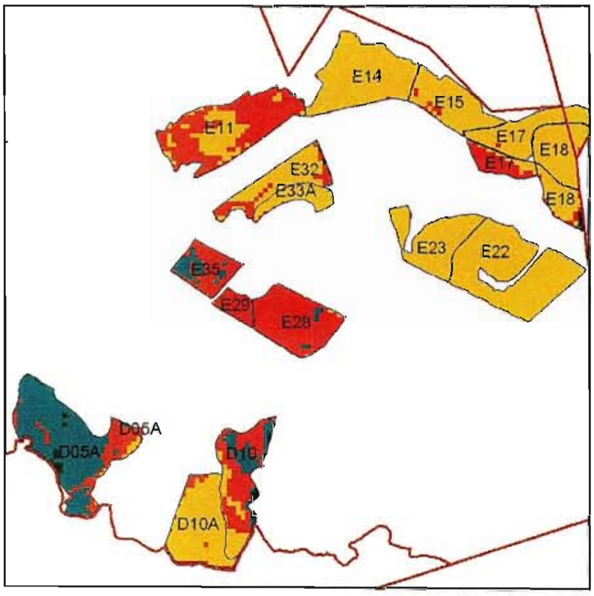


Fig.d Four-Class Unsupervised Classification Image: April 2003

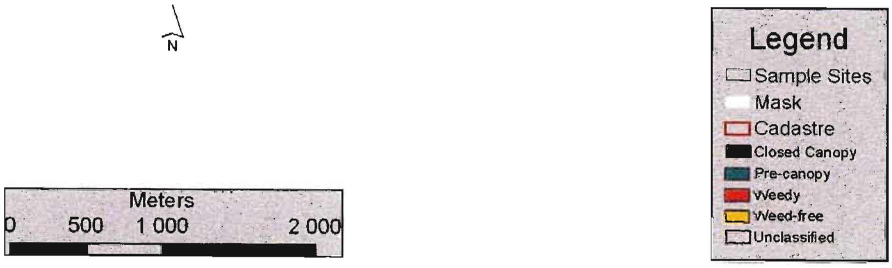


Figure 4.2.5 Four-Class Unsupervised Classification Images

The error matrix for the pooled data of all four images gave a producer accuracy of 90.7% for the Class 4, weed-free, which represented all felled compartments, or newly planted areas that were weed-free (see Table 4.2.12). The balance of these, i.e. the misclassifications fell into Class 3, weedy (7.8%) or Class 2, pre-canopy (1.6%). The differentiation between Class 1, full canopy and Class 2, pre-canopy was less distinct, especially in the June image (Table 4.2.14), where the producer accuracy was 50% for both classes. This was most probably due to the same reason as discussed under Supervised Classification above, in terms of the seasonal effect on canopy density, where some leaves either wilt or are shed in winter, thereby reducing the canopy density. Overall, the producer accuracy of Class 1, full canopy, was 76.5%, with the misclassified compartments (23.5%) being in Class 2, pre-canopy. The equivalent value for Class 2, pre-canopy, was 80%, but with the misclassified compartments falling into Class 3, weedy (20%). Both of these results reflected the overlap expected across the continuum of values created by an unsupervised classification process.

As far as monitoring the weed state was concerned, the March image of compartment D05A illustrated the difference between a weedy and weed-free state, where a weeding operation was in progress (the western portion was weedy, while the eastern portion had been weeded). However, as the crop grew it became increasingly difficult to distinguish between weed and crop, although it did follow the general flow of figure 4.2.4, i.e. from weedy to weed-free to pre-canopy to closed canopy. Results from the error matrices reflected this (see Tables 4.2.13 to 4.2.16), as is illustrated by Class 3, weedy, with a producer accuracy, for all images combined, of 76.5%, with 14.7% being misclassified as Class 4, weed-free, and 8.8% being misclassified as Class 2, pre-canopy. In the April image (Table 4.2.16), there was a producer accuracy of 100% for Class 3, weedy, but when compared to the January image producer accuracy of 62.5% for this class (Table 4.2.15), there did not appear to be a consistently accurate classification of this class. Replanted stands less than a year old and unplanted stands tended to be classified into the same class, "weed-free", even if there was weed present. An example of this is seen when comparing compartments E14, E15 and E17 using the January and April images.

Table 4.2.12 Error Matrix: Four-Class Unsupervised Classification – Combined Data - All Images

Observed	Reference Class 01	Class 02	Class 03	Class 04	Row Total	Incremental Chi Square	User Accuracy
Class 01	**13**	0	0	0	**13**	136.118	100.0%
expected	*1.133*	*1.000*	*2.267*	*8.600*			
Class 02	4	**12**	3	2	**21**	79.628	57.1%
expected	*1.831*	*1.615*	*3.662*	*13.892*			
Class 03	0	3	**26**	10	**39**	67.288	66.7%
expected	*3.400*	*3.000*	*6.800*	*25.800*			
Class 04	0	0	5	**117**	**122**	48.787	95.9%
expected	*10.636*	*9.385*	*21.272*	*80.708*			
Columns Total	**17**	**15**	**34**	**129**	**195** *Grand Total*	331.821 *Chi Square Total*	86.2% *Overall Accuracy*
Producer Accuracy	76.5%	80.0%	76.5%	90.7%	**DF**	9	
Khat 0.742					**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.13 Error Matrix: Four-Class Unsupervised Classification – March 2002 Image

Observed	Reference Class 01	Class 02	Class 03	Class 04	Row Total	Incremental Chi Square	User Accuracy
Class 01	**10**	0	0	0	**10**	55.833	100.0%
expected	*1.519*	*0.633*	*1.772*	*6.076*			
Class 02	2	**4**	3	0	**9**	27.658	44.4%
expected	*1.367*	*0.570*	*1.595*	*5.468*			
Class 03	0	1	**11**	5	**17**	26.514	64.7%
expected	*2.582*	*1.076*	*3.013*	*10.329*			
Class 04	0	0	0	**43**	**43**	27.771	100.0%
expected	*6.532*	*2.722*	*7.620*	*26.127*			
Columns Total	**12**	**5**	**14**	**48**	**79** *Grand Total*	137.775 *Chi Square Total*	86.1% *Overall Accuracy*
Producer Accuracy	83.3%	80.0%	78.6%	89.6%	**DF**	9	
Khat 0.770					**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Compartment E14 was pure slash in January and bare soil in April, having been burnt in the intervening period. In both images it was classified as weed-free, which was correct. Compartment E17 had been planted to wattle in January 2002, and compartment E15 in February 2002. In both the January and April ground-truthing exercises, E15 was much more weed-free than E17, but they had both been classified into the same category. Compartment E17 could not be classed as weed-free, and in both cases, required a weeding operation. Compartment E15 was correctly classified, being substantially weed-free at the times when these images were acquired. Compartment E15 also showed better growth and stocking than did compartment E17.

Table 4.2.14 Error matrix: Four-Class Unsupervised Classification – June 2002 Image

Observed	Reference Class 01	Class 02	Class 03	Class 04	Row Total	Incremental Chi Square	User Accuracy
Class 01	**1**	0	0	0	**1**	19.000	100.0%
expected	*0.050*	*0.050*	*0.150*	*0.750*			
Class 02	1	**2**	0	0	**3**	30.333	66.7%
expected	*0.150*	*0.150*	*0.450*	*2.250*			
Class 03	0	0	**4**	4	**8**	8.000	50.0%
expected	*0.400*	*0.400*	*1.200*	*6.000*			
Class 04	0	0	2	**26**	**28**	5.143	92.9%
expected	*1.400*	*1.400*	*4.200*	*21.000*			
Columns Total	**2**	**2**	**6**	**30**	**40** ***Grand Total***	62.476 ***Chi Square Total***	82.5% ***Overall Accuracy***
Producer Accuracy	50.0%	100.0%	66.7%	86.7%	**DF**	9	
Khat 0.602					**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.15 Error Matrix: Four-Class Unsupervised Classification – January 2003 Image

Observed	Reference Class 01	Class 02	Class 03	Class 04	Row Total	Incremental Chi Square	User Accuracy
Class 01	**0**	0	0	0	**0**		
expected	*0.000*	*0.000*	*0.000*	*0.000*			
Class 02	0	**3**	0	2	**5**	20.103	60.0%
expected	*0.000*	*0.375*	*1.000*	*3.625*			
Class 03	0	0	**5**	0	**5**	20.000	100.0%
expected	*0.000*	*0.375*	*1.000*	*3.625*			
Class 04	0	0	3	**27**	**30**	5.017	90.0%
expected	*0.000*	*2.250*	*6.000*	*21.750*			
Columns Total	**0**	**3**	**8**	**29**	**40** ***Grand Total***	45.121 ***Chi Square Total***	87.5% ***Overall Accuracy***
Producer Accuracy		100.0%	62.5%	93.1%	**DF**	9	
Khat 0.704					**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Compartments older than a year tended to be classified as a Class 2, weedy status, passing onto the Class 3, pre-canopy status as they matured. However, there was some cross-classification between the weedy and pre-canopy closure states, depending on the season and density of ground cover. The January and April images of compartments E28, E29 and E35 illustrated this.

Table 4.2.16 Error Matrix: Four-Class Unsupervised Classification – April 2003 Image

Observed	Reference Class 01	Class 02	Class 03	Class 04	Row Total	Incremental Chi Square	User Accuracy
Class 01	**2**	0	0	0	**2**	22.000	100.0%
expected	*0.167*	*0.278*	*0.333*	*1.222*			
Class 02	1	**3**	0	0	**4**	15.200	75.0%
expected	*0.333*	*0.556*	*0.667*	*2.444*			
Class 03	0	2	**6**	1	**9**	18.382	66.7%
expected	*0.750*	*1.250*	*1.500*	*5.500*			
Class 04	0	0	0	**21**	**21**	13.364	100.0%
expected	*1.750*	*2.917*	*3.500*	*12.833*			
Columns Total	**3**	**5**	**6**	**22**	**36** *Grand Total*	68.945 ***Chi Square Total***	88.9% ***Overall Accuracy***
Producer Accuracy	66.7%	60.0%	100.0%	95.5%	**DF**	9	
Khat 0.809					**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

In an attempt to improve the weed status classification, the Ten-Class Unsupervised Classification Class 7 was extracted as a unique layer, and overlain on the Four-Class Unsupervised Classification, where a visual comparison was made to see how closely it corresponded with the "weedy" class classification. While it corresponded very closely with the "weedy" class, in that it only appeared where this class was present, it did not appear to show much more than where there was a real concentration of weed. In some compartments (e.g. D05A in the March image) it covered the majority of the compartment. However, this was seldom the case, with the bulk of this class appearing as concentrated patches within an overall "weedy" class compartment. When assessing the usefulness of the Class 7 data, there was unfortunately insufficient ground-truth data to identify, with certainty, what this class did actually represent. Despite this, it does appear to have the potential to be a key indicator of the presence of major weed concentrations. When results of the Four-Class Unsupervised Classification are visually assessed, it was very useful to have the Class 7 data overlain as well, in order to flag these compartments for further investigation.

The lack of very clear thresholds between the weedy and weed-free states meant that one could not assign a definite weedy or weed-free status to any specific compartment. At best one could only assign a possible "flag" to a compartment that would act as warning that a compartment might need to be checked in the field to determine its actual status.

The age of the crop, the density of the vegetation cover (both crop and weed), and the season in which the image was acquired all affected the outcome of the Four-class unsupervised classification. A stand could move from a pre-canopy closure status to a "weed-free" status simply because some of the crop canopy density was lost as a result of a reduction in growth vigour, exposing the lower story weed vegetation or ground cover. Compartment E35 is an example of this when comparing the January and April images. This was also reflected in the results obtained by the supervised classification.

However, where the normal sequence of forestry operations was followed, one could estimate the most likely status that the unsupervised classification represented when interpreted in conjunction with the operational history recorded in the database.

4.2.2.8 NDVI Value Estimation

The overall impression gained when observing the results of the NDVI images was that it mirrored both the Ten- and Four-Class Unsupervised Classification results, both in its strengths and weaknesses (see Figure 4.2.6). It was able to clearly identify clear-felled areas, and areas of closed canopy, but it was not very successful in separating weedy from non-weedy areas. A pattern similar to that derived by the unsupervised classifications was noted, where weedy or more densely vegetated areas had higher values (e.g. greater than 0.37 in compartments D05A and D10 in the March NDVI image) than the weed-free areas, which had values ranging from 0.05 to 0.17 in the March image.

What was found was that classes with higher vegetative cover had indices close to 1, while areas of low vegetative cover had indices less than 0 (e.g. clear-felled compartments ranged from -0.06 to -0.15, with burnt compartments having values close to -1). Although the absolute values of these figures were affected by the season in which the image was acquired, the ranges tended to move in the same proportion, thus maintaining some form of identifiable range. As NDVI is actually a measure of the degree of "greenness", this result was expected. However, this range was narrower than anticipated.

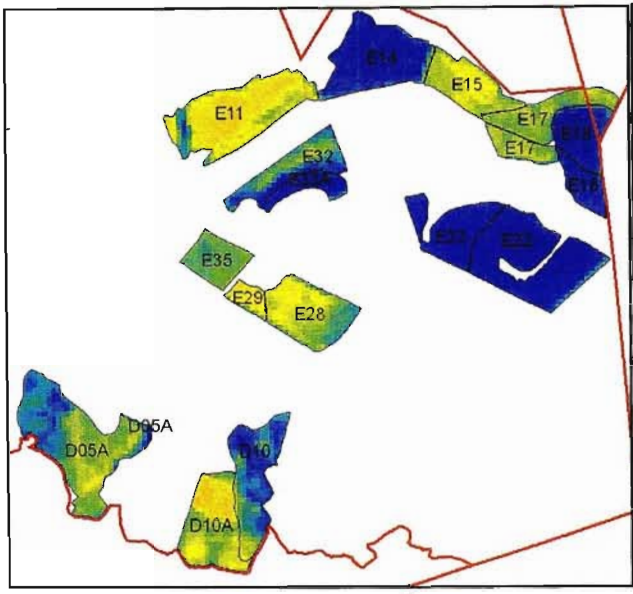


Fig.a NDVI Value Estimation: March 2002

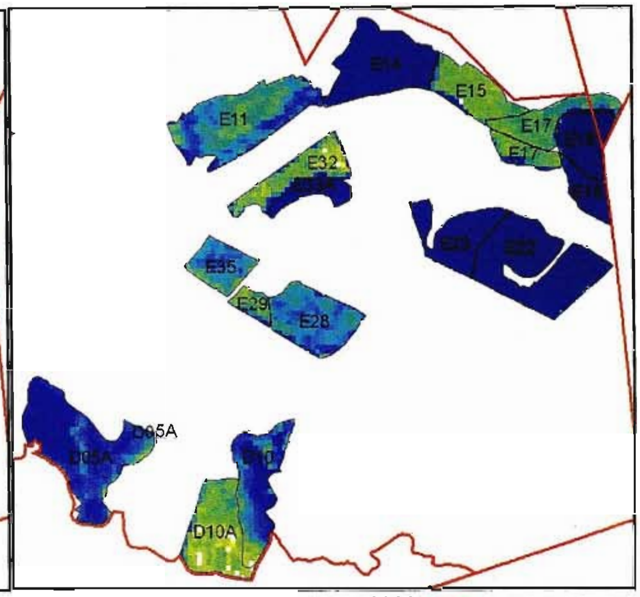


Fig.b NDVI Value Estimation: June 2002

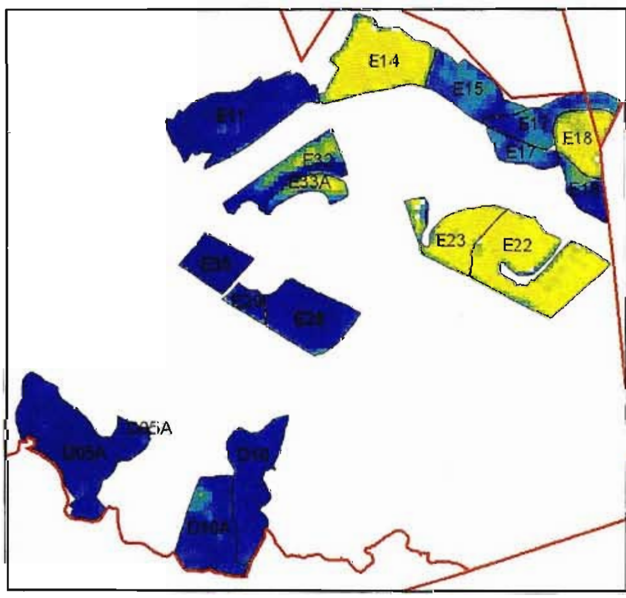


Fig.c NDVI Value Estimation: January 2003

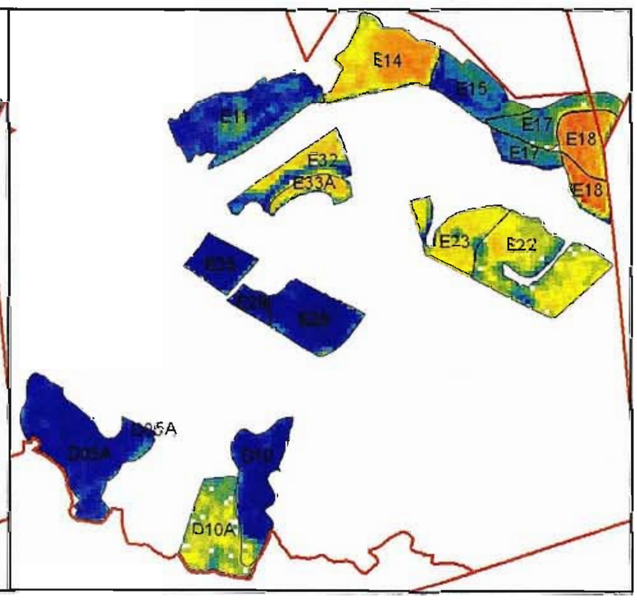


Fig.d NDVI Value Estimation: April 2004

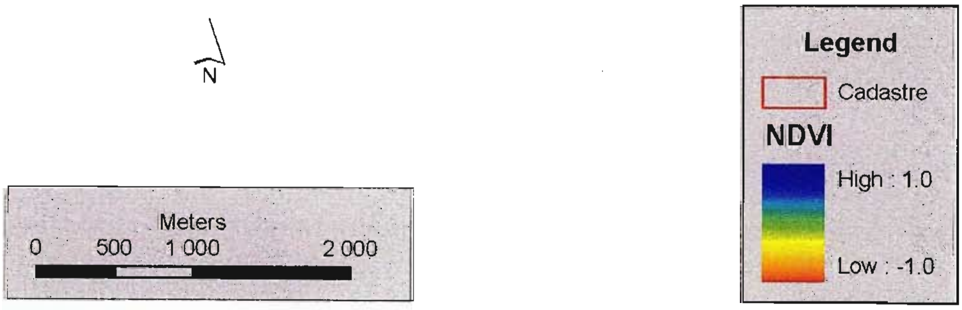


Figure 4.2.6 NDVI Value Estimation Images

When one follows the progression of the NDVI values across the four images (March, June, January to April - see Figure 4.2.6), one can identify the same pattern as seen in the Four-Class Unsupervised Classification. From a weedy western portion and weed-free eastern portion in the March image through a weedy or an intermediate crop growth stage in the June and January images, to a pre-canopy closure stage in the April image, the same grouping of pixels can be detected. The value range within each of these groups is not sufficiently discrete to be able to reclassify them into new classes of separable features.

A point of interest was noted in the January image in compartment E17, a portion of which was being thinned at the time of image acquisition. This portion had NDVI values ranging from 0.13 to 0.20, compared to the unthinned section which, having a higher vegetation density, returned values in the order of 0.23 to 0.40. However, in the adjacent compartment E15, which had been thinned several months earlier, the same range of values was returned, depending on whether there were weed patches present or not.

The fact that a greater degree of separation was not possible using NDVI values was rather disappointing, as theoretically, the best chance of separating spectral signatures of different vegetation classes should be provided by a process based on vegetative indices, such as the NDVI.

In terms of monitoring weed cover, it was not possible to clearly distinguish weedy from non-weedy areas. No additional separation between crop and weed or even crop and soil could be achieved, compared to that which was achieved using either the supervised or unsupervised classification processes.

Concerning the thinning that was able to be identified in the NDVI image (compartment E17 – see note above), one could not run a classification across the image using these values to separate thinned, weed-free stands from weedy stands. However, it was interesting to note that this thinning was identifiable in the NDVI image, whereas it was not identifiable in the unsupervised classification images (either the Ten-Class or the Four-Class). It could well indicate a possible avenue for further research.

4.2.3 Change Detection

4.2.3.1 Assisted Change Detection: "Classified" Images

The results of the Ten-Class Unsupervised Classification assisted change detection process are described under this section, and illustrated in Figure 4.2.7. There were three resultant change images, March to June, June to January and January to April. In each case, if the class had changed, the change image reflected the new class (i.e. the class as it was in the later image). Where there was no change, it was unclassified. The error matrices again gave overall probabilities of less than 0.05, indicating a good result for the overall classification (see Tables 4.2.17 to 4.2.20), but there was cross-classification between some classes.

As identifying clear-felled compartments was one of the primary focuses of change detection in this study, it was important that this could be reliably identified. The error matrix for the "Classified" Image pooled data change detection procedures, showed that Class 10, clear-felled, could be identified with a producer accuracy of 97.9% (see Table 4.2.17). The misclassified portion (2.1%) fell into Class 9. Both the March/June (Table 4.2.18) and January/April (Table 4.2.20) change detection images had 100% correct classification for this class. In terms of a visual assessment, when one compares the patterns of compartments E14, E18 and E22 over all three change images, one can readily pick up the change from closed canopy to felled (see Figure 4.2.7).

The other change of interest was that of weed status. Compartment E35 illustrates a normal development pattern from weed-free in the early change image to pre-canopy in the latter changes, which is what one would expect. The pattern of Compartment E28 also shows a reasonably normal development pattern, moving from weed-free initially to a weedy status, with some pre-canopy development in the June/January image, but reverting back to a very weedy status in the January/April image. While a strong weed presence was noted in both the January and April ground-truthing, the weed was more pronounced in January than in April. However, the tree growth was much greater in April, and so this might have been misclassified as weed growth, rather than crop growth. The problem is that this was not consistent across the images, and so it is difficult to draw specific conclusions.

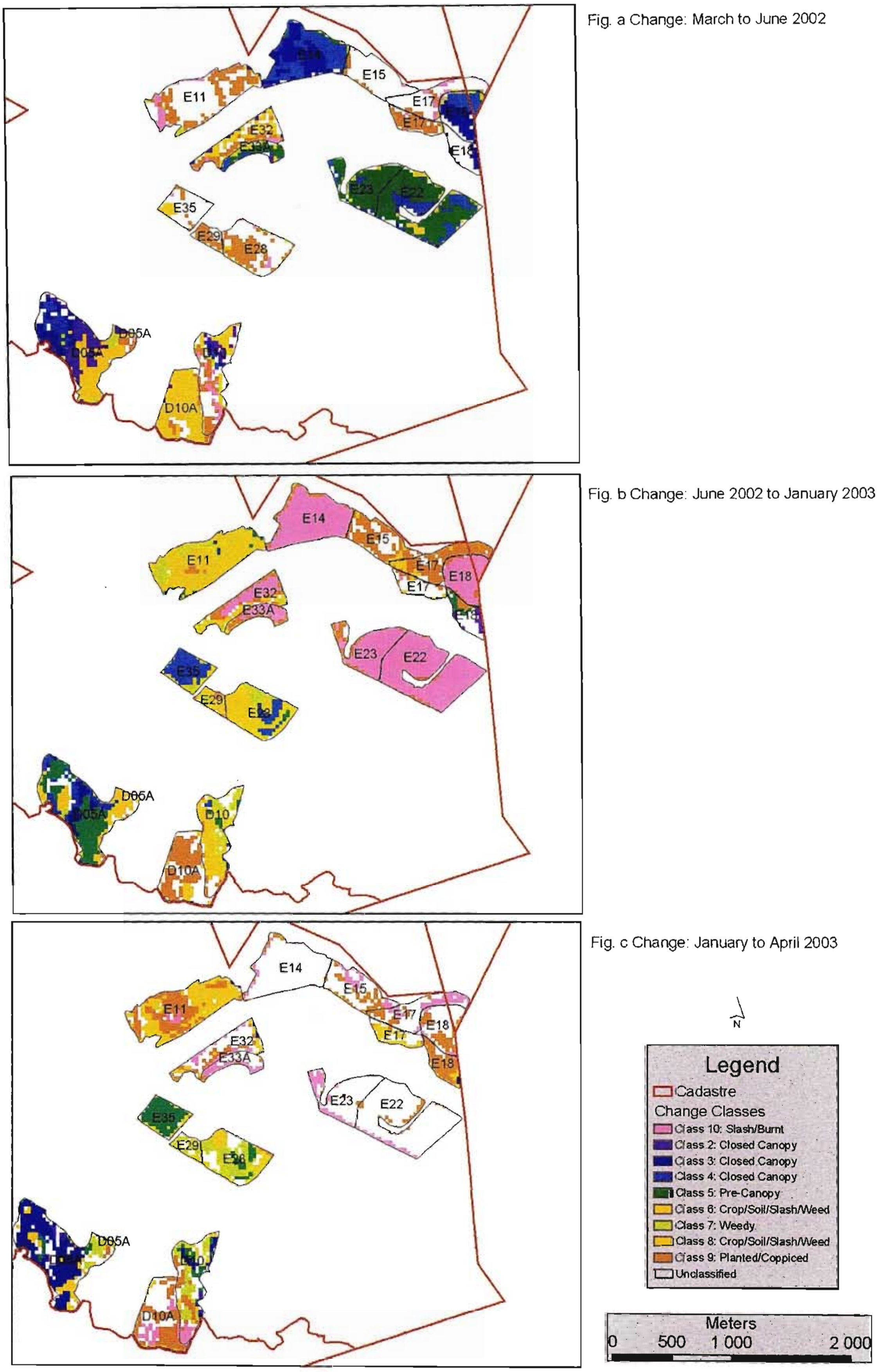


Fig. a Change: March to June 2002

Fig. b Change: June 2002 to January 2003

Fig. c Change: January to April 2003

Figure 4.2.7 Assisted Change Detection: "Classified' Images

Table 4.2.17 Error Matrix: Classified Image Change Detection – Combined Data - All Images

Observed	Reference: Class 02	Class 03	Class 04	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**2**	1	0	0	1	0	0	0	0	4	78.167	50.0%
expected	*0.069*	*0.103*	*0.310*	*0.138*	*0.069*	*0.103*	*0.483*	*1.103*	*1.621*			
Class 03	0	**1**	1	1	0	0	0	0	0	3	23.852	33.3%
expected	*0.052*	*0.078*	*0.233*	*0.103*	*0.052*	*0.078*	*0.362*	*0.828*	*1.216*			
Class 04	0	1	**5**	1	0	0	0	0	0	7	48.698	71.4%
expected	*0.121*	*0.181*	*0.543*	*0.241*	*0.121*	*0.181*	*0.845*	*1.931*	*2.836*			
Class 05	0	0	2	**1**	0	0	0	0	0	3	23.852	33.3%
expected	*0.052*	*0.078*	*0.233*	*0.103*	*0.052*	*0.078*	*0.362*	*0.828*	*1.216*			
Class 06	0	0	1	0	**1**	0	1	0	0	3	23.392	33.3%
expected	*0.052*	*0.078*	*0.233*	*0.103*	*0.052*	*0.078*	*0.362*	*0.828*	*1.216*			
Class 07	0	0	0	1	0	**1**	2	0	0	4	21.202	25.0%
expected	*0.069*	*0.103*	*0.310*	*0.138*	*0.069*	*0.103*	*0.483*	*1.103*	*1.621*			
Class 08	0	0	0	0	0	0	**7**	3	0	10	33.863	70.0%
expected	*0.172*	*0.259*	*0.776*	*0.345*	*0.172*	*0.259*	*1.207*	*2.759*	*4.052*			
Class 09	0	0	0	0	0	0	3	**24**	1	28	49.323	85.7%
expected	*0.483*	*0.724*	*2.172*	*0.966*	*0.483*	*0.724*	*3.379*	*7.724*	*11.345*			
Class 10	0	0	0	0	0	2	1	5	**46**	54	47.408	85.2%
expected	*0.931*	*1.397*	*4.190*	*1.862*	*0.931*	*1.397*	*6.517*	*14.897*	*21.879*			
Columns Total	2	3	9	4	2	3	14	32	47	116 *Grand Total*	349.756 *Chi Square Total*	75.9% *Overall Accuracy*
Producer Accuracy	100.0%	33.3%	55.6%	25.0%	50.0%	33.3%	50.0%	75.0%	97.9%	DF	64	
Khat	0.691									P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Applying the process flow described in Figure 4.2.4 to the change detection image, one could quickly see what class the compartment had changed to, and so see where in the process it was placed. This then allowed one to derive a status for that compartment, which could then be compared to the database in order to ascertain whether this reflected what the status of the compartment was on the ground. However, as had been the case throughout this study, while the two extreme states (full canopy or felled) could be determined with a high degree of accuracy, the intermediate states of weedy and weed-free still had a great deal of overlap, which did not allow a categorical allocation to a specific class. This was further complicated by the presence of more than one class within a single compartment, even where this presence had been correctly determined.

When comparing the error matrices results, the cross-classification between the classes that reflect a weedy or highly vegetated state (Classes 6, 7 and 8) is apparent, with producer accuracies of 50%, 33.3% and 50% respectively (see Table 4.2.17). There is also cross-classification with Classes 3, 4 or 5.

Table 4.2.18 Error Matrix: Classified Image Change Detection – March/June 2002 Image

Observed	Reference Class 03	Class 04	Class 05	Class 07	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 03	**1**	0	0	1	0	0	0	**2**	38.000	50.0%
expected	*0.050*	*0.100*	*0.050*	*0.050*	*0.250*	*0.850*	*0.650*			
Class 04	0	**1**	0	0	0	0	0	**1**	19.000	100.0%
expected	*0.025*	*0.050*	*0.025*	*0.025*	*0.125*	*0.425*	*0.325*			
Class 05	0	1	**0**	0	0	0	0	**1**	19.000	0.0%
expected	*0.025*	*0.050*	*0.025*	*0.025*	*0.125*	*0.425*	*0.325*			
Class 07	0	0	1	**0**	0	0	0	**1**	39.000	0.0%
expected	*0.025*	*0.050*	*0.025*	*0.025*	*0.125*	*0.425*	*0.325*			
Class 08	0	0	0	0	**3**	2	0	**5**	11.282	60.0%
expected	*0.125*	*0.250*	*0.125*	*0.125*	*0.625*	*2.125*	*1.625*			
Class 09	0	0	0	0	1	**14**	0	**15**	16.278	93.3%
expected	*0.375*	*0.750*	*0.375*	*0.375*	*1.875*	*6.375*	*4.875*			
Class 10	0	0	0	0	1	1	**13**	**15**	20.357	86.7%
expected	*0.375*	*0.750*	*0.375*	*0.375*	*1.875*	*6.375*	*4.875*			
Columns Total	**1**	**2**	**1**	**1**	**5**	**17**	**13**	**40** ***Grand Total***	162.918 ***Chi Square Total***	80.0% ***Overall Accuracy***
								DF	36	
								P	0.000	
Producer Accuracy	100.0%	50.0%	0.0%	0.0%	60.0%	82.4%	100.0%			
Khat	0.714									

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.19 Error Matrix: Classified Image Change Detection – June 2002/January 2003 Image

Observed	Class 02	Class 04	Class 05	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**1**	1	0	0	0	0	**2**	14.667	50.0%
expected	*0.100*	*0.150*	*0.100*	*0.300*	*0.300*	*1.050*			
Class 04	1	**2**	0	0	0	0	**3**	21.444	66.7%
expected	*0.150*	*0.225*	*0.150*	*0.450*	*0.450*	*1.575*			
Class 05	0	0	**0**	1	0	0	**1**	5.667	0.0%
expected	*0.050*	*0.075*	*0.050*	*0.150*	*0.150*	*0.525*			
Class 08	0	0	0	**3**	0	0	**3**	17.000	100.0%
expected	*0.150*	*0.225*	*0.150*	*0.450*	*0.450*	*1.575*			
Class 09	0	0	0	2	**3**	1	**6**	8.762	50.0%
expected	*0.300*	*0.450*	*0.300*	*0.900*	*0.900*	*3.150*			
Class 10	0	0	2	0	3	**20**	**25**	11.076	80.0%
expected	*1.250*	*1.875*	*1.250*	*3.750*	*3.750*	*13.125*			
Columns Total	**2**	**3**	**2**	**6**	**6**	**21**	**40** ***Grand Total***	78.616 ***Chi Square Total***	72.5% ***Overall Accuracy***
Producer Accuracy	50.0%	66.7%	0.0%	50.0%	50.0%	95.2%	**DF**	25	
Khat	0.594						**P**	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 4.2.20 Error Matrix: Classified Image Change Detection – January/April 2003 Image

Observed	Reference: Class 02	Class 03	Class 05	Class 06	Class 07	Class 08	Class 09	Class 10	Row Total	Incremental Chi Square	User Accuracy
Class 02	**2**	0	1	0	0	0	0	0	3	27.000	66.7%
expected	*0.167*	*0.417*	*0.167*	*0.083*	*0.083*	*0.250*	*0.750*	*1.083*			
Class 03	0	**3**	0	0	0	0	0	0	3	18.600	100.0%
expected	*0.167*	*0.417*	*0.167*	*0.083*	*0.083*	*0.250*	*0.750*	*1.083*			
Class 05	0	1	**1**	0	0	0	0	0	2	10.600	50.0%
expected	*0.111*	*0.278*	*0.111*	*0.056*	*0.056*	*0.167*	*0.500*	*0.722*			
Class 06	0	1	0	**1**	0	0	0	0	2	19.600	50.0%
expected	*0.111*	*0.278*	*0.111*	*0.056*	*0.056*	*0.167*	*0.500*	*0.722*			
Class 07	0	0	0	0	**1**	2	0	0	3	25.000	33.3%
expected	*0.167*	*0.417*	*0.167*	*0.083*	*0.083*	*0.250*	*0.750*	*1.083*			
Class 08	0	0	0	0	0	**1**	1	0	2	6.000	50.0%
expected	*0.111*	*0.278*	*0.111*	*0.056*	*0.056*	*0.167*	*0.500*	*0.722*			
Class 09	0	0	0	0	0	0	**7**	0	7	21.000	100.0%
expected	*0.389*	*0.972*	*0.389*	*0.194*	*0.194*	*0.583*	*1.750*	*2.528*			
Class 10	0	0	0	0	0	0	1	**13**	14	19.714	92.9%
expected	*0.778*	*1.944*	*0.778*	*0.389*	*0.389*	*1.167*	*3.500*	*5.056*			
Columns Total	**2**	**5**	**2**	**1**	**1**	**3**	**9**	**13**	**36** *Grand Total*	147.514 *Chi Square Total*	80.6% *Overall Accuracy*
									DF	49	
									P	0.000	
Producer Accuracy	100.0%	60.0%	50.0%	100.0%	100.0%	33.3%	77.8%	100.0%			
Khat	0.752										

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Because of the tendency of compartments to change between weedy and weed-free, depending on the season and what silvicultural operations have occurred in them, it is not always possible to arrive at the correct status of a compartment without reference to its history. An example of this is seen in compartment E11, where the June/January change image shows it to be in a weedy status, while the January/April change image shows it to be in a weed-free status. Viewing the latter image in isolation would not tell one whether it was recently planted, or whether it had been weeded at some time between the two images. However, by knowing its history, i.e. when it had been planted, one could then arrive at a correct conclusion as to its status.

An alternative method would have been to calculate the area of each class within a compartment, and by ranking these areas, allocate a dominant class. However, this would not necessarily have provided the information that would give the best interpretation of events in the compartment, particularly as such a ranking based on the classification would have classification errors carried over into it.

4.2.3.2 Assisted Change Detection: "Quantified Classified" Images

This section focuses on the results obtained from the change detection procedure applied to the Four-Class Unsupervised Classification images in order to establish what change, if any, had occurred. Figure 4.2.8 illustrates these results. This process differed from the previous process above in that both the before and after classes were given in the change image, so that one could determine exactly what change had occurred. This was achieved by assigning a two-digit code to each change class, such that the first digit was the class TO WHICH it had changed (i.e. the class it was in the later image), and the second digit was the class FROM WHICH it had changed (i.e. the class it was in the earlier image). The error matrices produced the same overall probability results, i.e. less than 0.05 (see Table 4.2.21)

The primary focus of interest in this change detection process was the change in weed status. While the Four-Class images gave a total of twelve combinations, two weed status classes were of particular interest. These were the change from weed-free to weedy (code 34 in the two digit code, i.e. to class 3, from class 4), and weedy to weed-free (code 43). The former was used to flag possible problem compartments, while the latter was used to see where progress had been made. As a visual assessment, a good example of this could be seen in compartment D10A, where in the March/June change image there was a weed increase, while in the June/January image there was both an increase and decrease in patches, but in the January/April image there was a weed reduction (see Figure 4.2.8). In the latter image, the reduction was due to weeding operations having occurred between January and April. The ground-truthing in January showed that this compartment had a high weed density at the time, especially compared to the ground-truthing undertaken in June. The April ground-truthing showed that there was not much weed at that time. Thus, this change detection was shown to be accurate. When assessing the classification accuracy reflected in the Chi-square tests, the accuracy of the Class 43, weedy to weed-free status, was 100%, while that of Class 34, weed-free to weedy, was only 75.0% (see Table 4.2.21). The remainder were classified as unchanged. This implied that where weeding operations had occurred, they could be detected. However, there was less certainty in detecting that weed was becoming a problem.

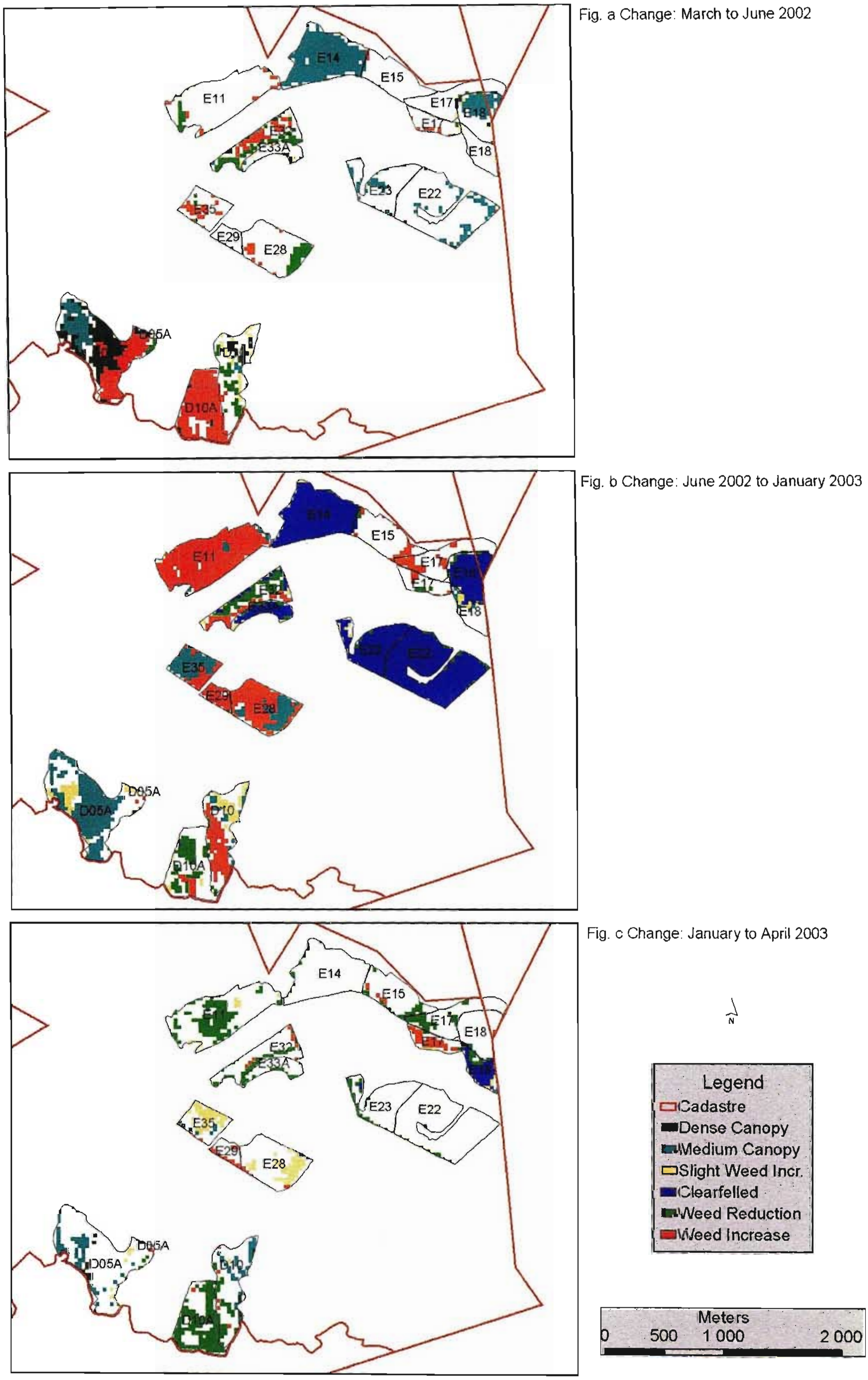


Figure 4.2.8 Assisted Change Detection: "Quantified Classified" Images

Table 4.2.21 Error Matrix: Quantified Classified Image Change Detection – Combined Data – All Images

Observed	Reference Class 12	Class 24	Class 34	Class 41	Class 42	Class 43	No Change	Row Total	Incremental Chi Square	User Accuracy
Class 12	**4**	0	0	0	0	0	0	4	99.000	100.0%
expected	*0.155*	*0.078*	*0.505*	*0.117*	*1.049*	*0.194*	*1.903*			
Class 24	0	**2**	0	0	0	0	0	2	101.000	100.0%
expected	*0.078*	*0.039*	*0.252*	*0.058*	*0.524*	*0.097*	*0.951*			
Class 34	0	0	**9**	0	0	0	3	12	43.057	75.0%
expected	*0.466*	*0.233*	*1.515*	*0.350*	*3.146*	*0.583*	*5.709*			
Class 41	0	0	0	**3**	0	0	0	3	100.000	100.0%
expected	*0.117*	*0.058*	*0.379*	*0.087*	*0.786*	*0.146*	*1.427*			
Class 42	0	0	0	0	**26**	0	0	26	73.185	100.0%
expected	*1.010*	*0.505*	*3.282*	*0.757*	*6.816*	*1.262*	*12.369*			
Class 43	0	0	0	0	0	**5**	0	5	98.000	100.0%
expected	*0.194*	*0.097*	*0.631*	*0.146*	*1.311*	*0.243*	*2.379*			
No Change	0	0	4	0	1	0	**46**	51	38.775	90.2%
expected	*1.981*	*0.990*	*6.437*	*1.485*	*13.369*	*2.476*	*24.262*			
Columns Total	4	2	13	3	27	5	49	103 *Grand Total*	553.017 *Chi Square Total*	92.2% *Overall Accuracy*
								DF	36	
								P	0.000	
Producer Accuracy	100.0%	100.0%	69.2%	100.0%	96.3%	100.0%	93.9%			
Khat	0.886									

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

It was also noted that the change detection image differentiated between stands that were bare soil or slash from those that were newly planted (with or without weed). This is seen when comparing compartments E15 and E17 with E14 and E18 in the June/January change image. There was no separation between any of these compartments in the January Four-Class unsupervised image. However, in the change image, there was a clear distinction between the two groups (soil/slash vs. planted/weed-free/weedy). The Ten-Class unsupervised image did show a degree of separation between these two groups, but still with considerable overlap.

Another change class of interest was that of the change from standing to felled (or closed canopy to weed-free). Although this change was a focus of the Assisted "Classified" Change Detection procedure (see section 4.2.3.1), it was also of concern in this process as it could be used as a confirmation of the results obtained above. The class codes of interest for clear-felling were code 41 (closed canopy to weed-free) or 42 (pre-canopy to weed-free). Compartments E14, E18 and E22 illustrated this well over all three change detection images, in that there was a change to pre-canopy status in the March/June image (due to the winter slow-down in growth), a change to felled status in the June/January image and no change in the January/April image. All these conditions were confirmed as correct by the ground-truthing field observations. The error matrix also reflected this, with classification accuracies of 96.3% recorded (see Table 4.2.21).

In order to confirm the ability of the "Quantified Classified" Change Detection process to accurately detect clear-felled stands from standing compartments, which was the primary concern of this study, a further test was done. In this test a sample of 360 compartments that were classified as felled or standing (including compartments that were partly felled) was tested for its level of accuracy. The error matrix for this data set produced a classification accuracy of 100%, with a kappa value (K_{hat}) of 1.00 (see Table 4.2.22). The remaining change classes were of less interest as they covered small increases in vegetation density (either crop, weed or both) or the change to pre-canopy or closed canopy status. While they assisted in the interpretation of the change process over time, they did not add much new information in terms of weed density or infestation.

Table 4.2.22 Error Matrix: Quantified Classified Image Change Detection – Felled vs. Standing Accuracy Assessment

Observed	Reference: Felled	Reference: Standing	Row Total	Incremental Chi Square	User Accuracy
Felled	**145**	0	**145**	215.000	100.0%
expected	*58.403*	*86.597*			
Standing	0	**215**	**215**	145.000	100.0%
expected	*86.597*	*128.403*			
Columns Total	**145**	**215**	**360** *Grand Total*	360.000 *Chi Square Total*	100.0% *Overall Accuracy*
			DF	1	
			P	0.000	
Producer Accuracy	100.0%	100.0%			
Khat	1.000				

The chi square test result of the observed frequencies was significant using a one-tailed test

A very useful feature with this method was its ability to show the exact state of change in terms of what the original state was, and to what state the pixel had changed. The "Classified" Image process described above (section 4.2.3.1) did not describe the change in this manner, but simply showed the new change state.

Cohen and Fiorella (1999) noted this factor when comparing image differencing and CVA to composite analysis, stating it as a disadvantage of composite analysis in not describing the exact nature of the change. Although the "Quantified Classified" Change Detection methodology could not be described as a pure composite analysis method, this study supports that contention, in that this methodology was of more use in describing the change than the "Classified" Image Change Detection.

As was the case with the other methods, there was still limited success in being able to clearly differentiate between weed and crop, despite the apparent increase or decrease in the weedy class. However, a major finding was the ability of this Assisted "Quantified Classified" Change Detection method to distinguish between the soil/slash classes and the weedy/weed-free classes, so demonstrating the added information value obtained through running this procedure, even though it added another step to the whole process.

4.2.3.3 NDVI Image Differencing Change Detection

The NDVI change detection routine produced two change images for each routine run. The one was simply an image (known in this study as an NDVI change image) that returned a value indicating the amount each pixel had changed by after comparing the two (before; after) images. This was either a positive value for an increase in value, or a negative value for a decrease in value. The second image was a difference image (known as an NDVI difference image) showing all change above a user-defined threshold. For the purposes of this study a threshold of 25% was chosen, after several thresholds were visually tested.

The NDVI change image, illustrated in Figure 4.2.9, gave useful indications of trends occurring over time. What was also of interest was that it gave slightly more detail of what change occurred within compartments, than was the case with either the Ten-Class or the Four-Class Unsupervised Classification. An example of this is seen in compartment D10A in the March/June NDVI change image (see Figure 4.2.9a), where a portion of the compartment increased in NDVI values (i.e. there was an increase in growth), while another portion decreased in value, indicating a decrease in growth. When one compared this result against the same area in the unsupervised classification images, neither of these reflected this change. In the Four-Class image, the bulk of the compartment was classified as "weed increase",

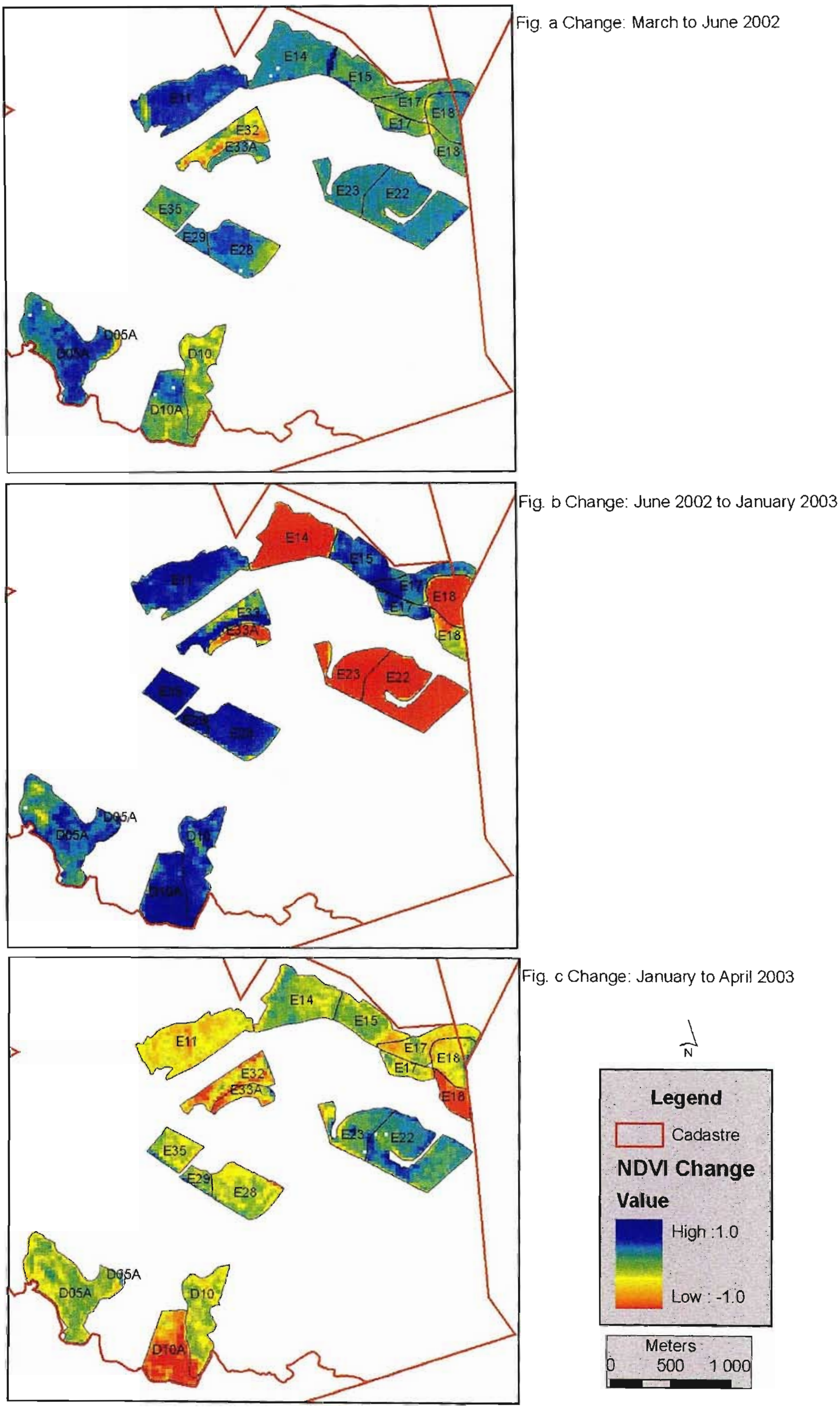


Figure 4.2.9 NDVI Change Images

and in the Ten-Class image it was classified as Class 8, i.e. a “weedy” class. In compartment E28, a similar classification occurred as in compartment D10A (i.e. a portion had an increase in NDVI, and another part had a decrease in NDVI). In this case, the Four-Class image classified the area of decrease as a “weed reduction”, and the area of increase as “no change”. These patterns were repeated across all three NDVI change images. Without more detailed ground-truthing data it was not possible to relate these patterns to the presence or absence of weed, as opposed to crop, but it does strengthen the possibility of further research being able to identify a methodology that can do so.

What was encouraging was that clear-fellings were again very distinct (see compartments E14, E18 and E22 in the June/January NDVI change image, Figure 4.2.9b). In addition to being very distinct they were also very uniformly classified across the whole compartment. The only exception was, as expected, where a compartment was only partially felled. This was in contrast to the variation displayed for any other state. This was also noteworthy in view of the unsupervised classifications’ inability to distinguish between clear-felled (i.e. bare soil or slash) and newly planted or weeded areas. An example of this is seen in the June/January NDVI change image, where compartments E15 and E17 (planted, with some weed present) are both clearly different from E14 and E18 (clear-felled).

The NDVI Difference image data (see Figure 4.2.10) did not add much new information, apart from confirming trends identified in the NDVI change image. The only operation that exceeded the 25% threshold level was that of the clear-felling, which simply provided further confirmation that clear-fellings were readily detectable (again, compartments E14, E18 and E22 in the June/January difference image provide examples of this).

The only other change classes described were all below the 25% threshold level and fell into the “some decrease” or “some increase” classes. These were much too general to supply specific data as to the status of a compartment, but merely showed the general trend over the change period being monitored.

Because of the slow growth rate of forest crops there was never any increase in NDVI change large enough to exceed the 25% threshold level.

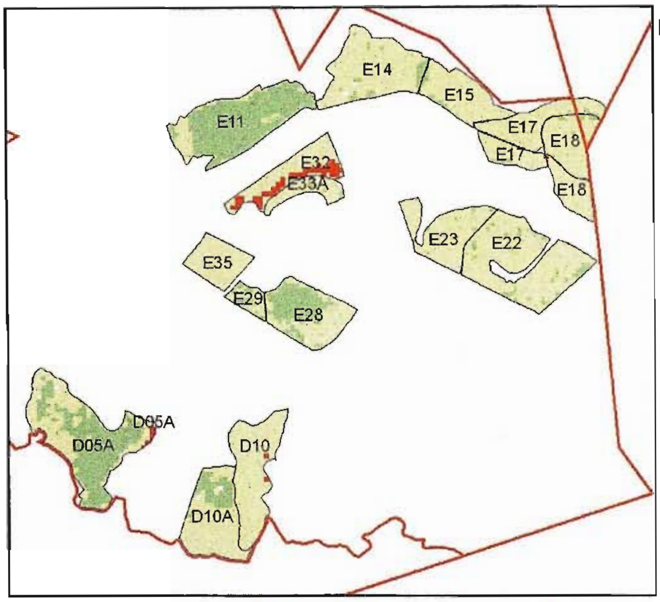


Fig. a Change: March to June 2002

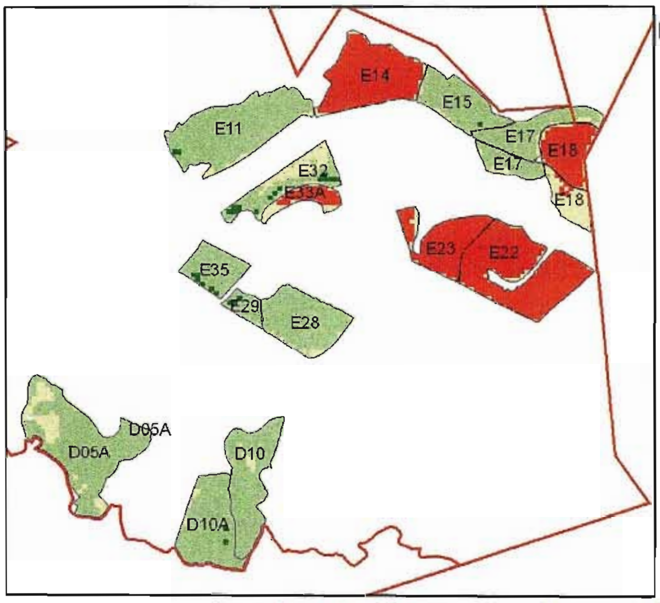


Fig. b Change: June 2002 to January 2003

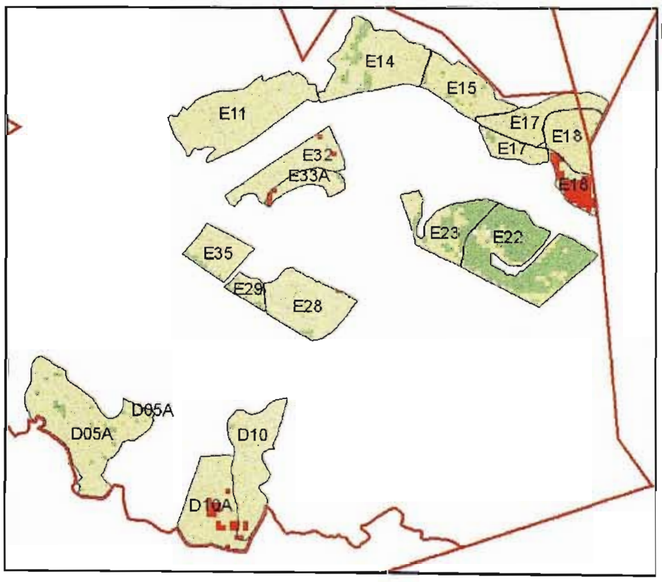


Fig. c Change: January to April 2003

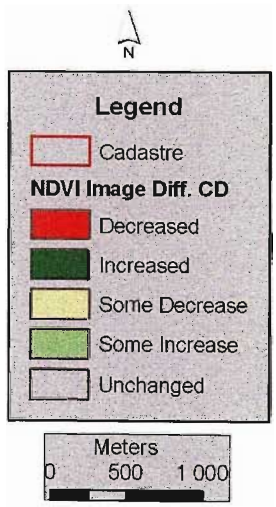


Figure 4.2.10 NDVI Image Differencing Images

The NDVI difference images were dependent on where the thresholds were set and using 25% as a threshold, only clear-felling was detected. However, setting lower thresholds produced images that showed too much change to really be effective in highlighting true change. If sufficient ground-truthing were done within compartments to determine the status of each portion of change reflected in the NDVI change image, it might then be possible to adjust the threshold levels on the NDVI difference image such that additional information is produced and when interpreted in conjunction with the NDVI change image, could supply useful information. However, this is an area that requires more research to test this. Possibly utilising the "change-versus-no change binary mask" method suggested by Lillesand and Kiefer, 2000, would aid the identification of suitable threshold levels.

4.2.4 Comparison between Classification Results and Compartment Status in FMS

By interpreting the records of operations in FMS, a compartment status could be inferred. For example, if the database recorded that a weeding operation had been done shortly before an image had been captured, one could assume that the compartment should be weed-free. The classification results were compared to the inferred compartment status in the forestry database (see Table 4.2.23). Overall, the classification results reflected what was recorded as compartment status in the database. A sample of 50 compartments from the January image was tested against the database, and produced the following percentage agreement:

Supervised Classification	: 66%
Unsupervised Ten-Class Classification	: 88%
Unsupervised Four-Class Classification	: 86%
"Classified" Image Change Detection	: 86%
"Quantified Classified" Change Detection	: 90%

There was a 100% agreement between both the clear-felled and closed canopy classes and their status in the database. However, in the case of six compartments tested (i.e.12% of the total of 50), the difference in status between the classified images and the database was such that it indicated that this difference was not due to a misclassification, but reflected a discrepancy between the status on the ground (as recorded by the classifications) and the recorded status in the database. In all cases, the status involved was the weed status.

Table 4.2.23 Sample of the Comparison between Classification Data and FMS Forestry Database

Compt	Month	FMS Record	Compt. Status	Superv. Classific.	Unsup 10-Class	Unsup. 4-Class	"Classified" CD*	"Quantif. Class". CD*
D05A	Feb.'02	Weeding Op.	Weed-free	Soil/Crop Weed	Soil/Slash Weedy	Weed-free Weedy	N/A	N/A
D10	Jan.'03	No Ops.	Weedy	Weed	Weedy	Weedy	Weedy	Weed Incr.
E14	Jan.'03	Felling Op.	Felled	Slash	Soil	Weed-free	Soil	Felled
E17	Apr.'02	Weeding Op.	Weed-free	Crop/Weed	Soil/Slash	Weed-free	Soil	Unchanged
E18	Jan.'03	Felling Op.	Felled	Slash	Soil	Weed-free	Soil	Felled
E28	Mar.'02	Weeding Op.	Weed-free	Soil	Soil/Slash	Weed-free	N/A	N/A

*(CD = change detection)

As can be seen from Table 4.2.23, by interpreting the FMS record to produce a compartment status, a meaningful comparison can be produced.

An example of this is seen with compartment E14, which was reported, in FMS, as felled in January 2003, and therefore should have been classified as such in the imagery. All the classes allocated by the classification procedures were classes equivalent to clear-felled stands (soil; slash; weed-free etc.) Compartments D05A, E17 and E28 had weeding operations reported in various months, and when the closest image to that was queried, the classified record indicated agreement with a weed-free status (i.e. weed-free; soil/slash, soil etc.)

What was of interest was that, over the period that this study covered (i.e. March 2002 to April 2003), seven compartments that were classified by the imagery as being felled were not recorded as such in the database. The reasons why these compartments had not been recorded as felled in the forestry database were not established, but it did show that the processes applied in this study could highlight such anomalies, which could then be followed up in an operational application of these procedures. This is reinforced by the results from the comparison of the 50 compartments described above, and demonstrates the validity of the hypothesis.

4.2.5 General Discussion

4.2.5.1 Effect of Mixed Pixels

When one examined every image, irrespective of whether it was a raw image or a classified one, the boundaries of compartments consisted of mixed pixels. The only exception was where the canopy was the same height and type for both adjacent compartments.

The effect of these mixed pixels was to add additional classes that were either incorrect or were so small in relation to the rest of the compartment as to be irrelevant to any classification. However, when a process such as a zonal statistical function was run on the data these mixed pixels were included and introduced some confusion into the process.

One way in which this could have been avoided was to buffer all compartment boundaries with at least a 30 m buffer (i.e. one pixel width) and only run processes using the inner pixels of the resultant polygons. A disadvantage with this process is that it would negatively affect narrow compartments.

Rather than creating a more complicated data set, it was decided to ignore edge pixels in any visual assessment. It was initially anticipated that the results from such automated processes as the zonal statistics function were only important to determine the dominant class, and this would not be significantly affected by the inclusion of minor pixel values that the mixed pixels would represent. Therefore, it was felt that the inclusion of these minor classes was not of sufficient concern as to necessitate the additional processing.

4.2.5.2 Effects of Spatial and Spectral Resolution

The basic cause of the difficulty in identifying weed status was the spatial resolution available with the Landsat 7 imagery. In terms of the basic unit of observation being the compartment, and not the pixel, this spatial resolution was not problematic, a fact supported by the good fit between the spectral groupings that represented the compartments and the compartment vector data that was overlain on it. In contrast to Varjo's (1997) findings regarding the delineation of stands, this finding was probably due to the fact that compartment boundaries are much more clearly defined in plantation forestry than those defining natural forest stand management units. Therefore, in terms of the spatial resolution for plantation forestry, the compartment is a useful unit of observation, even with spatial resolutions as coarse as Landsat's 30 m. The findings of Varjo (1997) and Varjo and Folving (1997) support this. However, the spectral resolution was problematic when it came to separating weed cover from crop cover, as discussed above in section 4.2.2 on Classification.

4.2.5.3 Role of Temporal Resolution

Varjo and Folving (1997) found that change detection results were more accurate the shorter the interval between images. The intervals in the study ranged between one and three years, with accuracies ranging from 93.1% to 87.6%, respectively. As far as the detection of clear-fellings is concerned, this study supports their findings, in that with the periods between consecutive images being between three and six months for this study, a higher accuracy than Varjo and Folving's (1997) was achieved.

The temporal resolution used in this study was found to be adequate to meet the objective of being able to identify critical change and compare this against the forestry database such that its accuracy could be assessed. With respect to clear-fellings, such is their distinctiveness that they could be determined in successive images (i.e. every sixteen days, cloud-free imagery permitting). However, in order to achieve a suitable cost-benefit ratio, quarterly or even half-yearly images would allow the database to be regularly audited.

4.2.5.4 Effect of Compartments as Units of Observation

One of the more problematic issues encountered in this study was the methodology used to allocate classification classes to compartments in order to determine their status. This was achieved by overlaying the compartment spatial data on the difference images produced by the change detection processes. Then, using the Majority statistical function in ArcGIS 8 Spatial Analyst Zonal Statistics function, a table listing every compartment with the dominant classification class was produced. However, the degree to which multiple classes occurred within compartments was underestimated, and so the majority statistical function proved to be an unreliable method of assigning a class to a compartment due to the extent of these multiple classes within a single compartment. This resulted in compartments being classified as one class in the ground-truthing exercise, but a different class (or classes) in the image classification process, when in actual fact this was not the case. An example of this was where a compartment was classified as being a class 5, slash/crop/weed land-cover in the ground-truthing exercise, but as a class 7, soil/slash/crop/weed land-cover in the image classification process, as a result of there being a majority of this class according to the classification process. Compartments that had operations in progress (e.g. partly felled or weeded) could not be clearly identified, and this tended to create misclassifications. This resulted in a significant under-estimation of the classification accuracy when the statistics were calculated. However, because compartments are the base unit of management, they could not be ignored in favour of classifying on a purely pixel-based system. A combination of both pixel-based classification and utilising the compartments as units of observation would provide a more appropriate methodology.

4.3 Conclusions and Recommendations

4.3.1 Conclusions

In order to test the hypothesis of this study, the first requirement was to test whether the forestry operations of clear-felling, replanting and weed control in the KwaZulu-Natal Midlands could be successfully identified through the use of satellite imagery. It also required determining which classification technique was most successful in achieving this. A second requirement was to test whether these procedures could be applied as an audit mechanism on the relevant data recorded in a forestry database.

4.3.1.1 The Identification of Clear-felled Stands

The findings of this study confirm those of similar studies concerning the detection of clear-fellings (Sader *et al.*, 2001; Puhr and Donoghue, 2000; Häme *et al.,* 1998; Jeanjean and Achard, 1997), but with accuracy greater than that achieved in Sader *et al.'s* (2001) study.

While every method from the supervised and unsupervised classifications (both Ten- and Four-Class) to the change detection procedures could identify clear-felled compartments, the most successful process was the Quantified Classified Change

Detection technique, which was able to distinguish felled compartments from standing compartments with 100% accuracy (kappa = 1.00).

4.3.1.2 The Identification of Planted Stands

The Landsat imagery was not able to identify planted stands of an age younger than about 12 months. Also, weed free stands younger than 12 months were classified as being clear-felled. Stands older than this tended to be classified into one of the intermediary categories, along with weedy stands, until canopy closure was imminent, at which time it was classified as pre-canopy or closed canopy.

4.3.1.3 The Identification of Weed Status

The issue of weed status identification was, without doubt, the most difficult aspect of this study, and one that met with the least success, in terms of the overall aims of the project. Having said this, it was anticipated that it would be problematic, given the spatial resolution of the Landsat imagery and the planting espacement applied in plantation forestry.

To some degree, there was a measure of success that exceeded the more pessimistic expectations, but the findings of this study are supported by what Nilson, *et al.* (2001) found regarding the difficulty in quantitatively describing the effects on reflectance caused by the successional changes in ground and field-layer vegetation. Determining the effect the various stages of vegetative growth have on the reflectance characteristics of Landsat imagery, and establishing whether there is a correlation between these reflectance values and the composition of the vegetative cover might provide a key to interpreting weed growth patterns in young stands. In this study, it was not possible to accurately differentiate between a pure tree stand on the one extreme and a totally weeded cover on the other extreme in any stand less than one year old.

Although the results reflected in the statistical analyses of the weed state classification showed low classification accuracy, a visual assessment of the classified data enabled one to extract very useful information, based on the classification variation within the compartments, especially where ancillary information regarding the species, age, or operational history was available to assist this interpretation. What was also noted was the impact that genera/species had on the outcome of the classifications. By applying the data from the Ten-Class Unsupervised Classification Class 7, additional information could be provided to assist in flagging potential problem areas. It would, however, be necessary to devise a means of tabulating this information so that it could be compared with the forestry database.

The type of information that could be interpreted from a visual assessment included either possible weed concentrations or weed-free areas within compartments, and indications of crop uniformity, where areas of either improved or retarded growth could be identified within compartments. This aspect opens up possibilities of applying "precision farming" techniques to a forestry environment. This possibility would be dependent on devising means to overcome the limitations of the spectral and spatial resolutions encountered in this study.

While no attempt was made to undertake any individual tree counts or location, it was interesting to note the findings of Wulder *et al.* (2000) that when using one metre spatial resolution imagery a minimum diameter of 1.5 m was required for individual canopies to be detected. In this current study, the threshold level at which weed-free status from weedy status compartments was able to be differentiated was generally found to occur in compartments that were older than one year, approximately the time at which the individual canopies would have a diameter of between 1.5 and 2.0 m.

4.3.1.4 The Role of GIS

GIS was fundamental to the successful integration of the vector (compartment) and remotely sensed data in this study, due to its ability to integrate diverse data sets. The ease with which the compartment vector data was overlain on the classified imagery and analyses undertaken, such as the zonal statistical functionality, supports the literature (Lillesand and Kiefer, 2000; Lunetta, 1999, Eastman, *et al.*, 1995; Dunningham and Thompson, 1989), in this regard.

A key element in this study was the fact that a comprehensive GIS database, including both spatial and attribute data, of all forest compartments was available. This factor played an important role in allowing a coarser spatial resolution to be applied than might otherwise be the case where this information was not available as well as supporting the concept of the compartment being the base unit of observation for this study. Varjo (1997) was also able to use the forest stand (or compartment) as the base unit of observation.

4.3.2 Recommendations

4.3.2.1 Identification of Clear-felled Stands

The methodology described in this study may be used to identify clear-felled stands, in order to audit the forestry database. This would allow the accuracy of the "felled versus standing" status of all compartments in the database to be measured. Any discrepancies could then be queried with the relevant operational staff.

4.3.2.2 Identification of Weed State

As there was limited success in determining the weed state of forest compartments, it is recommended that more research be undertaken into this field, as there are good indications that greater success could be obtained in this area.

Several recommendations regarding the possibilities of improving weed status classification can be made on the basis of the results obtained in the medium resolution imagery study. These include:

1. Applying a pixel based unit of observation and using the compartment boundaries to delimit management units. The percentage of each class within the compartment could then be calculated, and used to rank classes within the compartment. This prevents the information loss that occurred when using only the majority class to allocate a classification class to a compartment.

2. A convolution filter, based on a standard deviation, minimum/ maximum values or some similar function, could be applied to the raw data as a pre-processing procedure prior to a classification being applied. The classification process would then be applied to the pattern data in conjunction with the spectral data. Included in this process, should be a focus on the role the genera/species plays in the classification result, as this would improve some of the spectral class definition.

3. The use of an object-orientated classification system, as opposed to the traditional spectral band classification systems, should be tested.

4. Applying Datt's (2000) findings regarding spectral matching to discriminate between dry and green vegetation might provide a means of creating a greater separation between a crop cover and weed cover where the weed has been treated, or is in a winter-senescent state.

5. Another possible method that could be investigated regarding the weed/plant separation is that of spectral unmixing, as described by Van der Meer (1999).

6. Although the NDVI results did not reveal as much separation as was anticipated, additional research into the role of vegetation indices could well provide useful applications that are able to discriminate between weed and crop cover.

7. Imagery having a greater spatial or spectral resolution, such as SPOT 4 or 5 "Vegetation" imagery could also be investigated, but this would have to be weighed against the additional cost of such imagery. A possible alternative could be to apply a multi-stage sampling approach, using Landsat imagery to find particular problem areas, and then acquiring Ikonos or QuickBird imagery for these specific areas. A further alternative would be to investigate the use of hyper-spectral imagery such as that of the Hyperion sensor.

Chapter 5: Monitoring Forest Operations using High Resolution (0.6 - 2.4 m) Imagery

5.0 Introduction

Based on the results and conclusions found in Chapter 4 above, it was seen that while medium resolution imagery has a wide geographic coverage, its spatial resolution limits its application to a "between-stand (compartment) variation" level. In other words, it can generally detect differences between, but not within, compartments. This problem was amplified by the cross-classification that resulted from the "within-stand" variation that did occur within the images. In order to overcome these problems, a much finer spatial resolution was required, hence the application of high resolution imagery, which was aimed at detecting forest operations, such as planting and weed control, at a "within-stand" level. This chapter describes in detail the process followed to develop and test a methodology to monitor and measure the planting and weed control operations at a "within-stand" level. Success in this process would provide forest managers with a means to quantifiably monitor these operations.

5.1 Materials and Methods

5.1.1 Introduction

The materials and methods utilised in the high resolution imagery study required the application of additional remote sensing image classification techniques, to those applied in the medium resolution study. These were based on methods recommended from the results of this earlier study, and chiefly involved the use of textural analysis as an enhancement to improve the classification and change detection results. A notable feature of this study was the level to which the classification and change detection techniques were applied, i.e. down to individual crop row level, the widths of which ranged from 0.5 to 3 m, depending on the age of the crop.

5.1.2 Materials

The data sets applied in this study were similar to those applied in the medium resolution study, in other words, suitable study sites; satellite imagery and forest stand management data. These three main data sets were again integrated through the application of GIS technology.

5.1.2.1 Suitable Study Sites

Due to the greatly reduced coverage available from high resolution satellites, the study sites chosen were from a subset of compartments selected for the medium resolution imagery study, and were all found on two adjacent plantations covered by the QuickBird imagery. The location of these study sites is shown in Figure 3.1.2 (see Chapter 3 Study Sites, above).The primary criteria for site selection was that the stands had to be clear-felled and replanted within a period of 24 months, as this was the most crucial time period in terms of weed suppression, as well as initial tree crop growth. The study sites selected also had to be in this stage for at least three consecutive image acquisitions, in order for the minimum change detection results to be obtained.

Unfortunately, the spread of genera available in this area was limited to chiefly wattle (*A. mearnsii*), with only one suitable Eucalypt coppice stand being available in the imaged area. No planted Eucalypt stands were available within the test sites. It had been hoped to have more Eucalypt stands tested, as well as some pine stands. However, the sites selected did have the advantage of having been continuously monitored throughout the whole study period, and so provided a very good source of ground-truthed data, which allowed a thorough testing of the methodology.

Initially twenty compartments were identified as potential sites, and were monitored throughout the test period. However, of these twenty compartments only twelve compartments eventually met the selection criteria and were used to develop and test the research methodology.

5.1.2.2 Satellite Imagery Data

The imagery selected for the high resolution imagery study was that available from the Digital Globe satellite, QuickBird 2. This imagery was selected because of its high resolution capability, having a panchromatic band of 0.6 m spatial resolution, and four multi-spectral bands, Red (630-690 nm); Green (520-600 nm); Blue (450-520 nm); and Near-Infrared (760-900 nm), each of 2.4 m spatial resolution (Digital Globe, 2003). Detailed specifications of the QuickBird satellite and sensor are given in Appendix 2. Due to cost constraints, and the number of repeat images required, only the minimum image size of 8x8km (64 km^2) could be obtained. However, this imagery did cover 95% of the selected study area, with a small part of the study area in the December 2003 image being lost.

Six repeat images of the study sites were obtained, and covered the period from December 2003 to June 2005. In order to cover the complete seasonal spectrum specified acquisition windows were supplied to Digital Globe, these being December 2003; April 2004; October 2004; December 2004; March 2005; and June 2005. However, the actual image acquisitions occurred in December 2003; May 2004; December 2004; March 2005; April 2005; and June 2005. This resulted in an uneven spread of images over the study period. Fortunately this did not affect the results too negatively, and even the very close repeat of the March, April and June 2005 imagery proved to add value, as this was instrumental in identifying a particular event that might not otherwise have been identified. The fast growth rates experienced in South African plantation forests also necessitates rapid repeat imagery.

Initially the standard imagery bundle product was ordered, but was found to be unsuitable due to the partial orthorectification that is done on this product, and which prevents further, more accurate image rectification being carried out on the imagery. As a result, a special request was submitted to the suppliers to provide the imagery as a basic imagery product, which could then be more accurately orthorectified (normally one is required to purchase full scenes when ordering the basic imagery product (Digital Globe (2005)).

5.1.2.3 Forest Management Attribute Data

As an additional source of verification of the results of this study, the operational data recorded in the forestry database was used to verify operations recorded from the imagery. However, once the methodology had been developed and tested, the results derived from the image processing could be used to validate the accuracy of the operations recorded in the database.

The timing, type of operation undertaken, as well as issues such as validating whether work paid for had been completed or not were examples of the use of the forest management attribute data available from the database.

5.1.2.4 Geographic Information System (GIS) Data

The compartment layer in the GIS database was a fundamental data input in the process, as it was used to identify and delineate compartments within the imagery. These compartment areas formed the basic data sets to which all processing operations were applied. This data set also provided the link to the forest management database, and the ancillary information available from it.

Other data sets utilised from the GIS included the plantation boundary data; digital terrain models (DTMs); and roads, which were used on different occasions, such as for enhancing the presentation of the results. The DTMs were used in the orthorectification procedures. All data sets were projected to UTM Zone 36 south, WGS 84 spheroid/datum.

5.1.3 Methods

While maintaining several similarities to the methodology applied to the medium resolution image processing, the methodology applied to the high resolution imagery was more complex, as additional steps were required in order to extract the required level of information. Also several different approaches had to be tested before arriving at a successful methodology. However, the fundamental principles of image classification and change detection techniques still formed the basis of the methodology, with textural analysis being utilised as an enhancement technique to these methods.

A major difference in approach to processing the high resolution imagery compared to that done on the medium resolution imagery was the scale of area processed. With the medium resolution imagery the level of processing was restricted to individual plantation (i.e. "farm") level, through the application of areas of interest defined by the plantation boundaries. All the variance within these boundaries was processed and contributed to the classification results. The problem with this approach was that it tended to result in a major level of cross-classification between classes which should have been separable, and was highlighted in the conclusions above. With the high resolution imagery, an improved process was applied, whereby all processing was restricted to an individual compartment level, where each compartment was treated as a separate study site, and processed individually. However, the down-side to this approach was the greater volume of work required, but this was made manageable by the restriction of the processing to only those compartments identified in the medium resolution imagery as having been felled, but the new crop had not yet reached canopy closure.

Figure 5.1.1 illustrates the complete process flow of the methodology applied to the high resolution imagery

5.1.3.1 Image Rectification and Atmospheric Correction

The image rectification process proved to be a difficult step in the work flow, due to the complex geometry inherent in the satellite platform. Some of the problems experienced in rectifying these images were in line with those reported by Toutin (2004). This resulted in less than optimal rectification on some of the imagery.

The Basic Imagery data sets were supplied as unprojected data sets, and were then projected to a WGS84 Datum, UTM Zone 36 South projection. Various different rectification techniques were tested, but in order to minimise the rectification problems, it was decided to ortho-rectify one image using the QuickBird RPC model in the Data Preparation Module of Erdas Imagine 8.7, in conjunction with a 20 m DTM derived from 10 m dot-rolled contours, and 15 ground control points established using a sub-metre GPS unit (17 points were acquired, but two points were discarded as their RMSE results were above acceptable limits). This was done on both the multi-spectral and panchromatic bands of the March 2005 image, using the RPC coefficients supplied in the *.imd* file provided with the imagery. An Image-to-Image registration process was then applied to all the other images, using the ortho-rectified March 2005 image as the Reference Image.

The image-to-image registration process was applied using polynomial models on the multi-spectral and panchromatic bands. Table 5.1.1 lists the various parameters obtained from the orthorectification. Most of the image rectification results approximated Digital Globe's stated accuracies of 3 – 6 m for rectifying Basic imagery products using high quality DTMs (equivalent to DTED Level 2) and sub-metre GCPs using the RPC method (Digital Globe, 2005), and were similar to levels

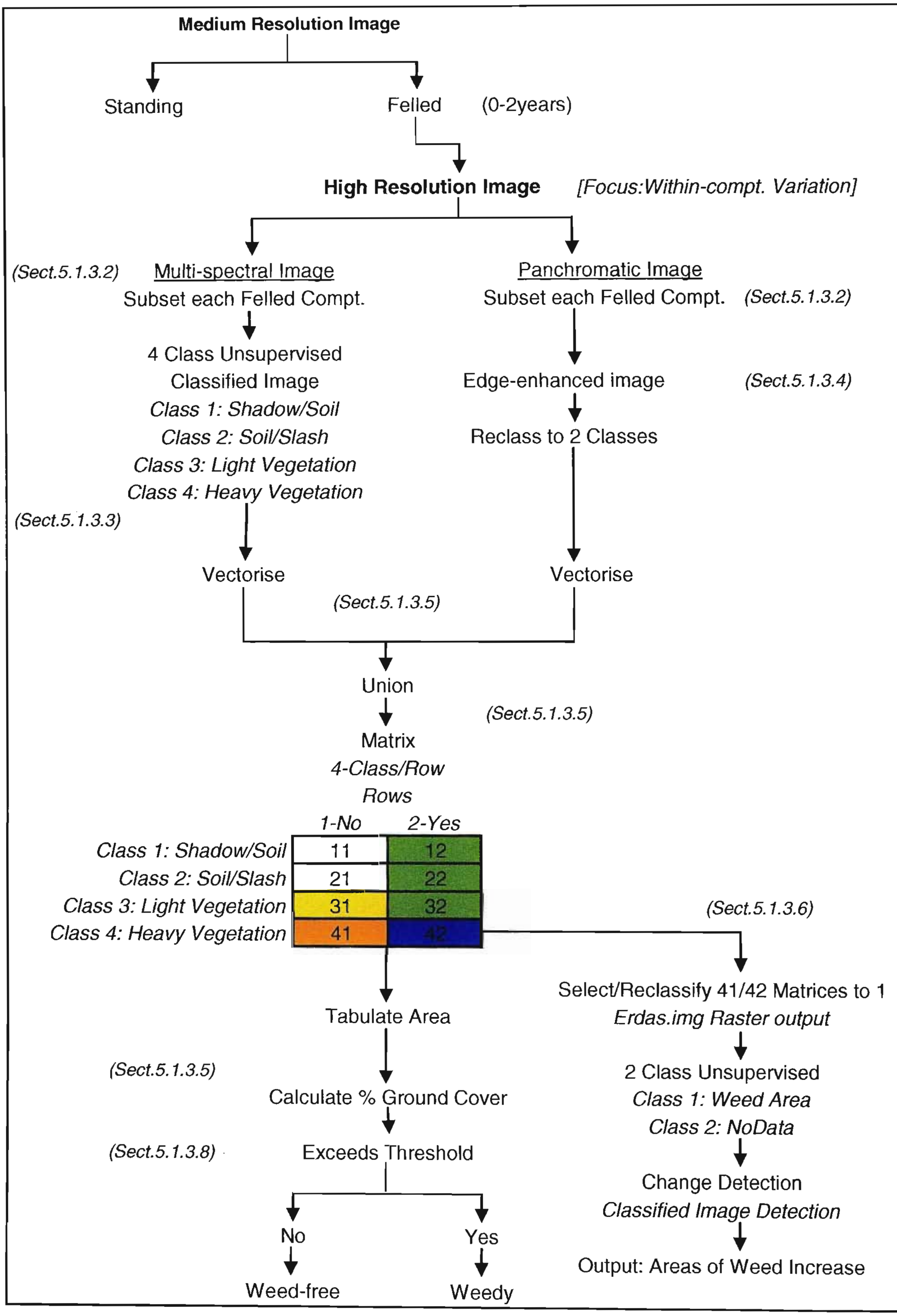


Figure 5.1.1 Process Flow for High Resolution Image Processing

Table 5.1.1 Orthorectification parameters for QuickBird Images

Image Date	Band	GCPs	RMSE	Resample Method	Output Cell Size
Dec-03	MSS	52	1.6	NN	2.4
	Pan	96	3.2	NN	0.6
May-04	MSS	22	1.4	NN	2.4
	Pan	90	2.8	NN	0.6
Dec-04	MSS	20	1.5	NN	2.4
	Pan	11	1.0	NN	0.6
Mar-05	MSS	13	1.7	NN	2.4
	Pan	12	4.6	NN	0.6
Apr-05	MSS	40	1.7	NN	2.4
	Pan	71	8.0	NN	0.6
Jun-05	MSS	50	1.1	NN	2.4
	Pan	72	3.7	NN	0.6

achieved by Kayitakire *et al.* (2002) where a positional circular error of 6.3m at a 95% confidence interval was achieved on 1m Ikonos imagery. However, those images where the accuracies were much lower (e.g. the April 2005 image) had been acquired using high off-nadir viewing angles.

Another complication that occurred with the ortho-rectification was that the panchromatic bands of the images did not accurately match their equivalent multi-spectral bands, due to the greater difficulty in achieving accurate and consistent image rectification on the panchromatic bands. However, the effect of these issues was greatly reduced once the data was vectorised and the compartments buffered (see section 5.1.3.5).

Following the ortho-rectification process, all the multi-spectral band images were converted to radiance, and then reflectance values, in order to normalise these images. This process was carried using a *.gmd* model created in the Modeler Module of Erdas Imagine 8.7. A layout of this model is presented in Appendix 3. The "absCalFactor" and sun elevation values required to run this model were provided in the *.imd* file supplied by Digital Globe with the imagery (see Appendix 4), while the formulae to calculate both radiance and reflectance were provided by Jha (2005), and are given in Appendix 5. The ESUN values were based on the Landsat 7 values, as the spectral band ranges of the QuickBird imagery are very similar to the Landsat 7 ranges (Jha, 2005). All the relevant parameters for the imagery utilised in this study are given in Tables A2.1 and A2.2; Appendix 2.

All further processing of the multi-spectral imagery occurred on the reflectance images.

5.1.3.2 Image Sub-setting

As was noted in the processing of the medium resolution imagery, edge effects along compartment boundaries caused problems due to the mixed-pixel effects. This phenomenon was also noted to occur in the high resolution imagery. In order to reduce this effect, compartment boundaries had a reduction or internal buffering applied to every compartment that was a study site. This was achieved by applying a -10 m buffer distance to the ArcGIS buffering process, which resulted in the compartment polygons shrinking inwards by 10 m. Based on a visual assessment of the study sites, 10 m was found sufficient to remove these edge effects. The effect of this was to reduce false spectral variation within the compartment study sites, thus improving the classification results. This helped counter the problems reported by Heyman *et al.* (2003) where the greater variability within the classes caused a reduction in classification accuracies, as well as reducing the misregistration problems.

This process was a distinct improvement on the procedures applied in the medium resolution imagery, where the sub-setting was restricted to the plantation boundaries. This greater coverage meant that in addition to the mixed-pixel edge effects, the digital number values were also diluted by the presence of non-afforested areas such as the riverine valleys and other open areas, which led to an increase in cross-classification as the statistical variance was skewed by irrelevant digital number values.

The subset compartment polygons were then converted to Areas of Interest (AOIs) in Imagine 8.7, and used in the Data Preparation module to subset each study site. Both the multi-spectral bands of the reflectance images and the panchromatic band of every image were subset in this manner. These subset data sets then served as the input data for the next phase of processing (see Figure 5.1.1).

This next phase split into two parallel process flows (see Figure 5.1.1), one utilising the multi-spectral bands, and the other utilising the panchromatic band. Again, all study sites across all six images were processed.

5.1.3.3 Image Classification – Multi-spectral Bands

Initially, several unsupervised classification test phases were run, using 20, 12 and 6 classes. This was done in order to try and identify and extract any unique classes or class combinations. These test classifications were applied to all forest stands simultaneously, but masking out any area that was not a forest compartment. The ranges of stands varied from mature standing trees to clear-felled areas with only soil or slash ground cover. No significant classes could be consistently identified in this manner, and so it was decided to work with individual compartments independently by sub-setting them (see 5.1.3.2 above).

The focus of the high resolution imagery study was restricted to compartments that were between 0 and 2 years of age from the time of last clear-felling, as the main aim was to identify weed infestation during the critical period from time of planting to canopy-closure stage. Canopy closure generally occurs within the first 24 months of growth.

Based on the major classes observed in the ground-truthing, it was decided to restrict the number of classes to four. These classes, described in detail in section 5.2.1 below, represented the following ground cover states:

Class 1: Shadow/Soil

Class 2: Soil/Slash

Class 3: Light Vegetation (< 60% ground cover)

Class 4: Heavy Vegetation (> 60% ground cover)

Photographs of typical examples of these classes are given in Appendix 10.

The unsupervised classification procedure was completed using the Classification module in Erdas Imagine 8.7, utilising a maximum of 6 iterations with a convergence threshold of 0.950.

5.1.3.4 Image Textural Analysis – Panchromatic Band

Despite the high resolution of 2.4 m, the multi-spectral bands could not identify the crop rows. However, these rows were very clear on the 0.6 m panchromatic imagery, and it was decided to optimise this feature to refine the classification results. This was undertaken by applying an edge-enhancement textural analysis process (Janssen, 2000).

Textural analysis utilising spectral signatures involves the application of a moving convolution window in order to produce the smoothing or sharpening effect of the analysis. In order to determine the optimal window size for every study site, it was necessary to undertake semivariogram analyses of the input data sets. This required converting the raster imagery to vector points, where every raster cell in the image was represented by a point with a value equal to the DN of that cell. This conversion was done using the Raster to Vector Conversion utility in ArcGIS Spatial Analyst extension (McCoy and Johnston, 2002). These point files tended to be very large, often containing millions of points. During the conversion process, all NULL data areas in the raster input image were also converted to points, and these had to be clipped out of the point data set using the buffered compartment boundary polygon in order to reduce the size (and hence processing time) of the point shapefiles. The resultant point shapefiles then served as the input into ArcGIS Geostatistical Analyst extension (Johnston *et al.*, 2001), in which an ordinary kriging procedure was run to derive the semivariograms. Based on a series of test runs it was found that the optimal number of lags was 12, while the lag distance was set at 0.6 m, i.e. the spatial resolution of the input data. Using the resultant Range values from the semivariogram calculation, the optimal convolution window size was determined, and applied to the textural analyses procedures. The window sizes ranged from a minimum of 3x3 to a maximum of 11x11. Although not definitive, there was a trend for the larger windows to be more applicable to more diverse stands, while the smaller windows tended to be applied to stands with less variation, such as stands with a closed canopy. However, it was clearly seen that no one single window size could be applied across all sites.

Because of the strong linearity of the crop rows observed in the panchromatic imagery, it was decided to focus the textural analysis on this feature. Several different techniques were tested before an Edge Enhancement process was selected. Prior to this selection, two textural analyses and a Fourier Transform technique were tested. The textural techniques were applied using the functionality available in the Radar Interpreter Module of Erdas Imagine 8.7, while the Fourier Transforms were carried out using the Fast Fourier Transform tool in the Image Interpreter module. Two different textural operators were applied, one being the Variance option, and the other being the Skewness option.

The Variance function is defined as:

$$Variance = \frac{\Sigma(x_{ij} - \bar{x})^2}{n-1}$$

where : x_{ij} = Brightness (DN) value of pixel $_{(i;j)}$

$_{i,j}$ = row; column

n = number of pixels in a window

$\bar{x}$ = Mean of moving window, where:

and the Skewness function is defined as:

$$Skew = \frac{\left[\sum\left(x_{ij} - \bar{x}\right)^3\right]}{(n-1)(V)^{\frac{3}{2}}}$$

where: x_{ij} = Brightness (DN) value of pixel $_{(ij)}$

$_{i,j}$ = row; column

n = number of pixels in a window

$\bar{x}$ = Mean of moving window

V = Variance (see above)

(Leica Geosystems, 2003)

Using the Edge Enhancement tool (based on a Prewitt detector) available in Erdas Imagine 8.7's Image Interpreter module (under Interpreter\Spatial Enhancement\Convolution), the applicable convolution window sizes were applied to the input image date sets. The output was an edge enhanced image for each study site. These images then had a grey-level thresholding process applied so that they were reclassified into two classes, "rows"; "no-rows", using the Reclassify function in ArcGIS Spatial Analyst. Reclass Values were assigned to a "Value" field as follows:

NoData:	0
No Rows:	1

Rows: 2

Class break values were assigned based on a visual assessment of the images under a range of break values in order to determine the optimal split between "rows" versus "no-rows." However, in order to automate this process, several regression equations were calculated based on the image means, ranges, medians and modes in order to determine which value could be used to programmatically calculate the optimal break value for the 2-class image reclassification process. The Image Mean proved to be the most significant statistic to use for this procedure, with an R^2 value of 0.9935 (see Table 5.1.2). The input data for this calculation is given in Appendix 6.

Table 5.1.2 Regression Analysis Results for Class Break Values based on the Image Means

Regression Statistics	
Multiple R	0.9968
R Square	0.9935
Adjusted R Squ	0.9788
Standard Error	24.5997
Observations	69

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	6302175.22	6302175.22	10414.34272	3.00728E-75
Residual	68	41149.78029	605.1438277		
Total	69	6343325			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
X Variable 1	1.0119	0.0099	102.0507	0.0000	0.9921	1.0317	0.9921	1.0317

The Break Threshold value in this table is the class break value assigned based on the visual interpretation of the imagery. Thus in an automated procedure, the image mean value could be read and assigned to the class break routine in order to reclassify the image into the required two-class image.

5.1.3.5 Image Vectorisation – Multi-Spectral and Panchromatic Bands

The four-class unsupervised classified images contained information regarding the amount of vegetation present, but could not separate crop from weed. The two-class reclassified panchromatic data sets contained the "Row; No Row" information, which could define what was crop. Thus by combining these two datasets, one could then classify the stands utilising all this information to determine what was crop, what was weed and what was soil or slash.

Thus, the two separate data sets, in terms of the multi-spectral and panchromatic bands (see Figure 5.1.1), had to be combined into a single data set in order to derive the final classified data set. However, this task was complicated by the fact that there were two different resolutions (2.4 m multi-spectral and 0.6 m panchromatic). Thus any raster merging of these data sets would mean either the larger resolution cell size being resampled down to the same cell size as the finer resolution cell size, or the finer cell size being resampled up to match the larger resolution cell size. Both of these methods are problematic, in that it is an incorrect procedure to run any analyses on data sets that have been resampled from a coarser to a finer resolution, while if one were to resample a finer resolution into a coarser one, the detail available in the finer resolution is lost, thereby negating the value of the finer resolution.

To test this process in Erdas Imagine 8.7, the various data sets were combined using the LayerStack routine available in Erdas Imagine 8.7. It was seen that the 2.4 m resolution data was resampled down to match the 0.6 m resolution data, which was problematic, for the reasons discussed above. In addition, the problems relating to the image registration accuracies further complicated the combination of these data sets.

In order to circumvent the problem of combining different raster resolutions (2.4 m vs. 0.6 m) described above, it was decided to vectorise both the 4-class unsupervised classification data sets and the 2-class reclassified panchromatic data sets. A generalisation technique was applied during this process in order to produce a result that more closely resembled the real world than would be the case if the data followed the raster pattern. In this way, the different resolution issues were overcome, as well as reducing the misregistration problem to a large degree.

Once vectorised, the two data sets for each study site were then unioned (see Figure 5.1.1), utilising the ArcGIS ArcToolbox Geoprocessing Tools functionality. This union function achieved the aim of having a single data set that contained all the information from both the multi-spectral and panchromatic bands, which a classification routine could then utilise to produce a more accurate classification.

Once unioned a new field called "MATRIX" was added to the resultant data set, and the matrix value was calculated by concatenating the "GRIDCODE" field value from the 4-class unsupervised classification polygon layer and the "GRIDCODE" field value from the 2-class reclassified "Row; No Row" polygon layer. Any polygons that had a zero value in either "GRIDCODE" field were deleted. These occurred where there was no intersection between the two input layers, and were an artefact of the different resolutions not matching along the edges. As a final step in this process, in order to simplify the data sets by reducing the number of polygons with identical values, a dissolve routine was applied to the unioned data sets, with the "MATRIX" field used as the dissolve variable (see Figure 5.1.2). This resulted in a table consisting of the unique records for each matrix variable present in the data set. Two additional fields were created in this table, one of which was used to calculate and record the area, in hectares, of the amount of each matrix value, and the other field used to calculate the overall percentage of the study site that each matrix value represented. This table then provided the quantified ground cover within each study site for the applicable image date (see Figure 5.1.2). The percentage ground cover measurements for those classes that related to potential weed cover were then compared against a threshold value and if the threshold was exceeded, the area was flagged.

Two threshold systems were tested. One was based on the "Plant-to-Canopy" requirement where no weeded area may exceed 5% of the total compartment area (Da Costa, 2005a), and any compartment that had heavy vegetation exceeding this threshold was then flagged. The other threshold tested was using the limits derived from the Ground Cover Percentage Model described below (see section 5.1.3.8 Ground Cover Percentage Model).

Attributes of 17dec03_weed_pot_e14

FID	Shape*	MATRIX	Ha	GC_Percent
0	Polygon	11	2.1	9.8
1	Polygon	12	2.4	11.2
2	Polygon	21	2.6	12.1
3	Polygon	22	5.7	26.6
4	Polygon	31	1.3	6.1
5	Polygon	32	5.7	26.6
6	Polygon	41	0.3	1.4
7	Polygon	42	1.5	7

Record: 1 Show: All Selected Records (

Figure 5.1.2 Example of Ground Cover Table

The Matrix values represented the following classes:

	Rows	
	1-No	*2-Yes*
Class 1: Shadow/Soil	11	12
Class 2: Soil/Slash	21	22
Class 3: Light Vegetation	31	32
Class 4: Heavy Vegetation	41	42

where classes 12; 22 and 32 represented crop areas, class 31 represented potential light weed areas (<35% ground cover = weed), while classes 41 and 42 represented potential heavy weed infestation (>65% ground cover = weed). Classes 11 and 21 represented no potential weed infestation.

5.1.3.6 "Classified" Image Change Detection Routine

The application of the change detection procedures was focussed on a much narrower group of classes than was the case with the medium resolution change detection routines. Two classes within the matrix stood out as indicators of potential weed problems areas, and the change detection routine on the high resolution imagery was restricted to measuring the level of change in these two classes. Several possible change detection procedures were investigated, including change vector analysis, and the modified change vector analysis (mCVA) developed by Nackaerts *et al.* (2005). However, it was felt that the level of change detection required in this study was such that a simple image differencing would highlight change sufficiently well. Using a post-classification comparison technique allowed advantage to be taken of its greater tolerance to image registration problems and atmospherics differences (Coppin *et al.*, 2004; Singh, 1989). This was important due to the problems experienced with the image registration process.

Therefore, the change detection methodology applied was the same as that utilised in the medium resolution study, except that only the "Classified" Image Change Detection module was utilised. A layout of the model is given in Appendix 7 below. In order for this module to be used, the vectorised data sets used to derive the matrix outputs had to be converted back to a raster format. However, only the two classes of interest were rasterised. Class 41 (Heavy Vegetation with no rows) and Class 42 (Heavy Vegetation with rows) were selected form the data sets by means of a definition query in ArcGIS 9.1, and converted to an Erdas Imagine image format using the feature to raster function in the ArcGIS Spatial Analyst extension. As part of the conversion process, a reclassification was also done to reclassify both classes to a common class, indicated by a value of "1".

A 2-class unsupervised classification was run on the reclassified data sets, using the Erdas Imagine 8.7 Classification module. The two classes were either "Class 1: Weed Area" (value = 1) or "Class 2: NoData". The maximum number of iterations was set to 6, with a convergence threshold set to 0.950. These data sets then served as the input into the change detection process, which utilised the add-on Assisted Change Detection model that is available from the ERDAS website (Erdas, 2005). The change detection procedures were run using any two consecutive images only. The outputs from the change detection process highlighted those areas where there had been a change **from** any other class **to** either Class 41 or Class 42, and supported Mas' (1999) findings relating to post-classification comparison, in that the nature of the change was given. If either of these classes were present in both images used in the change detection procedure, it did not display any change. In the same way, it did not display any data where neither class was present in both images. In this way it highlighted areas where there was an INCREASE in potential weed infestation, which was the important parameter of interest in this particular process.

5.1.3.7 Classification and Change Detection Accuracy Assessment

Because of the Vectorisation process it was decided to undertake the accuracy assessment on the unioned data set, as this was the final "classified" result. The accuracy assessment was undertaken using randomised points within every study site, as defined by the buffered compartment polygon (see 5.1.3.2 Image Sub-setting above). The random points were generated using the "Generate Random Points" facility in the Hawth's Analysis Tools, an add-on module for ArcGIS 9.1 (Beyer, 2005). A new set of random points was generated for every image date as well, in order to ensure a statistically valid process was applied. Using the knowledge of the study sites derived from field visits after every image acquisition, including referral to the digital photographs (see Appendix 10) and field notes taken during these visits, the actual and expected classes for every random point were recorded and Chi-Square tests for goodness of fit were applied to this data (Zar, 1984). User, Producer and Overall Accuracies were calculated on the error matrices derived from the comparison of the observed (i.e. classified image data) and reference (i.e. ground-truthed data) data (Khorram *et al.*, 1999).

Several different groupings of the data were tested, ranging from grouping all data into one pool, to testing each study site as a separate group, as well as testing various groupings of age classes. This was done to try and determine the grouping or set of data that provided the highest statistical probability of goodness of fit, i.e. the data set that provided the best classification result.

For the change detection accuracy assessment, the same error matrix methodology as the classification error matrix was applied (Khorram *et al.*, 1999), but with only two classes of interest being tested, *viz.* Weed Increase (Class=1) versus No Increase (Class=0). Two accuracy assessments were run. In the one test, called the "First Image vs. Second Image" test, random points were assessed for their status in the first-date image, compared to their status in the second-date image, based on the change detection error matrix theory described by Khorram *et al.*, (1999). This was done for both the "observed" and "reference" data. An example of how the change class was derived is given in Table 5.1.3. From these results, a change class was derived on which the chi-square test could be run.

A similar process was followed for the other accuracy assessment done using the actual Change Detection Results images (called the Change Detection Image accuracy assessment), in the same way a normal classification accuracy assessment is done, where the status of each point is derived for the observed and reference data.

Table 5.1.3 Example of "First Image vs. Second Image" Accuracy Assessment Input

		1st-Date Image			2nd Date Image				Change Image	
		(Actual)	(Expected)		(Actual)	(Expected)			(Actual)	(Expected)
Compt	Date	Observ.	Ref.	Date	Observ.	Ref.	CD Date		Observ.	Ref.
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	0	Dec-03	May-04	CD_WI	NC_NW
B025	Dec-03	0	0	May-04	1	0	Dec-03	May-04	CD_WI	NC_NW
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	1	1	Dec-03	May-04	CD_WI	CD_WI
B025	Dec-03	0	0	May-04	0	0	Dec-03	May-04	NC_NW	NC_NW

Where: CD_WI =Change: Weed Increase (i.e. weed increase from Image 1 to Image 2)

NC_NW = No Change: No Weed (i.e. no weed in Image 1 or Image 2)

NC_HW = No Change: Heavy Weed (i.e. heavy weed in Image 1 and Image 2)

Because of the relatively small area where change had occurred, compared to the total compartment area, use was made of the "Use Raster as Probability Distribution" function within the "Generate Random Points" facility in the Hawth's Analysis Tools (Beyer, 2005). This increased the likelihood of sample points being generated within the change areas, in order to provide a better test statistic, similar to the Special Effort Sampling method described by Khorram *et al.*, (1999). The change detection raster images were used as the input to the sample point selection.

Statistical analyses were undertaken in SPSS v11.51 (SPSS, 2002) and a Microsoft Excel add-in module, EZAnalyze (EZAnalyze, 2005).

5.1.3.8 Ground Cover Percentage Model

In addition to the "top-down" approach using the satellite imagery, it was also decided to test a "bottom-up" approach to be used as a means of deriving a threshold against which the observed weed or crop status could be compared, such that any compartment that exceeded the modelled ground cover percentage would then be flagged as having a potential weed infestation.

This model was based on the assumption that at any specified age, the crop should represent a certain percentage of the total ground cover. The balance of the ground cover should then be soil, slash or dead vegetation, on the basis that proper weed control measures had been applied. Where the vegetation signal was such that the ground cover percentage represented by that vegetation signal exceeded the threshold level for that crop age, it should indicate weed infestation, and be flagged appropriately. The concern with this approach is that it is extremely difficult to accurately model vegetation growth, due to the very large number of variables that can influence this growth. These include site conditions (slope, soil, aspect etc.), silvicultural operations, weather conditions, species and many other parameters. However, the aim was simply to model the general canopy development trend of a wattle stand over the first 18 months of growth in order to derive an "ideal" ground cover percentage for any specified age within this period. Knowing the age of a compartment at the time of an image acquisition would then allow one to derive this theoretical ground cover percentage for that compartment, and compare this to the calculated ground cover percentage derived from the imagery. An important concept in this process was that the crop row, not the individual tree, was of interest. This is particularly the case with early wattle growth as it grows in a "hedge" form rather than individual trees as is the case with pine and gum crops planted using seedlings or clones.

The model was developed by undertaking actual crown diameter measurements in 19 wattle compartments covering a total of 273.2 hectares. Circular sample plots, with a radius of 8.92m, were laid out on a grid pattern in every compartment, such that there were two plots/hectare. Each tree within a sample plot had its crown diameter measured twice, one measurement perpendicular to the crop row direction, and the other along the crop row direction. An assumption of a spherical crown form was made, in order to simplify the initial testing. These two measurements were then averaged, and the area of each crown calculated. A total crown area for each plot was then calculated by summing the crown areas of every tree in the plot. Using the plot size and the total crown area per plot, a ground percentage was calculated for each plot. These measurements were then plotted on a graph to derive the trend line, such that Age, on the x-axis, was plotted against Ground Cover Percentage, on the y-axis.

Regression analyses were run on the data in order to derive the trend line. Any ground cover percentage values which lay above the trend line could be considered to have a weed problem, while any values below the trend line could indicate sub-optimal crop growth.

5.2 Results and Discussion

5.2.1 Introduction

This section details the results achieved from the application of high resolution imagery to monitoring plantation forestry operations at a "within-stand" level. It was this level of detail that provided the greatest challenge to be solved in this project, and was due to the necessity of firstly identifying the stand crop, and then subsequently differentiating the crop from weed. This all had to be done in the first 12-16 months after planting, as after this period canopy closure occurs and the necessity of monitoring diminishes.

While several methodologies were tested, as described in the previous section on Methods, above, and the results obtained are briefly reported on, the emphasis is on the methods that proved most successful, and detailed descriptions of these results are discussed here. Two of the processes ran in parallel, the multi-spectral image classification and the panchromatic image textural analyses, prior to the resultant images from these processes being merged and additional processing done to obtain the final products (see Figure 5.1.1)

5.2.2 Multi-spectral Image Classification

The descriptions given in this section refer to the 2.4 m multi-spectral imagery prior to any enhancement effected through the textural analysis processes. Thus, the results obtained here were not final outcomes, but are given simply to explain why the textural analysis processes were required to improve the classification results.

5.2.2.1 Unsupervised Classification

Based on the success obtained with the medium resolution imagery, it was decided that only unsupervised classification processes would be utilised. The four classes defined by the unsupervised classification process were based on consistent visual estimates obtained during repeated ground-truthing visits, and were as follows:

Class 1: Shadow/Soil

Class 2: Soil/Slash

Class 3: Light Vegetation (<60% vegetation cover)

Class 4: Heavy Vegetation (>60% vegetation cover)

Class 1: Shadow/Soil tended to classify particular reflectance values which differed according to the age of the compartment. In stands less than six months, especially those that had been burnt, areas of very dark soil (usually where brushwood rows (see glossary) had previously been burnt) were classified as this class. However, once the crop rows were well established, usually in stands older than six months, the parts of the crop row, and the inter-row areas, that were in shade were classified as this class. Hence, it was not a pure class in all stages of the stand development. However, within the parameters described above, there was a consistency in the areas it classified, and was therefore considered a valid class.

It should be noted that wherever brushwood rows occurred as a result of harvesting operations, these caused a particular signature in the imagery that was noticeable for about a year after the felling operations. This was particularly the case once the rows were burnt, when these areas were consistently classified as Class 1: Shadow/Soil.

Class 2: Soil/Slash occurred in areas where either the new crop was too small to be identified as crop, or as the crop grew and the crop rows became more defined, the inter-row areas were classified as this class. There was no differentiation between pure bare soil and where residual slash was present. However, in terms of what was being investigated in this study, this had no effect on the results, as these conditions were considered the same class.

Class 3: Light Vegetation classified areas that had vegetation present, either in the form of young or sparse crop rows, or where weed was present to some extent, usually in the inter-row. However, it seldom indicated pure crop rows, but rather defined patches of light weed infestation, together with areas of true crop. This inability to define crop from weed was a critical factor in the decision to pursue textural analyses to improve these classification results.

Class 4: Heavy Vegetation classified those areas of major weed growth, as well as crop rows, particularly in stands that were older than 18 months. However, these classification results suffered from the same drawbacks as were experienced with the Class 3: Light Vegetation classifications. These limitations, however, did not mean that this classification process was of no value. On the contrary, these classifications gave accurate information regarding the areas where weed was most likely to be a problem, as well as indicating the areas of good crop growth, particularly as the crop approached an age of 16 months or more. Figure 5.2.2 is an example of the unsupervised classification results for one study site covering the full study period.

5.2.3 Panchromatic Image Texture Analyses

As was mentioned in section 5.1.3.4 above, although the multi-spectral resolution of 2.4 m is regarded as a high resolution (it is in fact that highest commercial resolution currently available from a satellite platform (Digital Globe, 2005)), it was still not sufficient to be able to separate crop from weeds on the basis of the crop rows. However, when viewing the 0.6 m resolution panchromatic imagery the crop rows were very apparent, particularly as the crop age exceeded four months (see Figure 5.2.3A). Even in very young stands, less than three months old, crop rows were often discernable where there had been a "line-cleaning" operation. This is where a clear row is hoed down to bare soil along the planting line. This line is usually 1 to1.5 m wide, with the centre line of this cleared area being a distance of 3 m perpendicular to the adjacent rows on either side (see Figure 5.2.1).

Figure 5.2.1 Line-cleaning along crop row

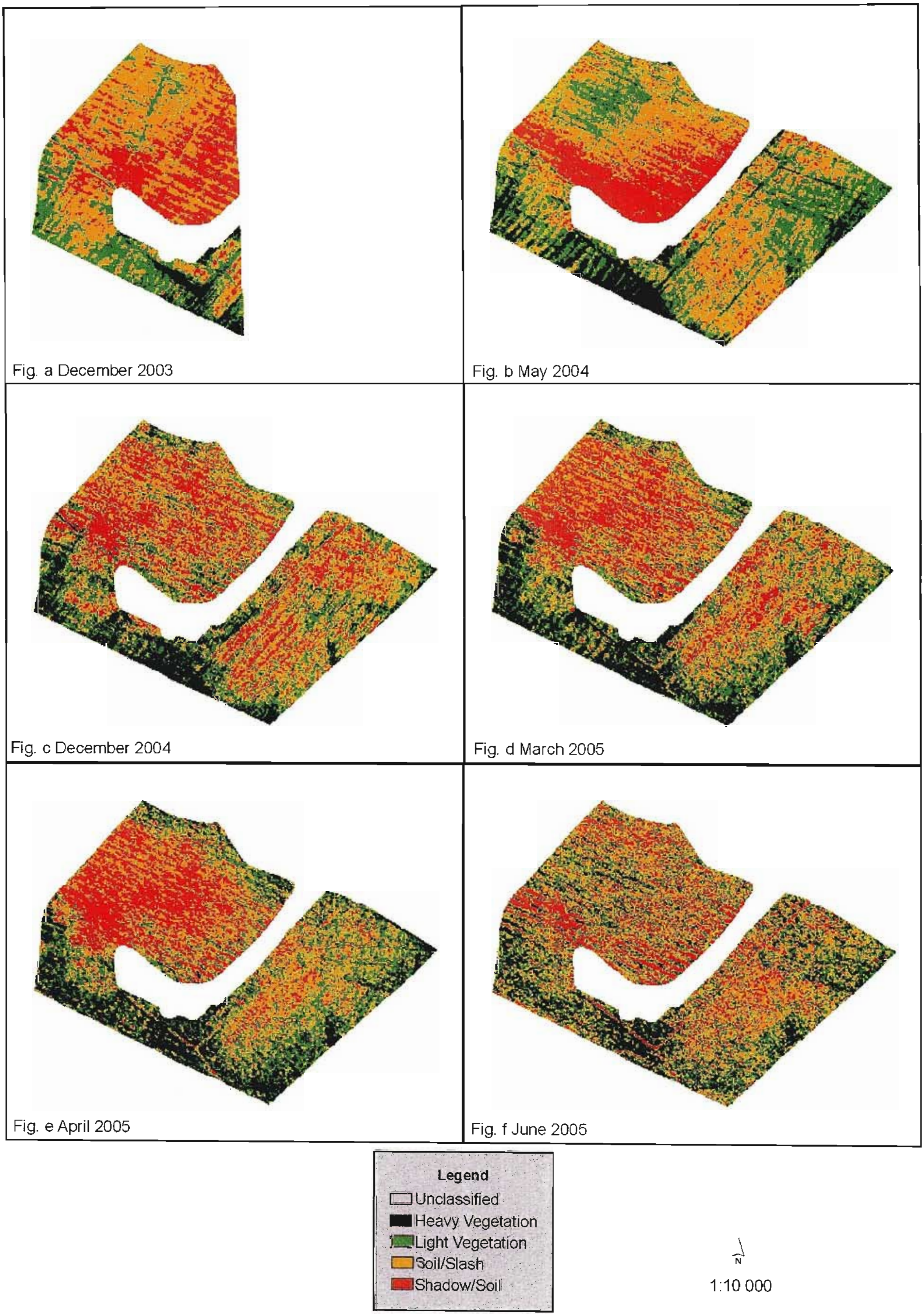


Figure 5.2.2 Example of Four-Class Unsupervised Classification (Compt. E022)

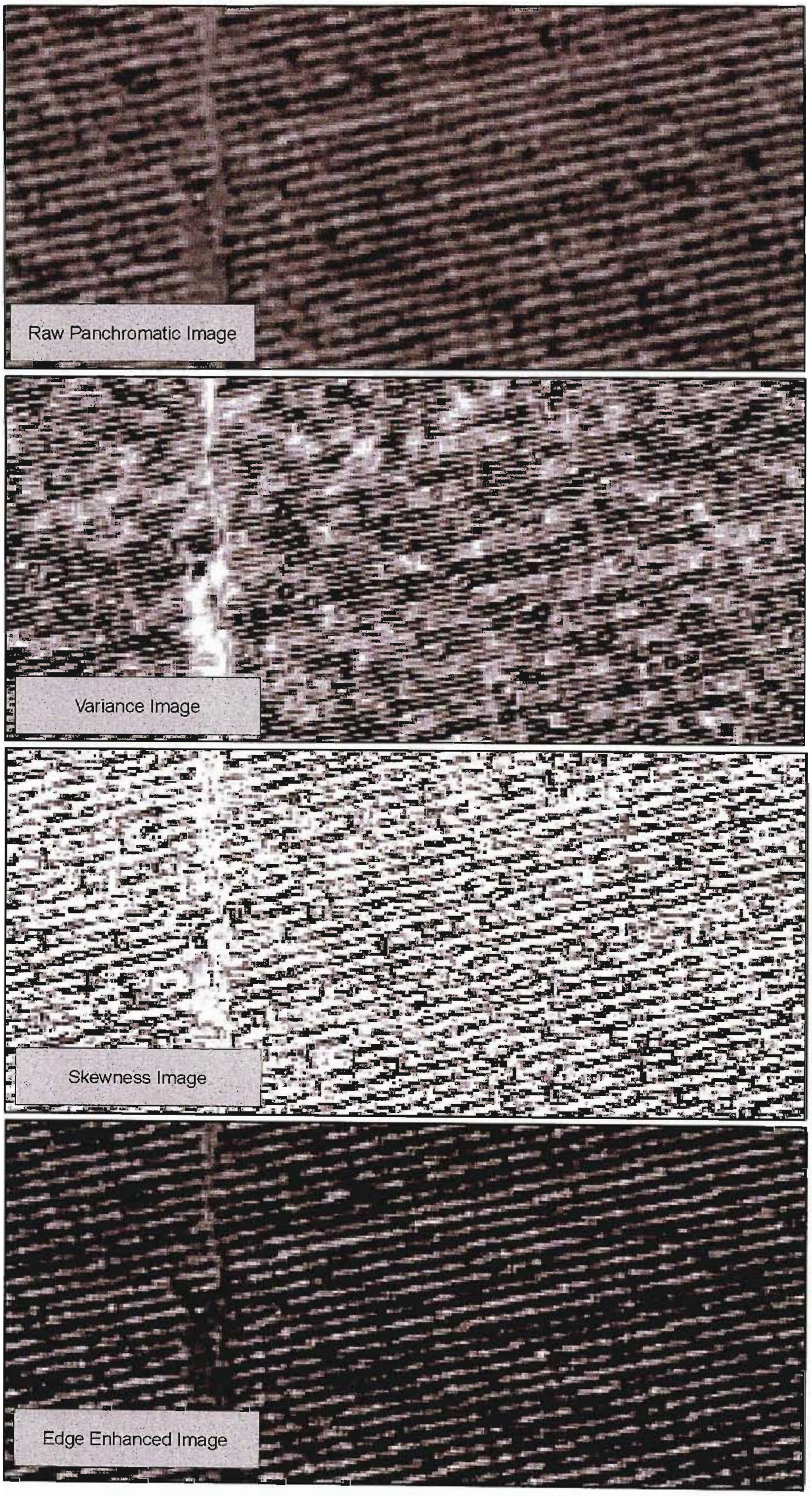


Figure 5.2.3 Comparison of Texture Analyses Processes (part of Compt. E014)

The purpose of this hoed row is to remove any initial weed competition as the plant crop becomes established, following its planting (if a seedling) or germination (where seed is sown directly into planting line – this occurs only in wattle establishment). It was this visibility of the crop rows that was believed to be a key element in being able to separate crop from weed within the vegetation signal, provided a means could be found to merge the two differing resolution datasets. The most effective methodology to utilise this characteristic was to apply some form of textural analysis (Tso and Mather, 2001; Lillesand and Kiefer, 2000; Janssen, 2000) to enhance the lineation features of the crop rows. Three textural parameters and a frequency domain parameter, Fourier Analysis, were tested in order to determine an optimal methodology. The textural parameters were edge enhancement, variance and skewness (see Figure 5.2.3), and were applied using a convolution window, the size of which was determined using semivariograms, as detailed in section 5.1.3.4 above.

5.2.3.1 Texture Analysis – Variance

The Variance function produced images that were smoothed and tended to group areas that had a similar texture into clumps. As such it actually did the opposite of what was intended, in terms of trying to define the crop rows more sharply (see Figure 5.2.3B). Only where the rows were already very sharply defined in the original image was there some definition of the rows, and then only at certain stages of the crop development. It was also noted that the convolution window size played a role in the amount of row definition that occurred. The only lineation that this methodology did highlight was the brushwood rows and roads within the compartments. However, this was due more to the fact that these features had sufficient uniformity within themselves to cause the smoothing function to group them together, rather than the lineation itself. What could be deduced from this test was that the crop rows themselves did not possess sufficiently uniform texture such that a smoothing function could uniquely identify them. Although not tested in this study, this methodology could play a role in trying to identify concentrations of vegetation growth that might indicate potential weed patches. It might also have application if one wanted to obtain a measure of stand uniformity. An inspection the histograms of the variance texture images showed that the bulk of the values were concentrated close to the origin. Even when the values were stretched, however, one gained little additional information. As this methodology did not assist in identifying crop rows it was discarded as a suitable enhancement method.

5.2.3.2 Texture Analysis – Skewness

The Skewness function did define linear features much more effectively, except that it tended to define the inter-row areas, rather than the crop rows as was expected (see Figures 5.2.3C; 5.2.4). This was probably due to the inter-row signal being the more dominant signal, particularly in the younger stages of the study sites. With the planting rows being 3 m apart, and early canopy width along the rows being less than 1.5 m, this meant that the inter-row signal would be about 60-70% of the signal range. This would result in the Skewness statistic highlighting this. However, this factor caused it to also be discarded as a suitable enhancement technique for the aims of this study. It could however have useful applications in some situations. As with the Variance function, the histogram data were again concentrated close to the origin, but stretching the values did not add much clarity or information to the resultant image. Up to the age of 12 months the Skewness function tended to define the image data into clumps, similar to the way the Variance function defined the data. After this age threshold, the lineation patterns became much more defined, as the inter-rows areas became more definitive.

5.2.3.3 Texture Analysis – Edge Enhancement

In contrast to both the above mentioned procedures, the Edge Enhancement function was able to detect the lineation virtually as soon as it had occurred in the form of a line-cleaning operation. In some cases this was even prior to the crop emerging as a distinctive feature. While other strong linear features such as the brushwood rows (both unburnt and burnt) were also highlighted, this did not hide the crop rows, as was the case with the other two processes (see Figure 5.2.3D). It also tended to maintain the crop row definition well into canopy closure, with the oldest study site at 26 months still having some indication of the crop rows. This methodology was by far the most successful at defining the crop rows (see Figure 5.2.5), and so was selected as the textural analysis method of choice for this study, which was based on the premise that crop rows could be used to assist in separating crop from weed. The edge enhanced images were the input to the two- class classified "Row; No Row" images (see section 5.1.3.4).

As mentioned in the literature review, various studies have attempted to produce tree counts based on individual tree identification (e.g. Jacobs and Mthembu, 2001; Wulder *et al.*, 2000), with minimum crown dimensions of 1.5 m required for 1 m

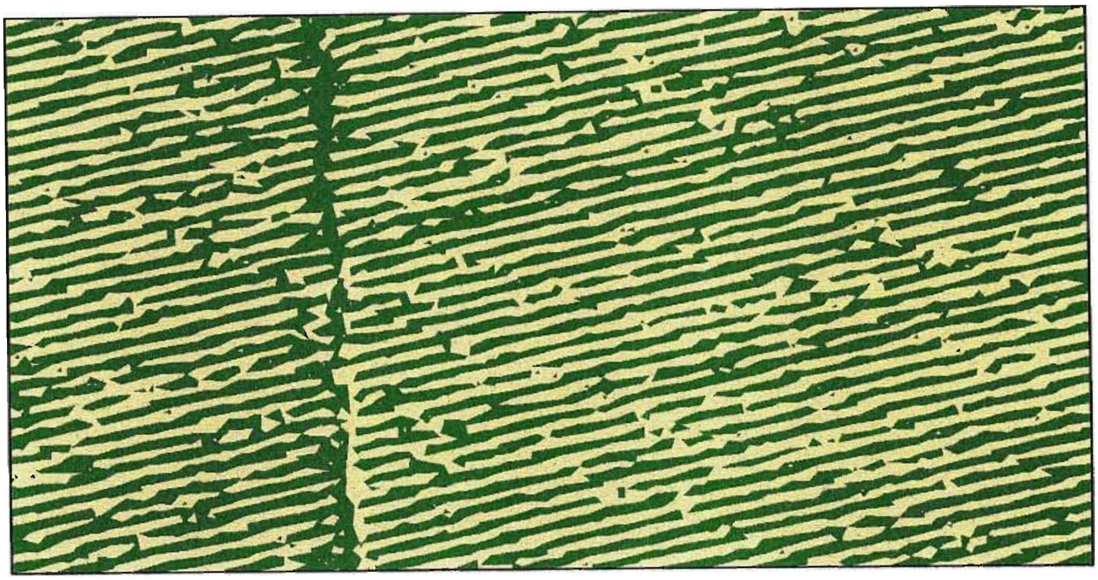


Fig.A Row Delineation

Fig.B Skewness Image highlighting Inter-Rows

Figure 5.2.4 Illustration of Skewness Image highlighting Inter-Rows (part of E014)

Skewness image overlain on Row Delineation image. Green is Crop Row; Black is Skewness image highlighting inter-row areas.

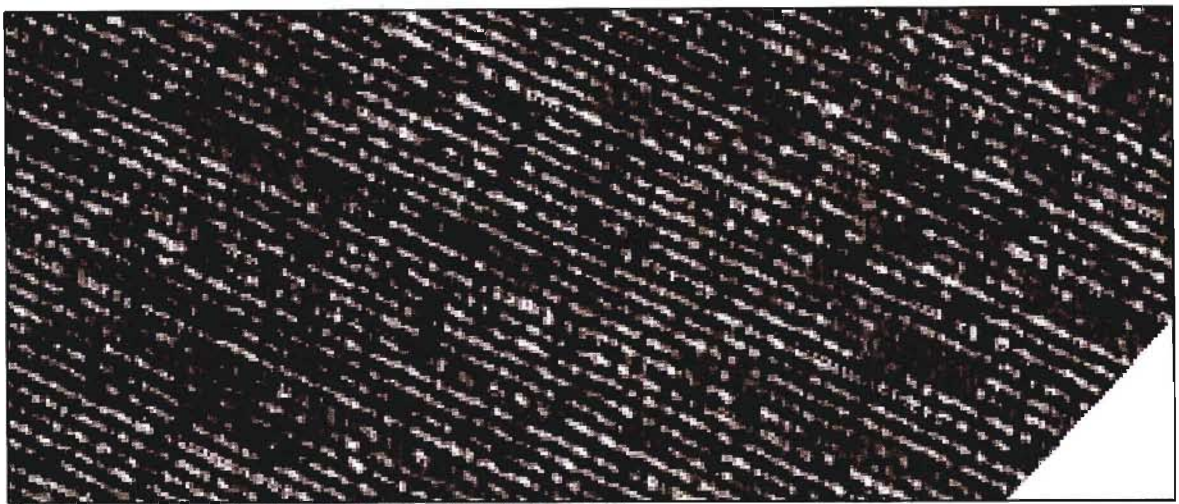


Fig. a Edge Enhanced Panchromatic Image (Bright pixels = Rows)

Fig. b Two CLass Reclassified Image highlighting Crop Rows

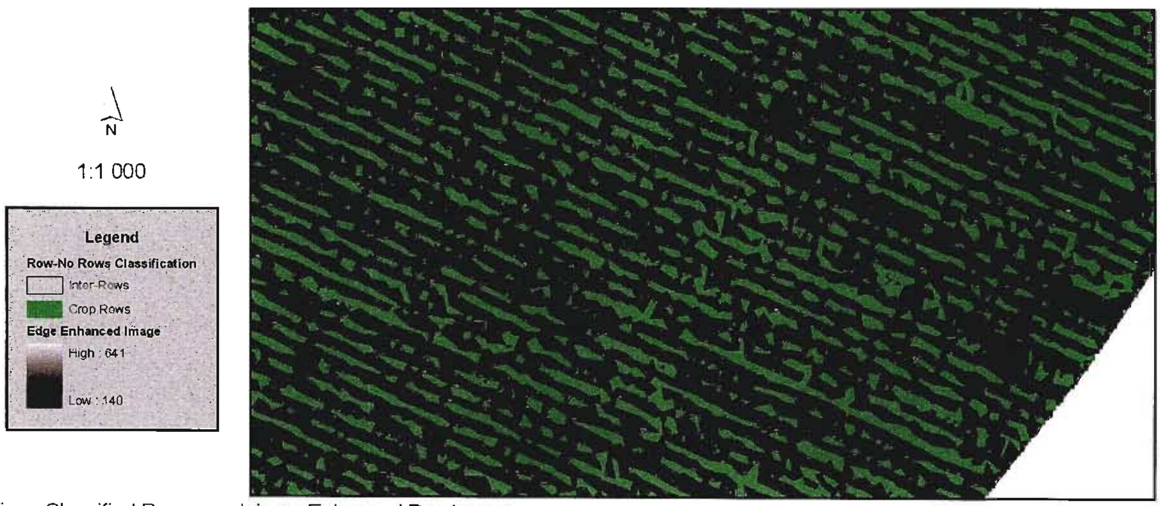


Fig. c Classified Rows overlain on Enhanced Pan Image

Figure 5.2.5 Illustration of Classified Row Image highlighting Crop Rows (part of Compt E014)

Fig. c shows Classified Row Image (Fig.b) overlain on Edge Enhanced Pan Image (Fig.a) spatial resolution imagery being reported (Wulder *et al.*, 2000). However, because this study focussed on the tree row as a whole, rather than individual tree crowns, successful identification of tree rows was achieved where crown dimensions were much smaller than figures reported in these other studies. This was a one of the unique findings of this study.

5.2.3.4 Frequency Domain Analysis – Fourier Transform

The Fourier Transform analysis did not provide a distinctive result that could be used to delineate the crop rows, although there were indications that crop rows were being identified to some extent. However, a great deal of processing was required to separate the "noise" signal from the crop row signal and in the end the edge enhancement process provided a much quicker and simpler solution, which was in agreement with Jensen (1996) regarding the application of the Fourier Transform.

What was particularly noticeable in some of the Fourier images was the presence of one or more frequency components (shown up as white dots), usually in some form of a linear arrangement, and based on the theory of the Fourier Transform, could indicate the frequencies associated with repeating lines across the image (Jensen, 1996). It was thought that these frequency components could indicate the crop rows. However, this was not investigated in this study, but could possibly warrant further investigation (see section 5.3.2, Recommendations, below).

5.2.4 Classification of Vectorised Data Sets

The unsupervised classification results of the multi-spectral images were then vectorised, while the edge enhanced panchromatic images were reclassified to two-class "Row, No Row" images, which were also then vectorised. These two vectorised data sets were then unioned to derive the final classified data sets, based on a matrix of values derived from the two input data sets. The results of these outputs are discussed in this section. Figures 5.2.6 to 5.2.9 are of compartment E022, and show examples of these classification results, illustrating the typical classification patterns. However, the same results were obtained from the other study sites.

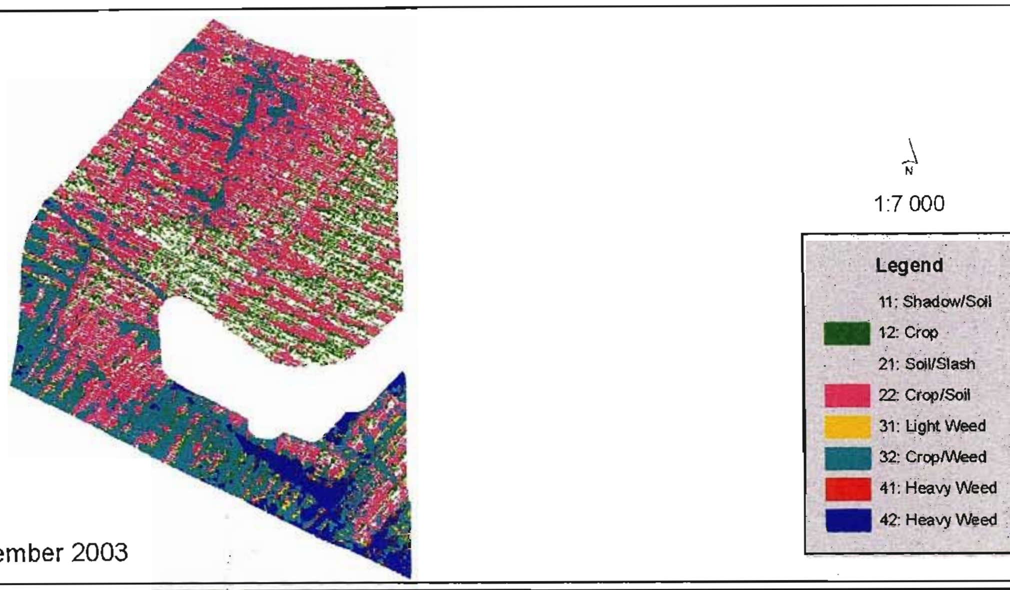


Fig. a December 2003

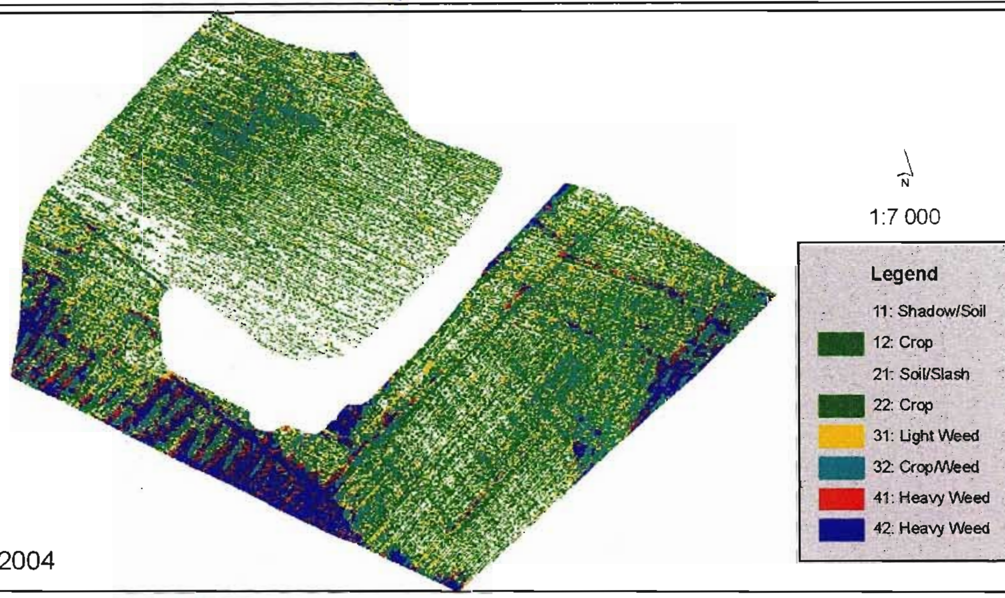


Fig. b May 2004

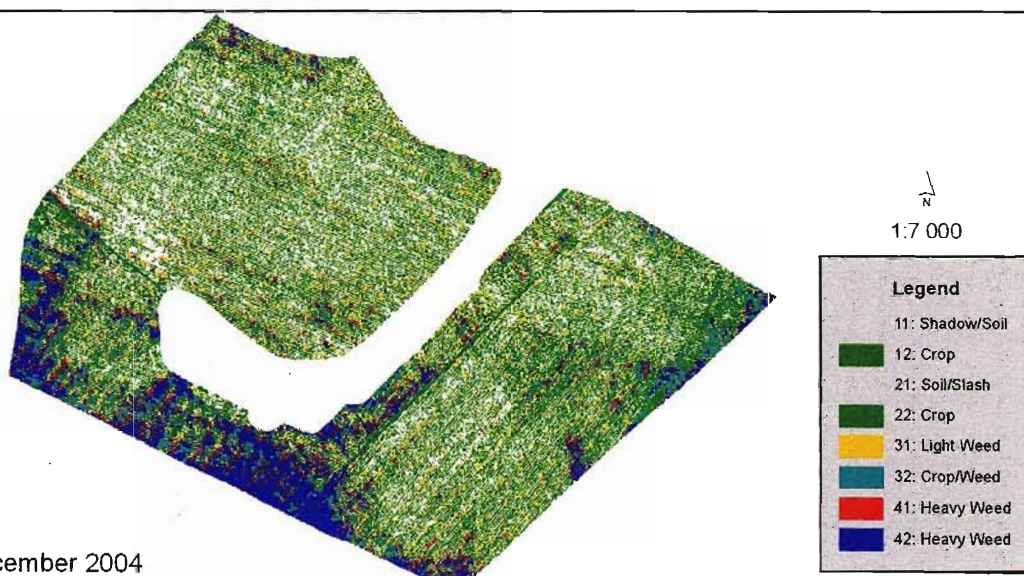


Fig. c December 2004

Figure 5.2.6A Example of Weed Potential Classification (First and Second Phases) of a study site (Compt. E022)

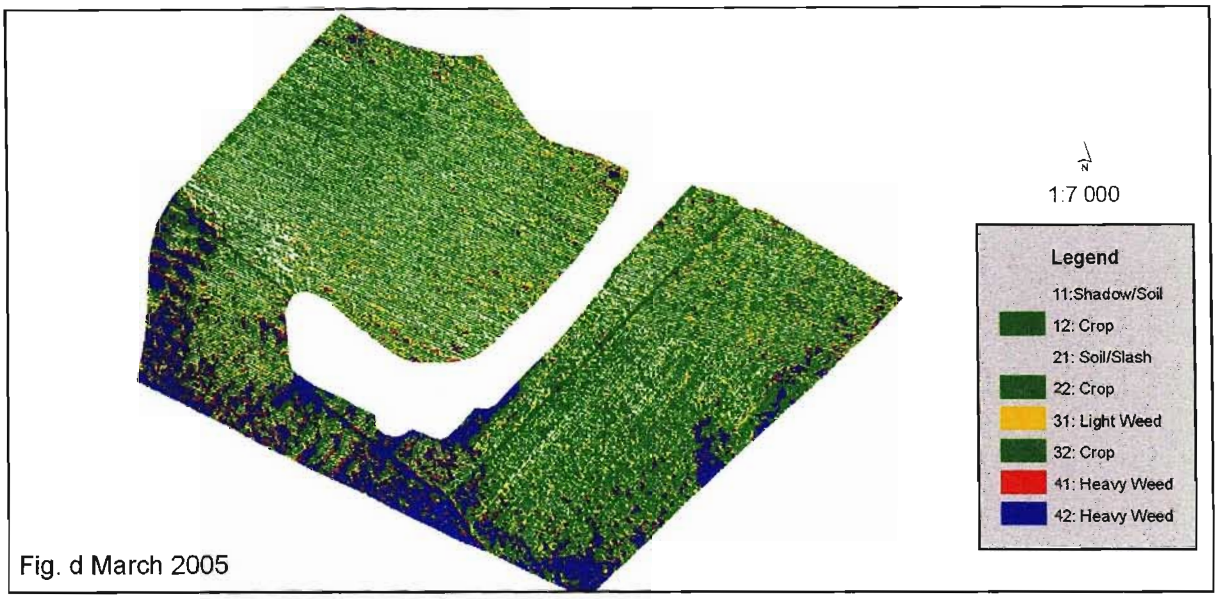


Fig. d March 2005

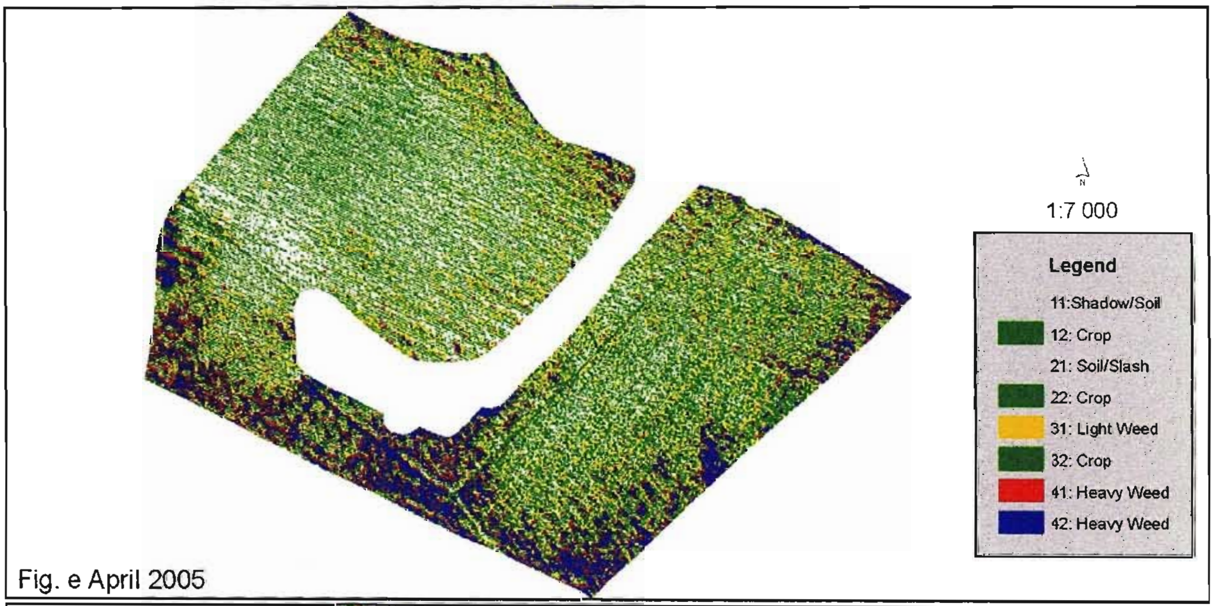


Fig. e April 2005

Fig. f June 2005

Figure 5.2.6B Example of Weed Potential Classification (Third and Fourth Phases) of a study site (Compt. E022)

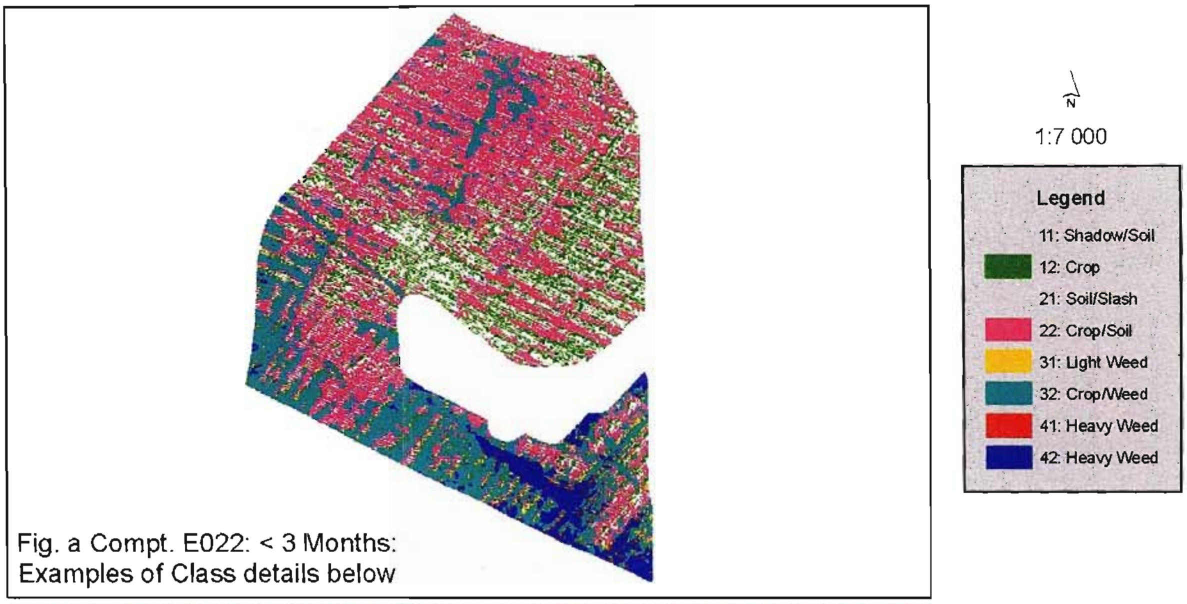
5.2.4.1 Classification Process

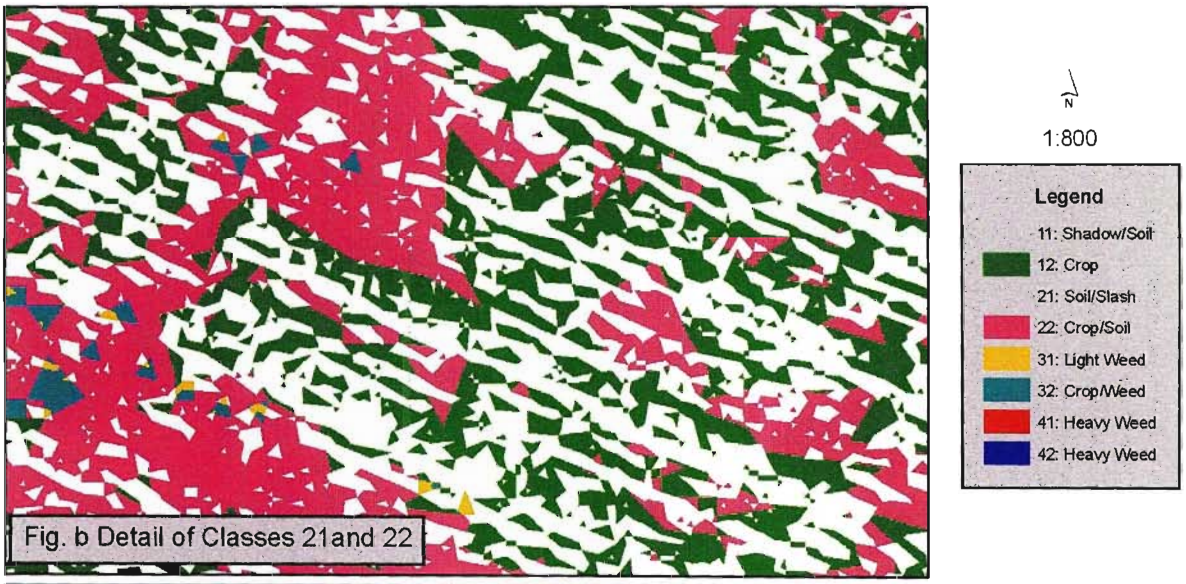
The objective of this process was to extract the vegetation signal of the multi-spectral classified imagery in combination with the crop row information derived from the higher resolution panchromatic imagery in order to define areas of potential weed growth, as opposed to crop growth. The logic behind this process was predicated on the basis that a vegetation signal within a crop row would be crop, as opposed to weed, while vegetation signals outside of a crop row should be weed. Where there was little or no vegetation signal but there was a row defined, this should indicate crop as well. A soil/slash signal outside of a crop row should indicate a weed-free environment, and hence not be a potential weed problem area. Based on these criteria, the classification matrix (see section 5.1.3.5 above) was assigned the following status:

Class 11: Shadow/Soil
Class 12: Crop
Class 21: Soil/Slash
Class 22: Crop (Crop/Soil in stands <3 months)
Class 31: Light Weed
Class 32: Crop (Crop/Weed in stands <3 months)
Class 41: Heavy Weed
Class 42: Heavy Weed

Three phases in this classification process were noted, each slightly different from the others. This was a function of the degree of crop row delineation, with classifications showing decreasing cross-classification from the very young stands up to an age between 14 and 16 months, after which cross-classification again increased.

In stands less than three months old, there tended to be insufficient differentiation between crop, soil and weed. The evidence for this was seen in the fact that instead of delineating the crop rows, Classes 22 and 32 tended to group larger areas beyond the true crop row, forming more clumped areas. This resulted in a cross-classification between Class 21 and Class 22, such that Class 22 was a mixed class of Crop and Soil (see Figure 5.2.7b). Where the vegetation signal was stronger a similar cross-classification occurred between Class 31 and Class 32, where the latter class was a mixed class of Crop and Weed (see Figure 5.2.7c). Having noted this,





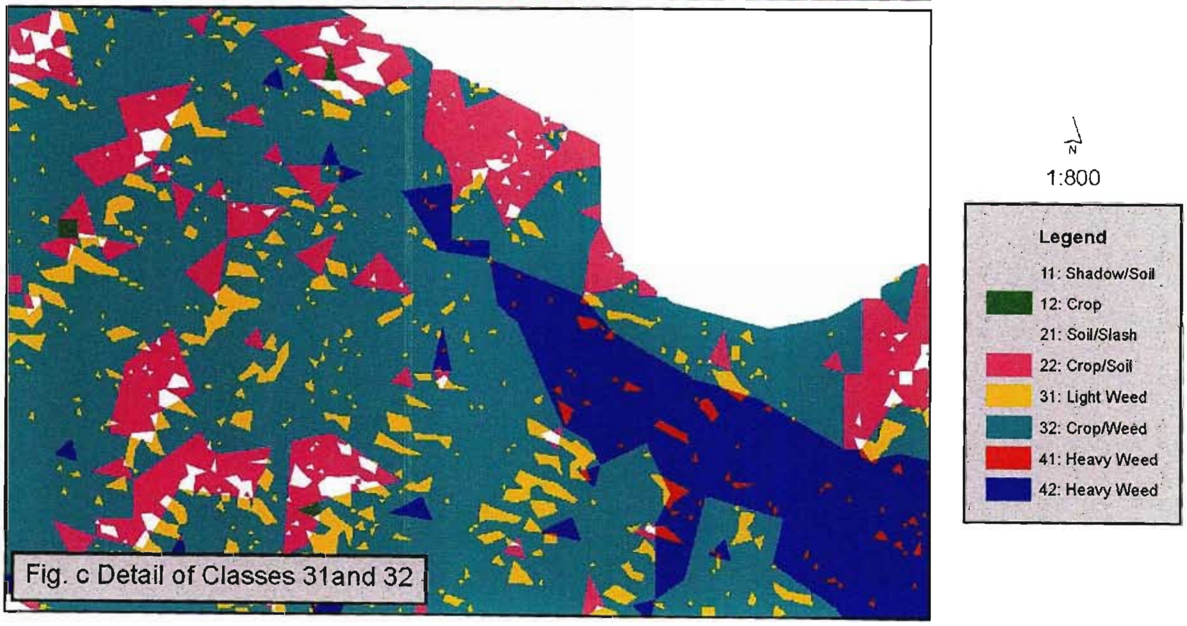


Figure 5.2.7 Close-up of Classes 21; 22; 31 and 32, at < 3 Months Phase

there were areas of pure crop where the crop row definition was clear enough to be highlighted by the edge enhancement process (see Figure 5.2.7b). Although present in subsequent images, this cross-classification had greatly decreased in extent, such that it became a minor class. Although not a pure class, Class 32 did provide useful indications of where the early stages of potential weed problems could occur, particularly as the Class 42: Heavy Weed areas were often associated with this Crop/Weed class. A similar pattern occurred with the Class 42: Heavy Weed, where these areas tended to be concentrated into clumps rather than being in rows, as was expected (see Figure 5.2.7c). However, in the vast majority of these areas, heavy weed growth did occur, and this class was highly indicative of problematic weed growth. Although crop areas did occur within these areas, the weed growth was such that it diluted the crop row delineation and so became more indicative of weed rather than crop. This cross-classification was only of concern in these very young stands, when there was very little crop row development (with any crop crown diameter generally being less than 20 cm). Crop row definition could only be derived from the delineation effect caused by the line cleaning operations.

In stands from three to about twelve months old, crop row delineation was much clearer, with Class 22 now able to effectively define crop areas (see Figure 5.2.8b). There was still a tendency for there to be some cross-classification between crop and weed in those areas classified as Class 32. However, where this was the case, it correctly identified those areas that did have a weed concentration, and was therefore not an inaccurate classification. Again, this class tended to extend beyond the true crop row and form clumps, although these clumps were smaller in extent than was the case in stands less than three months old (see Figure 5.2.8c).

This classification is what would be expected from a newly established stand as it grows, but it was encouraging to see that the classification process mirrored this development. What was clear from the classification results was that one could immediately tell where there were potential weed problem areas, particularly where there were patches of heavy weed. This would certainly provide useful management information to field staff that needed to monitor operations such as weed status, a finding supported by Shaw's (2004) research. It also gave some visual indication of where stands were under-performing, for instance due to poor stocking or sub-optimal growth (see Figure 5.2.8b).

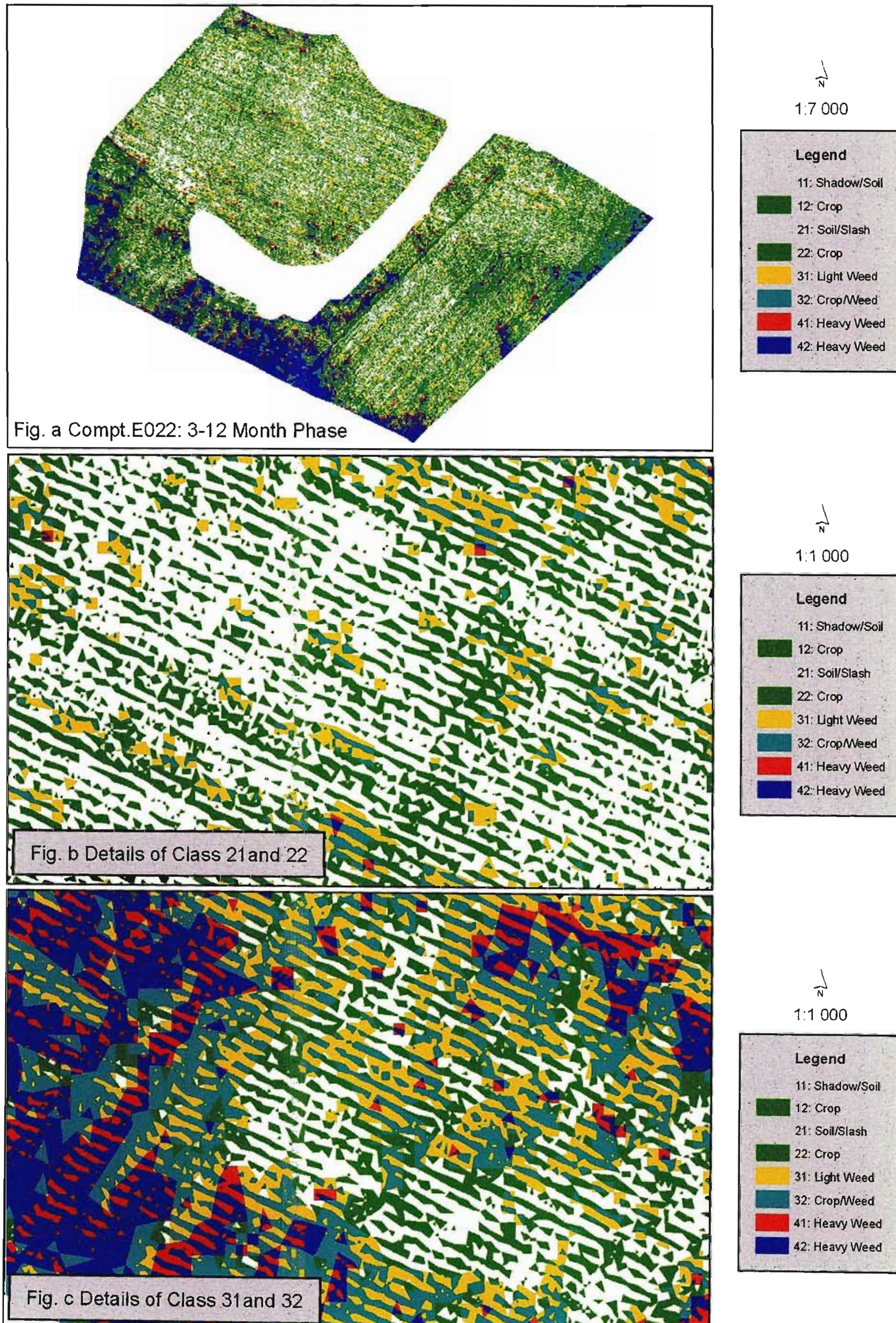


Fig. a Compt.E022: 3-12 Month Phase

Fig. b Details of Class 21and 22

Fig. c Details of Class 31and 32

Figure 5.2.8 Close-up of Classes 21; 22; 31 and 32, at 3-12 Months Phase

These could then be investigated on the ground and corrective action applied where possible. It was also interesting to note the degree to which the crop row lineation could be determined, and how early on it could be characterised. This was seen in the fact that Classes 12 and 22 correctly classified crop, as opposed to weed. Areas classified as Classes 11 and 21 did not have weed growth, but were either shadow or soil (see Figure 5.2.8b). The third phase of the classification occurred in compartments that were between twelve months and about 16 months old (it should be noted that these age ranges were not definitive, as these phases occurred at slightly different ages on different sites, due to factors such as site quality, silvicultural treatments etc.). In this stage the classifications were more pure, with the crop signature being much more definite (see Figure 5.2.9b). The anomaly with Class 42: Heavy Weed continued in this phase, with this class being particularly indicative of heavy weed patches, rather than crop, as was anticipated (see Figure 5.2.9c). For this reason, it was classed as heavy weed, rather than crop. However, it was still beneficial to keep it a separate class, rather than merging it with Class 41; Heavy Weed, as when viewed spatially one could obtain useful information about the distribution of the weed infestation as well as some crop row information (see Figure 5.2.9c). Once again the principle of the row delineation identifying crop as opposed to weed proved successful, and even more so than was the case in the younger stands of the first and second phases.

Once compartments were older than fourteen to sixteen months after establishment, greater cross-classification between the weed and crop classes tended to occur, with some areas being classified as weedy, but which were in fact crop. This was due to canopy closure occurring, with a subsequent loss of clear row delineation, but with a strong vegetation signal being present. Therefore, the cut-off limit for successful identification of weed potential was set at fourteen months. With the onset of canopy closure, weed infestation is no longer a major concern, and so the need to monitor this falls away. Thus this cross-classification is not a problem. Based on these results, the optimal period in which to identify potential weed infestation was from three to fourteen months after establishment.

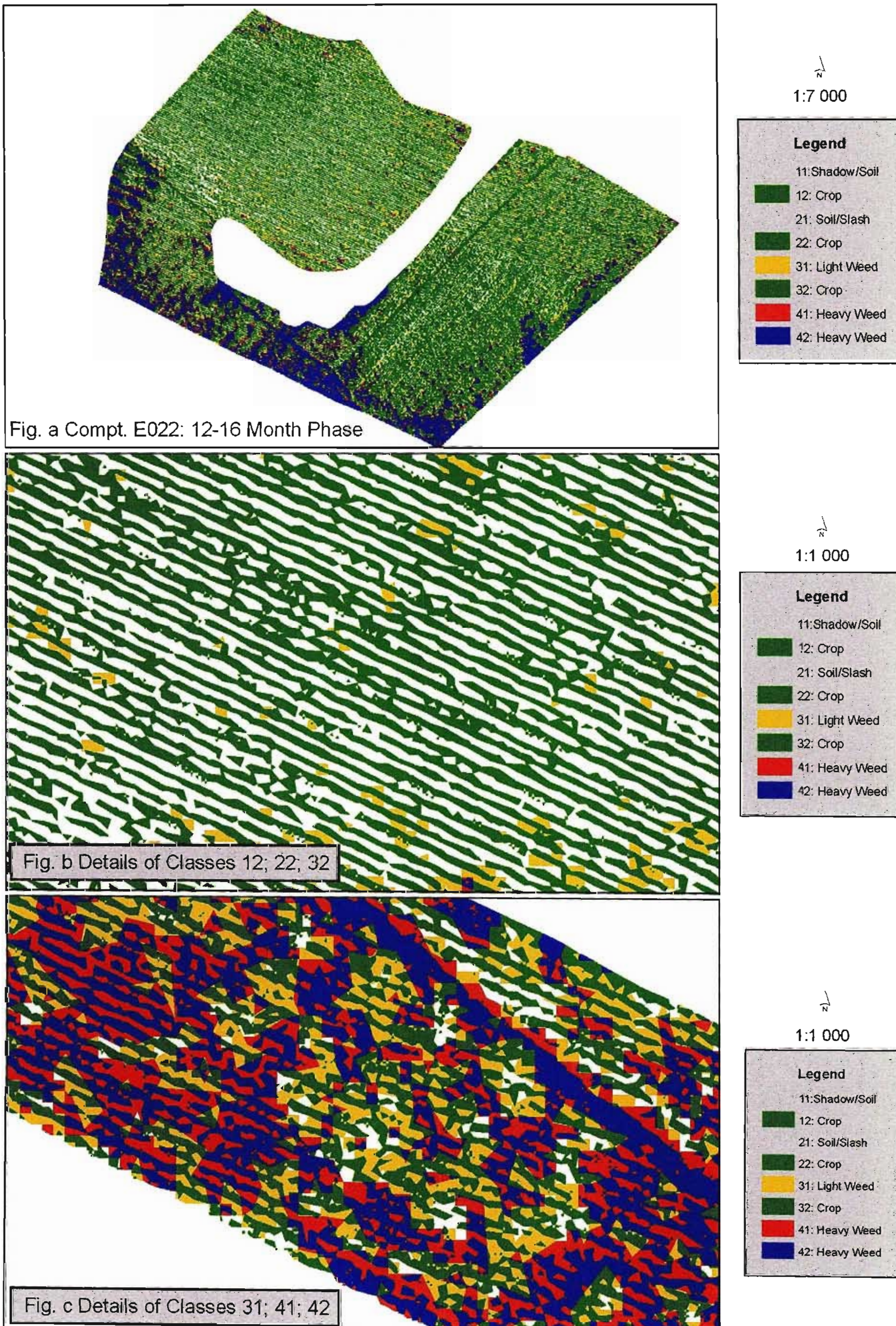


Fig. a Compt. E022: 12-16 Month Phase

Fig. b Details of Classes 12; 22; 32

Fig. c Details of Classes 31; 41; 42

Figure 5.2.9 Close-up of Classes 21; 22; 31 and 32, at 12-16 Months Phase

5.2.4.2 Accuracy Assessment of Classification Results

Accuracy assessment routines were performed on several combinations of the classification data sets, as well as on each of the individual study site classification results. The chi-square test result of the observed frequencies of all the data pooled together was significant ($P < 0.0001$) using a one-tailed test, with an overall accuracy of 80.8% (see Table 5.2.1); while a kappa of 0.748 was attained (see Table 5.2.2).This indicated a good level of agreement, and highly significant ($P < 0.001$), with a T-test result of 21.88. A contingency coefficient of 0.837 was obtained, compared to a highest possible value of 0.894 for a 5x5 table (see Table 5.2.2), showing a very high level of association between the observed and reference classes.

Results of the accuracy assessments done on the pooled data of compartments between three and fourteen months supported the finding that this was the optimal period to identify potential weed infestations. The overall accuracy for this grouping was 82.5% (see Table 5.2.3). In addition, the chi-square test results of the 3-14 Month pooled data also proved to be significant using the one-tailed test, while a kappa score of 0.767 was achieved, together with a contingency coefficient of 0.841(see Table 5.2.4). This latter measure again indicated a very high degree of association between the observed and reference classes. Gray *et al.* (2004) reported classification accuracies ranging from 49% to 69%. However, that study attempted to identify weeds by type, rather than simply differentiating weed from crop, which was the focus of this study. Nilson *et al.*'s (2001) study on the effect of successional changes in vegetation cover on ground reflectance values found it difficult to quantify these effects. However, this study was able to quantify the effect such vegetation succession had, in that it was able to calculate the area affected by weed infestation, as well as the change in crop cover.

Compartments less than three months old only achieved an overall classification accuracy of 73.3%, while compartments older than fourteen months achieved a slightly better overall classification accuracy of 80.0%. The chi-square was significant ($P < 0.0001$), indicating a good fit between the reference and observed data.

Table 5.2.1 Chi-Square; User; Producer and Overall Accuracies for Pooled Data

Results Report - Chi Square Table of Observed and Reference						**All Compartments**		
			Reference					
Observed	**Crop**	**Heavy Weed**	**Light Weed**	**Shadow/ Soil**	**Soil/ Slash**	**Row Total**	**Incremental Chi Square**	**User Accuracy**
Crop	64	3	3	0	1	**71**	93.455	90.1%
expected	*25.212*	*8.114*	*10.722*	*4.927*	*22.024*			
Heavy Weed	8	24	0	0	2	**34**	119.915	70.6%
expected	*12.073*	*3.886*	*5.135*	*2.359*	*10.547*			
Light Weed	2	0	32	0	2	**36**	153.019	88.9%
expected	*12.784*	*4.114*	*5.437*	*2.498*	*11.167*			
Shadow/Soil	5	0	1	17	10	**33**	105.315	51.5%
expected	*11.718*	*3.771*	*4.984*	*2.290*	*10.237*			
Soil/Slash	8	1	1	0	61	**71**	100.703	85.9%
expected	*25.212*	*8.114*	*10.722*	*4.927*	*22.024*			
Columns Total	**87**	**28**	**37**	**17**	**76**	**245** ***Grand Total***	**572.408** ***Chi Square Total***	**80.8%** ***Overall Accuracy***
Producer Accuracy	73.6%	85.7%	86.5%	100.0%	80.3%			
						DF	16	
						P	0.000	
The chi square test result of the observed frequencies of your variables was significant using a one-tailed test								

Table 5.2.2 Kappa and Contingency Coefficient for Pooled Data

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.837			.000
Measure of Agreement	Kappa	.748	.033	21.882	.000
N of Valid Cases		245			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Table 5.2.3 Chi-Square; User; Producer and Overall Accuracies for 3-14 Months Pooled Data

Results Report - Chi Square Table of Observed and Reference **Compartments 3-14 Months old**

Observed	Crop	Heavy Weed	Reference Light Weed	Shadow/ Soil	Soil/ Slash	Row Total	Incremental Chi Square	User Accuracy
Crop	46	2	2	0	1	**51**	60.967	90.2%
expected	*19.125*	*5.419*	*7.650*	*3.506*	*15.300*			
Heavy Weed	3	15	0	0	1	**19**	88.111	78.9%
expected	*7.125*	*2.019*	*2.850*	*1.306*	*5.700*			
Light Weed	2	0	20	0	2	**24**	68.841	83.3%
expected	*9.000*	*2.550*	*3.600*	*1.650*	*7.200*			
Shadow/Soil	5	0	1	11	4	**21**	74.615	52.4%
expected	*7.875*	*2.231*	*3.150*	*1.444*	*6.300*			
Soil/Slash	4	0	1	0	40	**45**	93.894	88.9%
expected	*16.875*	*4.781*	*6.750*	*3.094*	*13.500*			
Columns Total	**60**	**17**	**24**	**11**	**48**	**160** ***Grand Total***	**386.428** ***Chi Square Total***	**82.5%** ***Overall Accuracy***
Producer Accuracy	76.7%	88.2%	83.3%	100.0%	83.3%			
						DF	16	
						P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 5.2.4 Kappa and Contingency Coefficient for 3-14 Months Pooled Data

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.841			.000
Measure of Agreement	Kappa	.767	.040	17.901	.000
N of Valid Cases		160			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

5.2.4.3 Quantification Process

An important difference between the medium resolution image processing, which was purely qualitative in its approach, and the high resolution image processing was the quantification of the classes achieved during the classification stage. This was successfully achieved in this process, and Table 5.2.5 illustrates a sample of this quantification. The primary focus of this process was to be able to highlight compartments in which the potential weed infestation exceeded a specified threshold. This had important management implications, as silvicultural contractors are paid to maintain compartments in a weed-free status at all times, under a "Plant-to-Canopy" (PTC) system. Although field audits are done at specified times according to a schedule, this study sought to determine whether weed status could be independently and quantifiably monitored through remote sensing techniques.

Table 5.2.5 Illustration of Ground Cover Area and Percentage Quantification

	Compartments < 3 months			Compartments 3-12 months					Compartments > 12 months				
	Class	Dec. 2003		Class	May. 2004		Dec. 2004		Class	Mar. 2005		Apr. 2005	
Compt.	Description	Ha	%	Description	Ha	%	Ha	%	Description	Ha	%	Ha	%
B025	Soil/Slash	3.2	36.8	Soil/Slash	3.3	37.8	3.5	40	Soil/Slash	3	34.3	2.3	26.3
B025	Crop/Soil	1	11.5										
B025	Crop	0.3	3.4	Crop	1.6	18.3	1.5	17.2	Crop	2.7	30.9	3.6	41.2
B025	Crop/Weed	1.2	13.8	Crop/Weed	1.1	12.6	1.3	14.9					
B025	Light Weed	1.5	17.2	Light Weed	1.6	18.3	1.4	16	Light Weed	1.5	17.1	1.2	13.7
B025	Heavy Weed	1.5	17.2	Heavy Weed	1.3	14.9	1.1	12.5	Heavy Weed	1.5	17.1	1.7	19.4
C025	Soil/Slash	4.8	26.8	Soil/Slash	5.8	32.4	7.3	40.8	Soil/Slash	6.7	37.4	5.5	30.7
C025	Crop/Soil	3.6	20.1										
C025	Crop	1.4	7.8	Crop	4.2	23.5	4	22.3	Crop	6.6	36.8	7.2	40.2
C025	Crop/Weed	4.6	25.7	Crop/Weed	4.8	26.8	2.2	12.3					
C025	Light Weed	0.8	4.5	Light Weed	1.6	8.9	2.4	13.4	Light Weed	2.6	14.5	2.7	15.1
C025	Heavy Weed	2.8	15.6	Heavy Weed	1.5	8.4	2.1	11.7	Heavy Weed	1.9	10.6	2.4	13.4
D002	Soil/Slash	5.2	58.4	Soil/Slash	3.3	37.1	3.9	43.9	Soil/Slash	3.3	37.1	2.8	31.5
D002	Crop/Soil	0.8	9										
D002	Crop	0.4	4.5	Crop	1.2	13.4	2.6	29.2	Crop	3.2	35.9	3.2	36
D002	Crop/Weed	0.8	9	Crop/Weed	2	22.5	1.3	14.6					
D002	Light Weed	0.9	10.1	Light Weed	1.1	12.4	0.9	10.1	Light Weed	1.4	15.7	1.4	15.7
D002	Heavy Weed	0.8	9	Heavy Weed	1.5	16.9	0.2	2.2	Heavy Weed	1.2	13.5	1.5	16.9
E022	Soil/Slash	4.4	25.8	Soil/Slash	9.2	32.4	10.1	35.5	Soil/Slash	7.1	25	9	31.7
E022	Crop/Soil	6	35.3										
E022	Crop	1.8	10.6	Crop	6.6	23.3	6.7	23.6	Crop	13.9	49	10.3	36.2
E022	Crop/Weed	3.4	20	Crop/Weed	5.9	20.8	4.2	14.8					
E022	Light Weed	0.5	2.9	Light Weed	3.9	13.7	4.1	14.4	Light Weed	3.1	10.9	4.1	14.4
E022	Heavy Weed	0.9	5.3	Heavy Weed	2.9	10.2	3.4	12	Heavy Weed	4.4	15.5	5	17.6
E023	Soil/Slash	3.9	32.5	Soil/Slash	3.2	26.6	2.7	22.5	Soil/Slash	3.1	25.8	3.5	29.2
E023	Crop/Soil	2.5	20.8										
E023	Crop	0.5	4.2	Crop	3.3	27.5	4	33.4	Crop	5.9	49.1	4.8	40
E023	Crop/Weed	3.2	26.7	Crop/Weed	2.7	22.5	2.4	20					
E023	Light Weed	1.1	9.2	Light Weed	1.1	9.2	1.4	11.7	Light Weed	1.5	12.5	1.6	13.3
E023	Heavy Weed	0.8	6.6	Heavy Weed	1.6	13.3	1.5	12.5	Heavy Weed	1.4	11.6	2	16.7
E025	Soil/Slash	4.7	40.5	Soil/Slash	3.4	29.3	4.4	38	Soil/Slash	5.9	50.9	3.7	31.9
E025	Crop/Soil	0.9	7.8										
E025	Crop	0.3	2.6	Crop	2.7	23.3	2.4	20.7	Crop	2.7	23.3	4.4	38
E025	Crop/Weed	1.8	15.5	Crop/Weed	2	17.2	1.7	14.7					
E025	Light Weed	2.1	18.1	Light Weed	1.6	13.8	1.7	14.7	Light Weed	1.7	14.7	1.6	13.8
E025	Heavy Weed	1.9	16.4	Heavy Weed	1.8	15.5	1.3	11.2	Heavy Weed	1.4	12.1	2	17.3

A significant advantage of this approach was that in addition to the quantification of infestation levels, it could also highlight the spatial distribution of these infestations within the compartments (i.e. where the weed patches occurred within the stand). The table also illustrates the reduction in the number of classes that occurred over time, as the classification improved with increasing row definition. Class 11: Shadow/Soil and Class 21: Soil/Slash were sufficiently similar as to constitute a single class for the purposes of this table, and so the areas reported were combined under the Soil/Slash class. With the improved classification as the crop grew over the three to twelve month period, the cross-classification between crop and soil did not occur, resulting in Class 22 better defining crop, and so was combined with Class 12 to identify the crop area. After twelve months, the crop/weed cross-classification was no longer evident, with vegetation now being classified as crop or weed (light or heavy), and the areas of each class reported as such.

Each classification class had the area, in hectares, and the percentage that this represented across the compartment calculated. According to the specifications laid down for a PTC compartment, no weeded area may exceed 5% of the total compartment area (Da Costa, 2005a). Using this limit, it was a simple task to highlight compartments exceeding this specification. Although there are other PTC requirements in terms of weed type, weed height and similar specifications, these could not be measured by the remote sensing techniques applied in this study.

5.2.5 Change Detection Results

5.2.5.1 Assisted Change Detection: "Classified" Images

Unlike the medium resolution image processing, only one change detection methodology was appropriate for the change detection procedures applied to the high resolution imagery. In part, this was due to the fact that the bulk of the answers were actually provided by the classification process, and the change detection procedures simply highlighted areas of weed increase when comparing consecutive images. The focus of the change detection routine was only on changes in Class 41 and/or Class 42 (Heavy Weed), as these classes highlighted heavy weed infestations. With this in mind, the results were successful in highlighting where there had been an increase in weed infestation in the second image when compared to what was reported in the first image. This is reflected in the results of the change detection error assessment. Table 5.2.6 provides the chi-square as well as the user and producer accuracy assessments for the change image (i.e. observed versus reference data). An overall accuracy of 84.4%, together with a significant chi-square test result (P<0.0001), was achieved on the pooled data of "First Image vs. Second Image" test, while an overall accuracy of 88.3% and a significant chi-square result (P <0.0001) was achieved on the pooled Change Detection Images accuracy assessment (see Table 5.2.8). These match the accuracies achieved by Varjo and Folving's (1997) study. Overall, the accuracies attained were higher than generally quoted in the literature (e.g. Zukowskyj *et al.* (2001); Rowlinson *et al.* (1999); Singh (1989)) but it should be remembered that there was only one class of change being measured, and so is not strictly comparable.

Where the same area had a heavy weed infestation in both images, nothing was recorded. Neither was any indication given of a reduction in weed infestation. However, as the point of interest was the increase in weed, this was not a problem.

Not only did it answer the question of was there any increase in weed infestation, but it highlighted where it had occurred, and by how much, measured in hectares. Figure 5.2.10 illustrates the results of the change detection process, where the colours represent areas of weed increase between two consecutive images.

Table 5.2.6 Chi-Square; User; Producer and Overall Accuracies for "First Image vs. Second Image" Change Detection Pooled Data

Results Report - Chi Square Table of Observ. and Ref.

"First Image vs. Second Image" Change Detection

Reference

Observed	**CD_WI**	**NC_HW**	**NC_NW**	**Row Total**	**Incremental Chi Square**	**User Accuracy**
CD_WI	145	8	10	**163**	1.552	**89.0%**
expected	*139.456*	*9.961*	*13.583*			
NC_HW	3	2	0	**5**	10.195	**40.0%**
expected	*4.278*	*0.306*	*0.417*			
NC_NW	6	1	5	**12**	17.870	**41.7%**
expected	*10.267*	*0.733*	*1.000*			
Columns Total	**154**	**11**	**15**	**180** ***Grand Total***	29.617 ***Chi Square Total***	**84.4%** ***Overall Accuracy***
Prod. Accuracy	**94.2%**	**18.2%**	**33.3%**			
				DF	4	
				P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 5.2.7 Kappa and Contingency Coefficient for First Image vs. Second Image" Change Detection Pooled Data

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.376			.000
Measure of Agreement	Kappa	.286	.095	4.995	.000
N of Valid Cases		180			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Thus, such imagery could focus management attention into the most appropriate areas, resulting in a reduction in the necessity of having to check the whole area, as well as reducing the risk of missing problematic areas. Discussions with field and technical staff revealed that this latter point was of concern, as it was fairly common

Fig. a. Change Detection: Weed increase; Dec 2003 - May 2004

Fig. b. Change Detection: Weed increase; May 2004 - Dec 2004

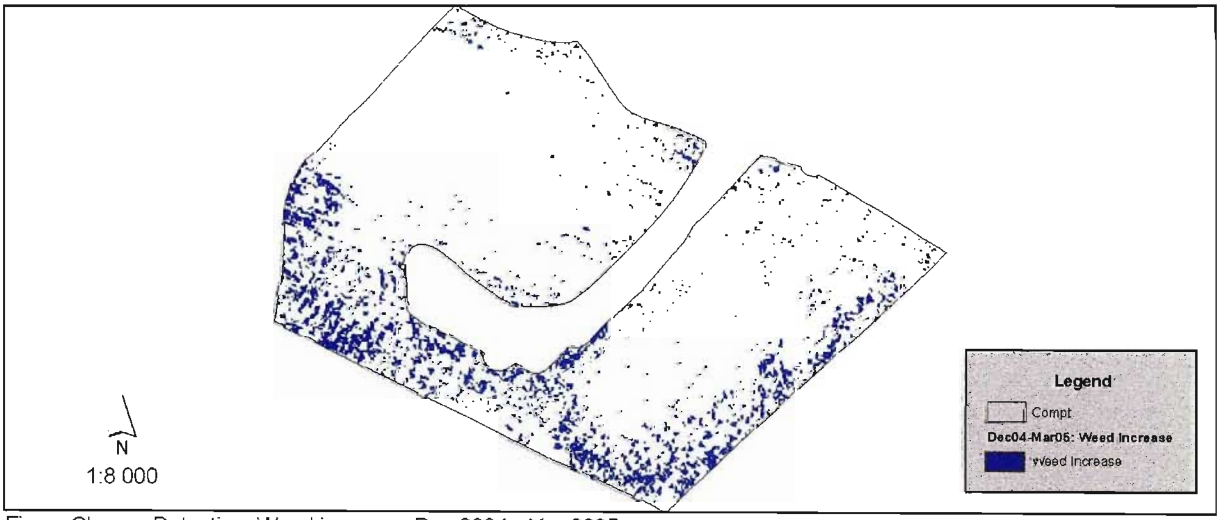


Fig. c. Change Detection: Weed increase; Dec 2004 - Mar 2005

Figure 5.2.10 Illustration of Change Detection for Weed Increase

Table 5.2.8 Chi-Square; User; Producer and Overall Accuracies for Change Detection Images Pooled Data

Results Report - Chi Square Table of Observ. and Ref.

Change Detection Images

Reference

Observed	**CD_WI**	**NC_HW**	**NC_NW**	**Row Total**	**Incremental Chi Square**	**User Accuracy**
CD_WI	154	8	10	**172**	1.000	**89.5%**
expected	*150.022*	*8.600*	*13.378*			
NC_HW	0	1	0	**1**	19.000	**100.0%**
expected	*0.872*	*0.050*	*0.078*			
NC_NW	3	0	4	**7**	23.862	**57.1%**
expected	*6.106*	*0.350*	*0.544*			
Columns Total	**157**	**9**	**14**	**180** *Grand Total*	43.862 ***Chi Square Total***	**88.3%** ***Overall Accuracy***
Prod. Accuracy	**98.1%**	**11.1%**	**28.6%**			
				DF	4	
				P	0.000	

The chi square test result of the observed frequencies of your variables was significant using a one-tailed test

Table 5.2.9 Kappa and Contingency Coefficient for Change Detection Images Pooled Data

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.443			.000
Measure of Agreement	Kappa	.285	.108	5.442	.000
N of Valid Cases		180			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

for some areas within compartments to be overlooked during weed control operations, particularly areas that were adjacent to unplanted areas where there was confusion as to the actual compartment boundary (Da Costa, 2005b). This also supports the fundamental tenet of this research that the effective use of remote sensing imagery and techniques can allow a more focused management of forestry operations, which in turn could produce cost savings, particularly in terms of supervisory time, and allow more effective management of resources (Shaw, 2004). Even in those operations where these techniques might not produce definitive results, the adage, “You get what you measure” applies, since the knowledge that one’s work could be monitored very often produces a greater attention to quality assurance.

5.2.6 Comparison between Classification Results and Operational Database Records

In order to determine the degree to which the image classification results could be used to validate operational records in the management database, comparisons were made between the operations recorded in the database against the compartment status as derived from the classified imagery results.

Table 5.2.10 shows an example of the typical results obtained from the database comparison. Despite weed control operations occurring during the period covered by the image acquisitions, data derived from the imagery indicated increases in weed cover in almost all cases. In several cases, there was a reduction in heavy weed growth following a weed control operation, but a slight increase in light weed growth for the same period. An example of this occurred in compartment C025, during the period from December 2003 to May 2004, where there was a decrease in heavy weed from 15.6% to 8.4% following line cleaning and inter-row weeding operations carried in March and April 2004. However, the light weed category in the image classification results increased from 4.5% to 8.9% in the same period. A similar pattern was recorded over the period from December 2004 to March 2005 in this compartment following another line cleaning operation recorded in January 2005.

Table 5.2.10 Example of Database Comparison Results (Operations vs. Ground Cover Status)

	Recorded Operations - Database							
	Operation Dates							
Compt	**Operation**	**Jan-04**	**Mar-04**	**Apr-04**	**Aug-04**	**Sep-04**	**Jan-05**	**May-05**
C025	LineClean	Y	Y		Y		Y	
C025	InterRow			Y		Y		
C025	Spacing					Y		
E022	LineClean	Y						
E022	InterRow		Y	Y		Y		
E022	Spacing			Y				Y
E023	LineClean	Y						
E023	InterRow		Y	Y		Y		
E023	Spacing			Y				Y

Change in Ground Cover Status - Image Data						
	Acquisition Dates					
Ground Cover	**Dec-03**	**May-04**	**Dec-04**	**Mar-05**	**Apr-05**	**Jun-05**
Weed Status	Slight decrease	Increase				
Crop Status	Increase	Decr.				
Weed Status	Increase					
Crop Status	Increase				Decrease	
Weed Status	Increase					
Crop Status	Increase				Decrease	

One operation where a consistent result was noted were the second or third spacing operations, which generally occurred at an age of 15-16 months, where there was a definite reduction in crop cover recorded by the imagery following these operations in all cases where these operations were recorded in the database (see Table 5.2.10). However, the same could not be said for the first spacing operation, which generally occurred at an age of about 4-5 months. This was probably due to the same reasons given above concerning the difficulties of accurate classifications at this age. An exception to this result occurred in a compartment that had a first spacing operation at a much later age of 9 months, where a reduction in crop cover was recorded by the imagery.

Overall, the results were somewhat disappointing, in that it was very difficult to draw conclusive results as to the accuracy of the database entries, especially for weed control operations recorded during the first three months of the crop being established. This was probably due to the difficulties experienced in obtaining accurate classification of crop as opposed to weed, as discussed above (see section 5.2.4.1). This was further complicated by the rapid crop development at this stage counter-acting a reduction in weed signal that would normally attend a weed control operation. Another complication in this particular process was that image acquisition did not correspond very well with the actual weed control operations being done. In several compartments within the study area a weed control operation was done in September, but the next image was only acquired in December, when there would already have been weed growth subsequent to the last weed control operation recorded in the database. The effect of chemical weed control operations generally take several weeks to become evident, which would make it difficult to derive an accurate result from image analysis, as this would be dependent on when the image was acquired in relation to the herbicide application. Manual weed control operations have an immediate effect, but these operations tend to occur over a smaller extent (e.g. only a narrow band along a crop row) than herbicide applications, and so are less evident in terms of image analysis.

Another factor complicating this process is the timing of the actual recording of the operations in the database, as the operations might extend over more than one month, but are only recorded once completed. In view of all these issues it was not possible to draw conclusive results as to the efficacy of the previous weed control operations.

5.2.7 Results of Theoretical Ground Cover Model

When considering this process it should be borne in mind that this was an exploratory study to test the proof of concept of whether a model could be developed that would provide suitable thresholds against which weed infestations could be identified, rather than trying to produce conclusive results. This fact had an impact on the procedures applied, as is discussed below.

The results of this test are shown in Figure 5.2.11, and the model that best fitted the results of the trial was a linear trend line, with the following equation:

$$\% \text{ Crop Cover} = 0.0387x_{age} + 0.0151 \qquad \text{(Equation 5.2.1).}$$

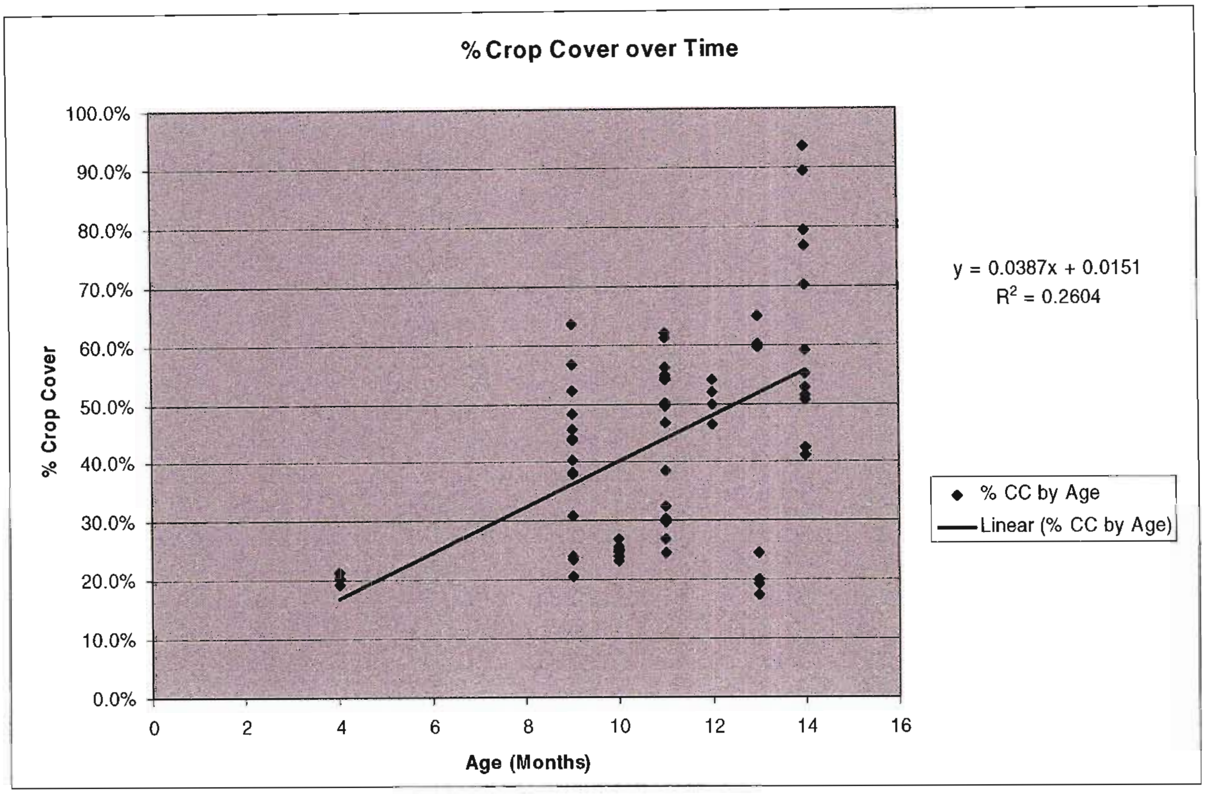


Figure 5.2.11 Graph of the Theoretical Ground Cover Model

Overall, with an R^2 value of only 0.26, the initial results of the theoretical ground cover model were disappointing, and did not provide a sufficiently robust model that could be used to derive threshold values that accurately reflected the ground cover status of the crop at specified ages. This was chiefly due to the large degree of variance inherent in seedling wattle crops, as was illustrated by 14 month old crop having an individual canopy area ranging from 0.2 m^2 to 8.3 m^2. This was also seen in other age classes, but to a slightly smaller degree, e.g. the 9 month class individual canopy area ranged from 0.2 m^2 to 5.5 m^2. However, there were many other sources of variance, including site, microclimate, genetics etc. that contributed to the poor model fit.

It was seen that the field measurements resulted in generally higher ground cover percentage values being obtained than those derived from the imagery. This was particularly the case as the age of the stands increased. For example, the average ground cover percentage derived from the imagery for 14 month old stands was 39% compared to a value of 53% derived field measurements. The reason for this discrepancy was due to the nature of the crown structure, which tended to be denser closer to the centre of the crown, but much thinner on the edges. This resulted in the imagery identifying much less crown area than was measurable on the ground. The full widths of the crowns were however measured in the field measurements, leading to a higher canopy cover figure for these results.

In order to relate the image-measured ground cover to the field-measured ground cover, the data was then further interrogated to determine whether there was a predictable relationship between the ground cover observed in the field (GC_{field}) and that obtained from the image data (GC_{image}). A visual inspection of plots of GC_{field} against GC_{image}, as well as GC_{field} against Age indicated that there was a relationship. One would expect this to be the case, as there should be an increase in ground cover with an increase in age, and that this relationship should be reflected in both the field data and the image data. After testing various regression models that utilised GC_{image}, Age and the interaction between these two, either independently or jointly, it was found that a simple linear regression of GC_{field} against a combined variable, Age x GC_{image} gave the best results, with an adjusted R^2 value of 0.95 (see Appendix 8), i.e.

$$GC_{field.predicted} = 0.1569 + 0.07579 * (Age \times GC_{image}) \qquad \text{(Equation 5.2.2).}$$

GC_{field} values were regressed against Age to derive a model that would predict $GC_{threshold}$ (see Figure 5.2.12). The fitted model had an R^2 value of 0.98, with the following form:

$$GC_{threshold} = 0.0544 * Age + 0.0613 \qquad \text{(Equation 5.2.3).}$$

Thus, ground cover values obtained from an image would be applied to equation 5.2.2 in order to calculate GC_{field}. These values would then be checked against the threshold value predicted by equation 5.2.3 for the same age, and where greater than the ground cover value for that age, it would then be assumed that weed was a problem and needed to be verified infield.

One area of concern in this whole process was that, at the time that the field measurements were able to be done, there were an insufficient number of suitable compartments within the study area that could be measured for the crown diameter field measurements. It was therefore necessary to do these measurements at sites outside of the imaged area, resulting in the problem whereby the field measurements were not identical to the image data. However, while being fully cognisant of this problem and its possible implications, it was decided to test the results obtained on the basis of this being a "proof of concept" study in order to provide a basis for a much more rigorous and comprehensive study to further develop accurate threshold values.

Despite the problems encountered with this process, it is anticipated that there would be a better correlation with seedling crops, which tend to be somewhat more uniform, particularly gum and pine seedling crops.

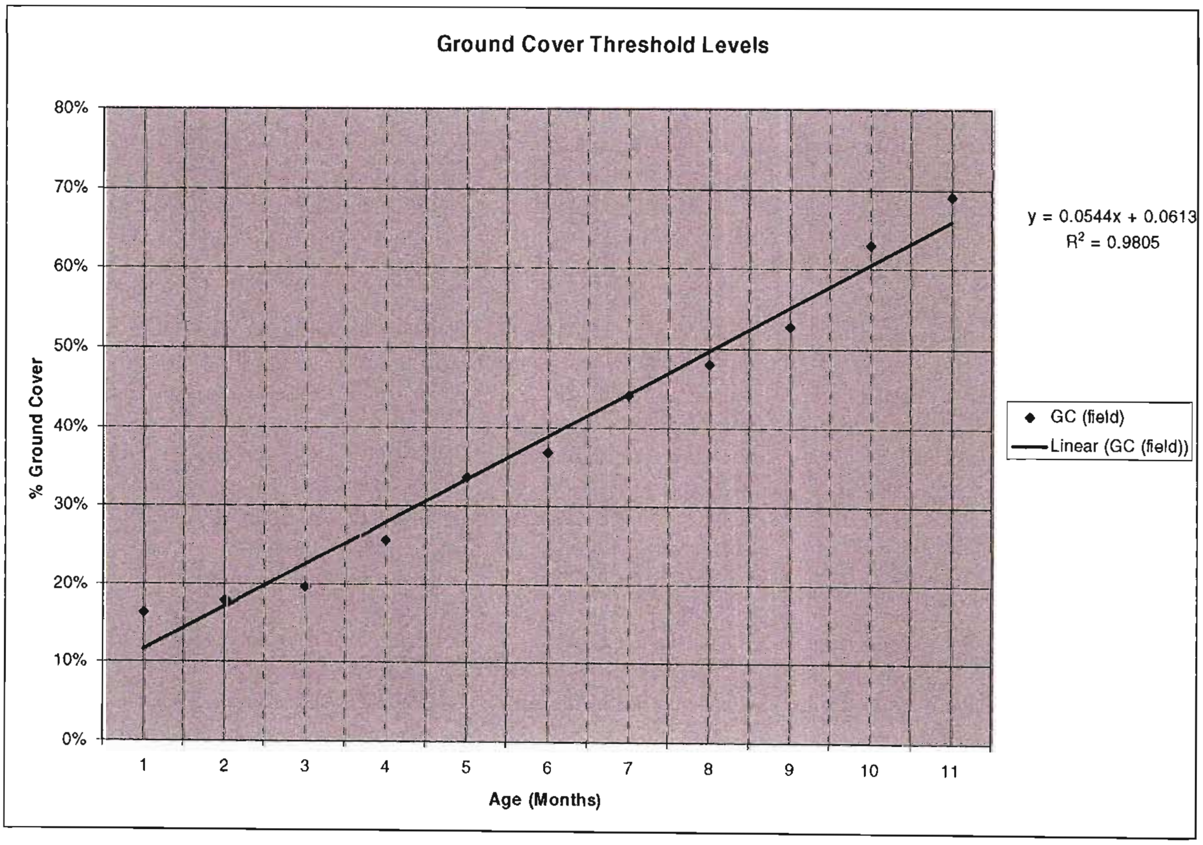


Figure 5.2.12 Threshold Model

5.2.8 Classification Results of Eucalyptus Coppice Stand

5.2.8.1 Detection of Weed Infestation

As previously mentioned, only one suitable *Eucalyptus* stand was available within the study area during the period covered by the imagery. However, although it was not possible to derive conclusive results because of this, there were strong indications that could be surmised from the results obtained. This would obviously require further research to confirm these empirical results.

In terms of the classification results, it was very apparent that the classes derived for the wattle stands did not fit the *Eucalyptus* stand very well. Being a coppice crop, with a very well developed root system from the previous crop, it grew a great deal faster than the equivalent aged wattle crop. Although the rows tended to form more quickly, the edge enhanced image of December 2003 (when the compartment was four months old) was not able to define the crop rows sufficiently well to provide a definitive row classification. By the time the next image was acquired in May 2004 (when the stand was nine months old) canopy closure was very close to completion. While the row definition was very clear from the edge enhanced imagery, the degree of vegetation growth was such that it tended to overshadow this and cause cross-classification between the "crop" and "light weed" classes, although there was very little weed present. This was due to the strength of the vegetation signal extending beyond the edge enhanced row definition and so creating a clump rather than a row effect.

Another confusing element, particularly in the December 2003 image, was the very strong influence of the brushwood lines (see glossary). As these had not been burnt, but were still in heaps, they produced a very strong shadow signal as received by the sensor, which tended to skew the digital numbers, and hence the unsupervised classification.

As the stand became older, a similar effect in terms of the cross-classification between the "crop" and "heavy weed" classes was evident, with areas being classified as heavy weed, when in fact there was little or no weed. Again this was due to the high level of the vegetation signal reflected back to the sensor from a more mature crop stand. Figure 5.2.13 illustrates the full range of classified results from this *Eucalyptus* coppice stand.

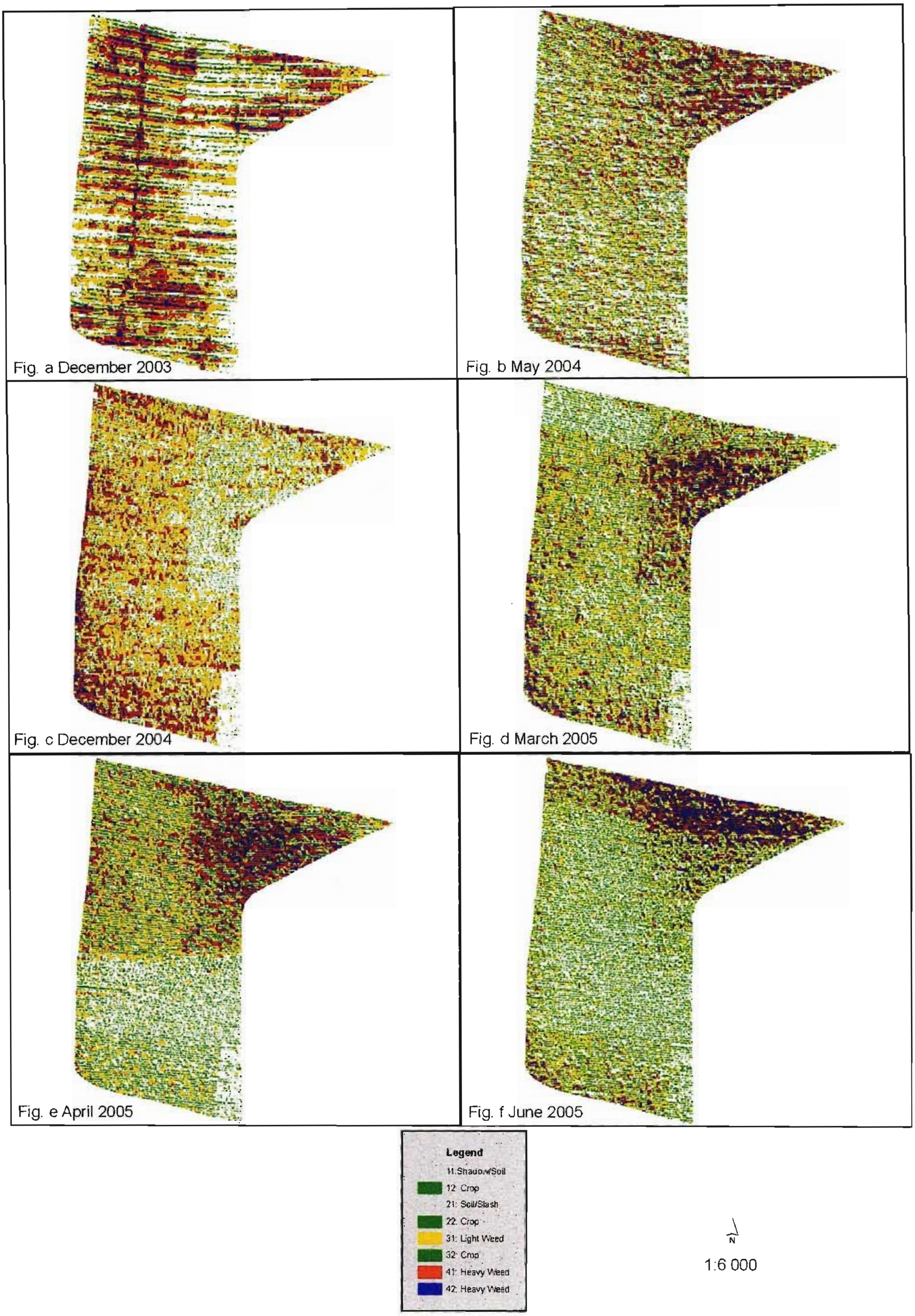


Figure 5.2.13 Weed Potential Classification of a *Eucalyptus* coppice stand (Compt. B031)

5.2.8.2 Detection of Eucalyptus Coppice Reduction

Eucalyptus stands that have been re-established by coppicing, rather than replanting with seedlings, require two coppice operations in order for the correct stocking, in terms of stems per hectare, to be achieved (Norris, 2000). Delays, portions of compartments missed and other such problems negatively impact on the quality and quantity of the final crop obtained. Therefore, if these operations could be monitored from remotely sensed imagery, it could have important management implications.

During the course of this study, the one *Eucalyptus* compartment that was re-established by coppicing was monitored both from the imagery and also ground truthed. Due to a significant response being observed in both the raw and classified imagery, it became very evident that a coppice reduction operation had occurred within the study period. This was confirmed when the forestry operation records for that compartment were checked and revealed that a coppice reduction operation was reported in April. What was also interesting to note was that while the records reported the operation had been completed and paid for in April, it was seen from the June imagery that the operation was still in progress. Subsequent queries with the field staff revealed that there were valid reasons for this discrepancy. However, it did indicate that monitoring such operations through remote sensing was feasible, and could enhance the operational management of forestry concerns. Unfortunately this was the only such compartment that was available to be monitored during the study period, and so statistical inferences could not be drawn to independently validate this result, but the results, illustrated in Figure 5.2.14, clearly show the visual effect the coppice reduction operation produced in the imagery.

5.2.9 Classification Results of Pine Stand

No suitable pine stands were available in the study area for analyses and so no results could be obtained from this research. However, based on the understanding gained from this work, it is surmised that because of the much slower growth rates of pines, any analyses would have to be done over a longer period than was the case experienced in this study, probably extending towards 36 months, with initial successful identification of the crop probably only occurring eight to twelve months after establishment. This is due to the wider espacement pine is planted at, as well

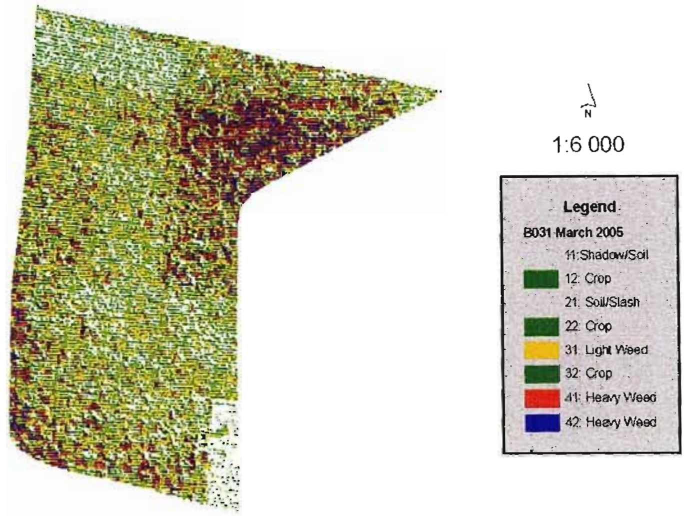


Fig. a March 2005 Prior to coppice reduction (rectangle in SE corner is different species)

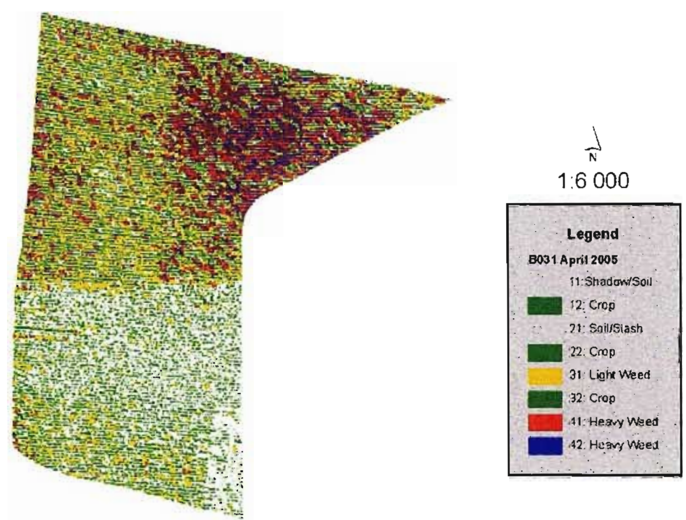


Fig. a April 2005 Coppice reduction in southern half of compartment

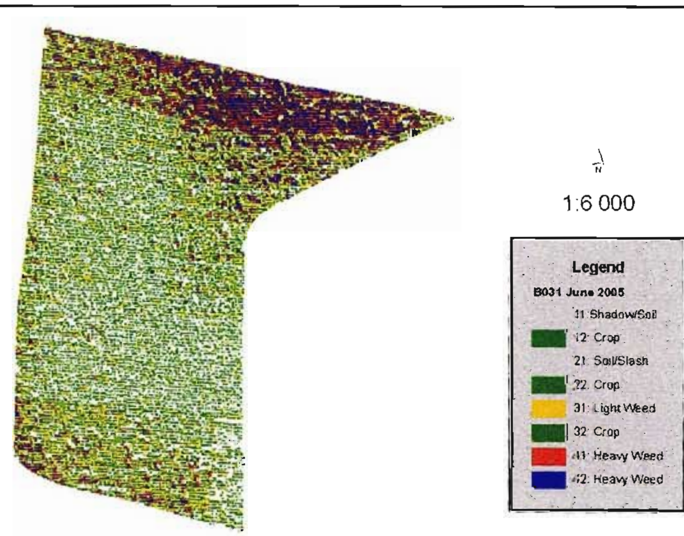


Fig. c June 2005 Coppice reduction continues in northerly direction

Figure 5.2.14 Identification of Coppice Reduction Operation as the fact that the row delineation that was so critical in this study would only occur at a later stage than was the case with wattle or eucalypts.

However, these issues would need to be properly investigated before firm conclusions could be drawn.

5.3 Conclusions and Recommendations

5.3.1 Conclusions

5.3.1.1 The Application of 2.4 m Multi-spectral Imagery

The 2.4 m multi-spectral imagery on its own was insufficient to identify potential weed infestations. However, in combination with the textural information provided by the panchromatic imagery, the vegetation signal inherent in this data was critical to the successful differentiation of crop from weed and subsequent identification of potential weed infestations.

5.3.1.2 The Application of Textural Analyses

Textural analysis proved to be an essential component in producing successful classification and change detection results in the context of this study. Of the textural analysis techniques tested the edge enhancement technique was the most successful in delineating crop rows. This delineation of crop rows was the key to distinguishing crop from weed, but it was still necessary to combine the crop row data with the multi-spectral data set to achieve a successful classification. These results agree with other studies (e.g. Ouma *et al.*, 2006; Tso and Mather, 2001; Coppin, 1991; Fung and Le Drew, 1987) that reported improved classification results due to the inclusion of textural analyses in the classification process.

5.3.1.3 The Effect of Stand Age

Stand age played a major role in the classification success, as those stands (or compartments) less than three months old or older than fourteen months were not classified as successfully as stands between these ages. The optimal period within which to identify potential weed infestation in wattle stands is three to fourteen months. However, identification of potential weed problems in stands younger than three months can still be done with reasonable success. Stands older than fourteen months tend to be close to canopy closure, when it is no longer necessary to monitor weed infestations. Hence, knowledge of stand age is probably a prerequisite.

5.3.1.4 The Effect of the Classification Matrix

Despite some level of cross-classification, particularly in the "early crop" stage, the four-class matrix provided a good basis for deriving the weed infestation levels.

5.3.1.5 Quantification of Weed Infestation Levels

In addition to effectively identifying weed infestations spatially, it was possible to quantify the level of infestation and report it on a hectare basis, as well as the percentage of the compartment affected. The success in identifying and quantifying weed infestation achieved in this study was higher than reported in other studies. (Gray *et al.,* 2004; Nilson *et al.,* 2001). However, this approach would most probably only yield meaningful results in plantation forestry, where regularly lineated forest stands is generally a feature.

5.3.1.6 The Success of the Change Detection Process

The change detection process was able to identify, and quantify, areas of weed increase between consecutive images. While only bi-temporal change detection was undertaken in this study, in terms of the actual change detection procedures, visual comparison of the results gave one an indication of the temporal trends that occurred in weed infestation.

5.3.1.7 Comparison of Classified Imagery with Operational Database

It was not possible to draw conclusive results when comparing operations recorded in the operational management database to the classified image results. This was mainly due to the imagery not being obtained sufficiently close enough to when the operations occurred, such that any weed or crop growth masked operations previously carried out. The only exceptions to this were the second or third spacing operations, where a reduction in crop cover was recorded by the imagery. Based on the image results, one could draw conclusions as to crop and weed status at the time of image acquisition, but not infer any conclusions regarding previous operations to the stands.

5.3.1.8 Application of Theoretical Ground Cover Model

While conclusive threshold values were not obtained, there was sufficient evidence to show that this concept could work, and that where required it was possible to rescale the values derived from field measurements such that threshold values could be derived for use with data derived from imagery. The net result would be thresholds that could be used to alert managers to potential weed infestation levels within forest stands.

5.3.1.9 Weed Detection in *Eucalyptus* Coppice Stands

There was insufficient evidence to draw any conclusions regarding the identification of weed status in *Eucalyptus* coppice stands as only one compartment was available within the study area. However, it was apparent that the wattle model developed in this study would not be suitable for application in *Eucalyptus* coppice stands. This appeared to be mainly due to the faster rate at which coppice stands attained canopy closure, compared to wattle stands.

5.3.1.10 Detection of Coppice Reduction Operations

Although there was only one sample site, there were strong indications that coppice reduction operations could be monitored using high resolution imagery.

5.3.1.11 Weed Detection in Pine Stands

No conclusions could be drawn regarding the application of these techniques in pine stands, as no suitable pine stands were available within the study site.

In summary, this study has shown that the application of change detection and textural analysis techniques to high resolution imagery can be used to quantitatively assess weed status in plantation forest stands less than 24 months old.

5.3.2 Recommendations

5.3.2.1 Identification of Weed Infestations

Techniques involving the combination of multi-spectral and edge enhanced panchromatic high resolution imagery should be used to identify and quantify potential weed infestations as a management tool to improve the monitoring of weed status within plantation forest stands. It will, however, be required to know stand ages when interpreting the classified data, due to the effect stand age has on this process.

5.3.2.2 Automation of Analysis Procedures

Due to the number of processes required to run these analyses, techniques should be developed to automate as much of the processing as possible. This will allow results to be provided more rapidly, which is a critical factor due to the time-sensitive nature of monitoring weed infestations.

5.3.2.3 Application in *Eucalyptus* and Pine Stands

The application of the techniques described in this study should be tested in both *Eucalyptus* coppice stands and *Eucalyptus* planted stands, as well as in Pine stands, as each of these types have some unique characteristics that differ from wattle stands, as well as from each other.

5.3.2.4 Further Development of Textural and Frequency Domain Techniques

Further investigation should be undertaken to determine whether the Variance function, in the textural domain, can be used to identify landscape fragments, or clumps, that might indicate weed concentrations. Similarly, further investigation of the Fourier Transform could reveal its potential in delineating crop rows.

5.3.2.5 Use of Imagery Results to Audit Operational Databases

It is not recommended to utilise image classification results to audit operational records in a management database for operations such as weed control, particularly where chemical control is applied, as these effects are only evident several weeks after application. Some assessment may be possible in cases where manual weed control operations are undertaken, and image acquisition coincides with these operations. It may also be possible to use such image results to check whether the later (second or later) spacing operations have been done, especially where the image acquisition is coincident with the actual operation. However, this would best serve a supplemental source of this information, rather than being a primary source.

5.3.2.6 Use of Theoretical Ground Cover Model

More rigorous testing should be done to produce conclusive threshold values in wattle stands. The possibility of better results being obtained from seedling crops, particularly gum or pine stands should also be tested.

Chapter 6: Study Conclusions and Recommendations

6.1.1 Introduction

Overall, the work done in this study supported the original hypotheses stated at the beginning of this study. The primary aim of being able to monitor specific plantation forestry operations was achieved, together with an understanding of the appropriate applications and limitations of both medium and high resolution imagery within this context. These are discussed below.

6.1.2 Monitoring Forestry Operations

As was highlighted in the literature survey, virtually no research has been reported on remote sensing applications in plantation forest conditions. This study has been able to address some of the issues involved, particularly in terms of the monitoring of plantation forestry operations.

The results of this study showed that it was possible to monitor a range of plantation forestry operations using both medium and high resolution imagery, although the degree of success was very much a function of the spatial resolution. Clear-felling operations could be very accurately identified using medium resolution imagery, even where compartments were only partially felled. However, weeding and planting operations could not be successfully identified using medium resolution imagery. Successfully identifying these operations required high spatial resolution imagery. Even the high resolution multi-spectral imagery was not able to identify weed infestations or newly planted stands without the textural information of the higher resolution panchromatic imagery. However, using this textural information to identify crop rows, in conjunction with the vegetation signal derived from the multi-spectral bands, it was possible to distinguish between crop and weed, particularly in wattle stands between three and fourteen months old. This could have useful applications to other forest management situations such as highlighting areas of poor crop growth due to poor stocking or other site conditions. Operations involving significant canopy reduction, such as those of clear-felling; gum coppice reduction and the later wattle spacing operations could also be successfully identified from image analyses.

Medium resolution imagery covers very large areas, of which only a small portion is actually of interest (i.e. the plantation areas), but cannot adequately identify features within compartments. High resolution imagery covers much smaller areas, but can identify features within compartments. Therefore, a multi-stage sampling process is recommended, whereby clear-felled compartments are identified from medium resolution imagery, and where a concentration of these falls within a high resolution image, that image could be obtained and the planting and weeding operations monitored. Alternatively other high resolution imagery options such as airborne multi-spectral imagery could also be utilised.

There are thus opportunities to allow more effective monitoring by field staff of forestry operations, as the results of such image analyses can highlight those areas that need to be verified on the ground. This allows a much more focussed approach to operational management, reducing supervisory time, while simultaneously reducing the risk of critical situations being overlooked. Where reasonably coincident repeat imagery is available, trends over time can be assessed, thereby assisting in the determination of appropriate management regimes to address trends such weed infestation increases or decreases; crop failures; poor stocking and similar trends. In view of the number of processes required to provide this data, it is also recommended that these procedures be automated as much as possible.

In an era where environmental, social and political pressures require that forestry companies relinquish direct control over some afforested land, remote sensing techniques such as these described above, in conjunction with other techniques, can provide a suit of tools that allow a measure of control and monitoring to occur without necessarily having to do this on the ground. This could assist in ensuring continuity of a sustainable raw material base.

6.1.3 Monitoring Vegetation Trends over Time

The above operations can be identified from single images. However, where repeat imagery is available it is possible to monitor trends over time using change detection techniques, such as the post classification comparison techniques applied in this study. What was of particular interest was that using high resolution multi-spectral imagery in conjunction with textural analyses of panchromatic imagery, one could identify and quantify the vegetation succession over time, both in terms of crop and weed development.

6.1.4 Methods to Increase Classification Accuracy

6.1.4.1 Reducing Spectral Variability

Irrespective of the type of imagery used, classification accuracy was affected by the degree of variability present within the area classified. On the medium resolution imagery the limitation set by using an Area of Interest (AOI) consisting of the plantation boundaries did not reduce variability sufficiently well due to the presence of the unplanted areas within these boundaries adding an unnecessary degree of variability. A major factor in the ability to distinguish crop from weed, and hence quantify weed infestation, in the high resolution imagery was due to the variability within each study site being restricted to the data of interest, i.e. only the vegetation and soil within the compartment. This was further improved by applying an internal buffer to remove the mixed pixels along the compartment edges, which in turn countered the problems described by Heyman *et al.* (2003) regarding a reduction in classification accuracy due to the greater variability encountered in high resolution imagery. An improvement in classification accuracy of the medium resolution imagery would probably have been obtained had AOIs been restricted to the forest stands only, removing the extraneous variability of the unplanted areas.

6.1.4.2 Units of Observation

An issue related to spectral variability was the decision on what to use as the basic unit of observation for the purposes of classification and change detection (Varjo, 1997). In the medium resolution imagery, compartments (or forest stands) were selected as the units of observation, on the basis that they formed the smallest management units (i.e. there should therefore be a level of consistency within a compartment, in terms of its status). However, one of the findings of the medium resolution study was that this was problematic due to the variation occurring within compartments such that a simple majority classification did not allow accurate classification, and that some form of pixel basis should be introduced as a unit of observation.

This problem was not encountered in the high resolution imagery study, even though the compartments were still used as the units of observation. However, the major difference was that every compartment was processed individually, rather than all compartments being processed together, as was the case with the medium resolution imagery. The net result was that where *inter-compartment* variability needed to be assessed, one could use medium resolution imagery, but assessment of *intra-compartment* variability required high resolution imagery. This latter point is fundamentally why it was possible to distinguish between crop and weed using the high resolution imagery.

6.1.4.3 The Application of Textural Analyses

It is important to understand that the focus of the textural analysis was to delineate the crop row, as opposed to individual tree crowns. Therefore, although the individual crown sizes were much less than the 1.5 m radius found by Wulder *et al.* (2000), the tree rows were sufficiently definable as to be able to be delineated using textural analysis techniques, and this delineation was successfully used to differentiate crop from weed, except where the weed density was such that it overshadowed the crop row delineation.

6.1.4.4 Effects of Spatial and Spectral Resolution

The advantage gained by the greater spatial resolution of the high resolution imagery is somewhat offset by the loss in spectral resolution, when compared to medium resolution imagery. While the former imagery has four bands covering the visible and near-infrared portions of the spectrum, medium resolution imagery has up to eight bands ranging from the visible to the thermal parts of the spectrum. In terms of vegetation analyses, the short-wave infrared band is particularly useful, but is not available when using standard high resolution imagery (Janssen, 2000). However, it was found that for the objectives of this study, the information gained from the greater spatial resolution more than offset this loss in spectral resolution. This may not always be the case, however, and one would need to be conversant with how these issues could affect the objectives of a particular study.

6.1.4.5 Image Rectification and Registration Issues

The whole issue of accurate orthorectification proved to be a major source of concern in this project, and highlighted the critical importance of this aspect when selecting the appropriate type of imagery for a particular remote sensing application. Fortunately, the impact of these registration problems was reduced by applying a generalisation function during the vectorisation of the multi-spectral and panchromatic images, such that the classification and change detection results were not seriously impacted. The use of a post-classification comparison methodology also assisted in this case, as it is more resilient to registration problems than some of the other change detection methodologies (Coppin *et al.*, 2004; Singh, 1989).

What was also found was that even if no further atmospheric correction is applied, DN to radiance/reflectance normalisation should be carried out on all satellite imagery, particularly when processes such as NDVI are undertaken, as without this correction, valid comparisons between images cannot be made.

In summary, the major findings were as follows:

- Medium resolution imagery can be used to successfully detect clear-felled areas.
- It cannot be used to detect new plantings less than one year old, or weed status.
- High resolution imagery can be used to detect new Wattle (*A. mearnsii*) plantings less than one year old, and the weed status of these stands. However this does require the application of textural analyses of the panchromatic band, in conjunction with unsupervised classification of the multispectral bands.
- Coppice reduction operations in Eucalyptus stands can be monitored using high resolution imagery.
- Vegetation trends over time can be monitored using both medium and high resolution imagery, where repeat imagery is available.

Further research is recommended for the following aspects:

- Automated processing methodologies need to be developed to operationalise the monitoring aspects of this application.
- Methodologies need to be refined for the application of these techniques to Pine and Eucalyptus stands.

Glossary:

Brushwood: See Slash.

Compartment: A defined area that has a common management regime within a forest plantation (James, 1983). It is the plantation forestry equivalent of an agricultural field, and is similar to the concept of a forest stand in northern hemisphere boreal forests. It is the basic management unit in plantation forestry.

Coppice: *Eucalyptus* species have the ability to produce new growth from epicormic and lignotuber buds found in the cambium or live bark at the base of the tree (Little and MacLennan, 2001). Once a tree is felled, these buds develop into new stems, and if managed correctly, can produce a new crop. This new growth is referred to as the coppice crop, or simply coppice. Multiple stems form initially, and it requires one or two coppice reduction operations for a utilisable crop to be produced.

Crop: Within the context of this study, crop refers to the commercial stand of trees grown specifically for the production of wood fibre for pulp and paper mills, as well as any other commercial timber product such as sawn timber, mining timber or veneer.

Plantation Forestry: The commercial application of growing trees for specific forest products, whereby the crop is managed on an intensive scale, usually as even-aged single species stands on short to medium term rotations (6 – 30 years, depending on product, species and geography). Regeneration is by artificial means rather than by natural regeneration, and the crop is managed in a similar fashion to an agricultural crop. An alternative name is tree farming.

Re-establishment: This is a generic term covering all forms of operations aimed at replacing harvested trees, usually by artificial means. For Pine and Wattle crops, re-establishment is by planting nursery-produced seedlings (although Wattle is also replanted using directly sown seed), but Gums are usually coppiced for one or two growth cycles, rather than having seedlings replanted after every felling.

Replanting (or planting): Unlike the term re-establishment, this only refers to establishing new crops by planting seedlings, clones or seed.

Slash: A term referring to the residue of branches, bark, foliage and timber left behind after a harvesting operation has removed the utilisable timber from a compartment. It is often disposed of by burning, although it is increasingly being left *in-situ* to rot down.

Weed: This term refers to any vegetation growth that occurs in the immediate vicinity of the forest crop (see above), either in the crop row or the inter-row between the crop rows, such that it competes with the crop for water and nutrients. Weed growth has a particularly severe impact when occurring within the first year of the crop's establishment.

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Appendices:

Appendix 1: Landsat 7 ETM+ Technical Specifications

Orbit Description: 705 km altitude; sun-synchronous; near-polar (inclination angle = 98.2°); approx. 10:00 am (local time) crossing.

Repeat Cycle: 16 days.

Swath Width: 185 km (FOV = 15°).

Spectral Bands:

Band 1: 0.45 - 0.52 µm	Band 2: 0.52 - 0.60 µm
Band 3: 0.63 - 0.69 µm	Band 4: 0.76 - 0.90 µm
Band 5: 1.55 - 1.75 µm	Band 6: 10.40 - 12.50 µm
Band 7: 2.08 - 2.34 µm	Panchromatic: 0.50 – 0.90 µm

Spatial Resolution: 15m (PAN)
30m (Bands 1 – 5; 7)
60m (Band 6)

Sensor: Enhanced Thematic Mapper Plus

Data archive: http://www.sac.co.za (Janssen, 2000)

Sample of raw Landsat Image

Appendix 2: QuickBird 2 Technical Specifications

Orbit Description: 450 km altitude; 98° sun-synchronous

Repeat Cycle: 1 to 3.5 days, depending on latitude.

Swath Width: 16.5 km at nadir.
Accessible ground swath: 544km centred on satellite ground track.
Single scene: 16.5 km x 16.5 km
Strip scene: 16.5 km x 165 km

Viewing Angle: In-track and cross-track pointing.

Metric Accuracy: 14.0 m RMSE.

Digital Globe (2005)

Calculation Parameters for QuickBird Spectral Radiance and Reflectance Values:

Table A2.1 Sun Elevation; Solar Zenith; Julian Day and Earth-Sun Distance Values

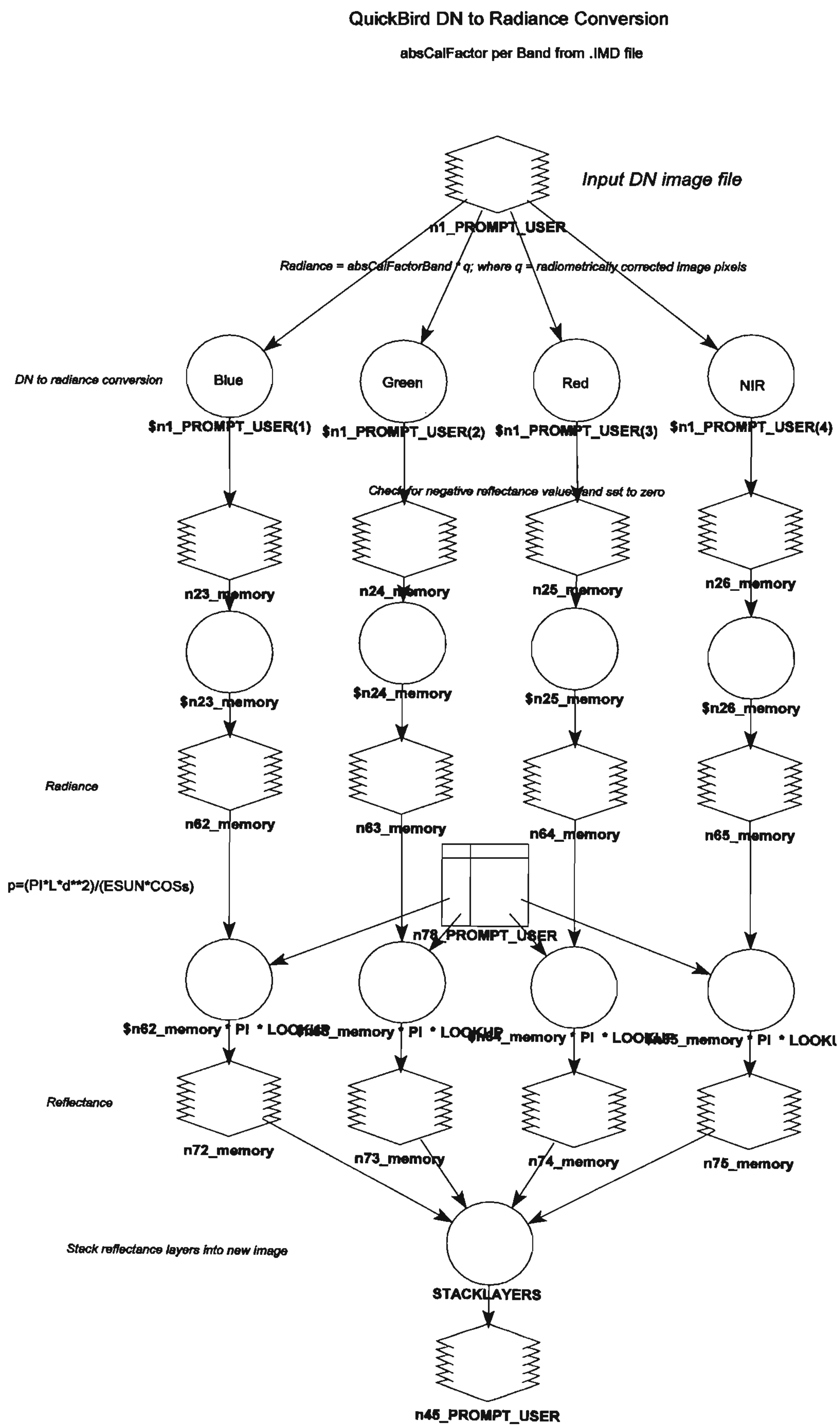
QB Image Date	Sun Elevation	Solar Zenith	Julian Day	d
17 Dec 2003	62.7	27.3	351	0.9842
22 May 2004	33.5	56.5	142	1.0122
06 Dec 2004	68.0	22.0	340	0.9854
03 Mar 2005	52.7	37.3	62	0.9914
11 Apr 2005	46.0	44.0	101	1.0020
17 June 2005	32.6	57.4	168	1.0159

Table A2.2 Band-specific values for Radiance and Reflectance Calculation

QuickBird Band	Effective Bandwidth	ESUN	absCalFactor
Blue	0.068 (450-520nm)	1969.000	$1.604120e^{-2}$
Green	0.099 (520-600nm)	1840.000	$1.438470e^{-2}$
Red	0.071 (630-690nm)	1551.000	$1.267350e^{-2}$
NIR	0.114 (760-900nm)	1044.000	$1.542420e^{-2}$

Jha (2005)

Appendix 3: QuickBird DN to Radiance to Reflectance Model



Appendix 4: Example of QuickBird .imd File

```
version = "Q";
generationTime = 2005-03-10T15:05:50.000000Z;
productOrderId = "000000194117_01_P001";
imageDescriptor = "Basic1B";
bandId = "Multi";
panSharpenAlgorithm = "None";
numRows = 7249;
numColumns = 6876;
productLevel = "LV1B";
radiometricLevel = "Corrected";
bitsPerPixel = 16;
compressionType = "None";
BEGIN_GROUP = BAND_B
	ULLon =  30.620;
	ULLat = -29.155;
	URLon =  30.74339499;
	URLat = -29.12251234;
	LRLon =  30.713;
	LRLat = -29.228;
	LLLon =  30.56344495;
	LLLat = -29.28842847;
	absCalFactor = 1.604120e-02;
END_GROUP = BAND_B
BEGIN_GROUP = BAND_G
	ULLon =  30.620;
	ULLat = -29.155;
	URLon =  30.74339499;
	URLat = -29.12251234;
	LRLon =  30.713;
	LRLat = -29.228;
	LLLon =  30.56344495;
	LLLat = -29.28842847;
	absCalFactor = 1.438470e-02;
END_GROUP = BAND_G
BEGIN_GROUP = BAND_R
	ULLon =  30.620;
	ULLat = -29.155;
	URLon =  30.74339499;
	URLat = -29.12251234;
	LRLon =  30.713;
	LRLat = -29.228;
	LLLon =  30.56344495;
	LLLat = -29.28842847;
	absCalFactor = 1.267350e-02;
END_GROUP = BAND_R
BEGIN_GROUP = BAND_N
	ULLon =  30.620;
	ULLat = -29.155;
	URLon =  30.74339499;
	URLat = -29.12251234;
	LRLon =  30.713;
	LRLat = -29.228;
	LLLon =  30.56344495;
	LLLat = -29.28842847;
	absCalFactor = 1.542420e-02;
```

```
END_GROUP = BAND_N
outputFormat = "GeoTIFF";
BEGIN_GROUP = IMAGE_1
	satId = "QB02";
	CatId = "101001000415C202";
	SceneID = "2";
	TLCTime = 2005-03-06T08:20:13.104638Z;
	numTLC = 2;
	TLCList = (
	(0,  0.000000),
	(7249,  4.202319)      );
	firstLineTime = 2005-03-06T08:20:13.104638Z;
	avgLineRate = 1725.00;
	exposureDuration = 0.00057971;
	collectedRowGSD =   2.507;
	collectedColGSD =   2.554;
	meanCollectedGSD =   2.530;
	rowUncertainty =   36.51;
	colUncertainty =   40.26;
	sunAz =  52.7;
	sunEl =  55.3;
	satAz = 261.2;
	satEl =  78.7;
	inTrackViewAngle =  -3.2;
	crossTrackViewAngle = -10.1;
	offNadirViewAngle =  10.5;
	cloudCover =   0.0;
	PNIIRS = 2.9;
	imageQuality = "Excellent";
	resamplingKernel = "CC";
	TDILevel = 13;
	positionKnowledgeSrc = "R";
	attitudeKnowledgeSrc = "R";
	revNumber = 18997;
END_GROUP = IMAGE_1
END;
```

Appendix 5: QuickBird DN to Radiance and Reflectance Formulae

Conversion to top-of-atmosphere spectral radiance is a two step process:

Step 1

Band-Integrated Radiance [W.m^{-2}.sr^{-1}]

Conversion to band-integrated radiance applies ***absCalFactors***, listed in the *.imd* files, as follows:

$$\mathbf{L}_{Pixel,Band} = \mathbf{absCalFactor}_{Band} \times \mathbf{q}_{Pixel,Band}$$

where $\mathbf{L}_{Pixel,Band}$ are top-of-atmosphere band-integrated radiance image pixels [W.m^{-2}.sr^{-1}],

$\mathbf{absCalFactor}_{Band}$ is the absolute radiometric calibration factor [W.m^{-2}.sr^{-1}] for a given band,

$\mathbf{q}_{Pixel,Band}$ are radiometrically corrected image pixels [counts].

Step 2

Band-Averaged Spectral Radiance [W.m^{-2}.sr^{-1}]

The second step in conversion to top-of-atmosphere spectral radiance is to divide the band-integrated radiance by an effective bandwidth (λ). Effective bandwidths were calculated from the QuickBird relative spectral radiance response curves for each band and are listed in Table 3

Table 3: QuickBird Effective Bandwidths (λ)

Spectral Band	Effective Bandwidth [μ m]
Pan	0.398
Blue	0.068
Green	0.099
Red	0.071
NIR	0.114

Conversion from band-integrated radiance to band-averaged spectral radiance is performed using the following equation:

$$\mathbf{L}_{\lambda Pixel,Band} = \frac{L_{Pixel,Band}}{\lambda_{Band}}$$

where $\mathbf{L}$ are top-of-atmosphere band-averaged spectral radiance image pixels [W.m^{-2}.sr^{-1}], $\boldsymbol{\lambda}_{Pixel,Band}$

$\mathbf{L}_{Pixel,Band}$ are top-of-atmosphere band-integrated radiance image pixels [W.m^{-2}.sr^{-1}], and

λ_{Band} is the effective bandwidth [μm] for a given band.

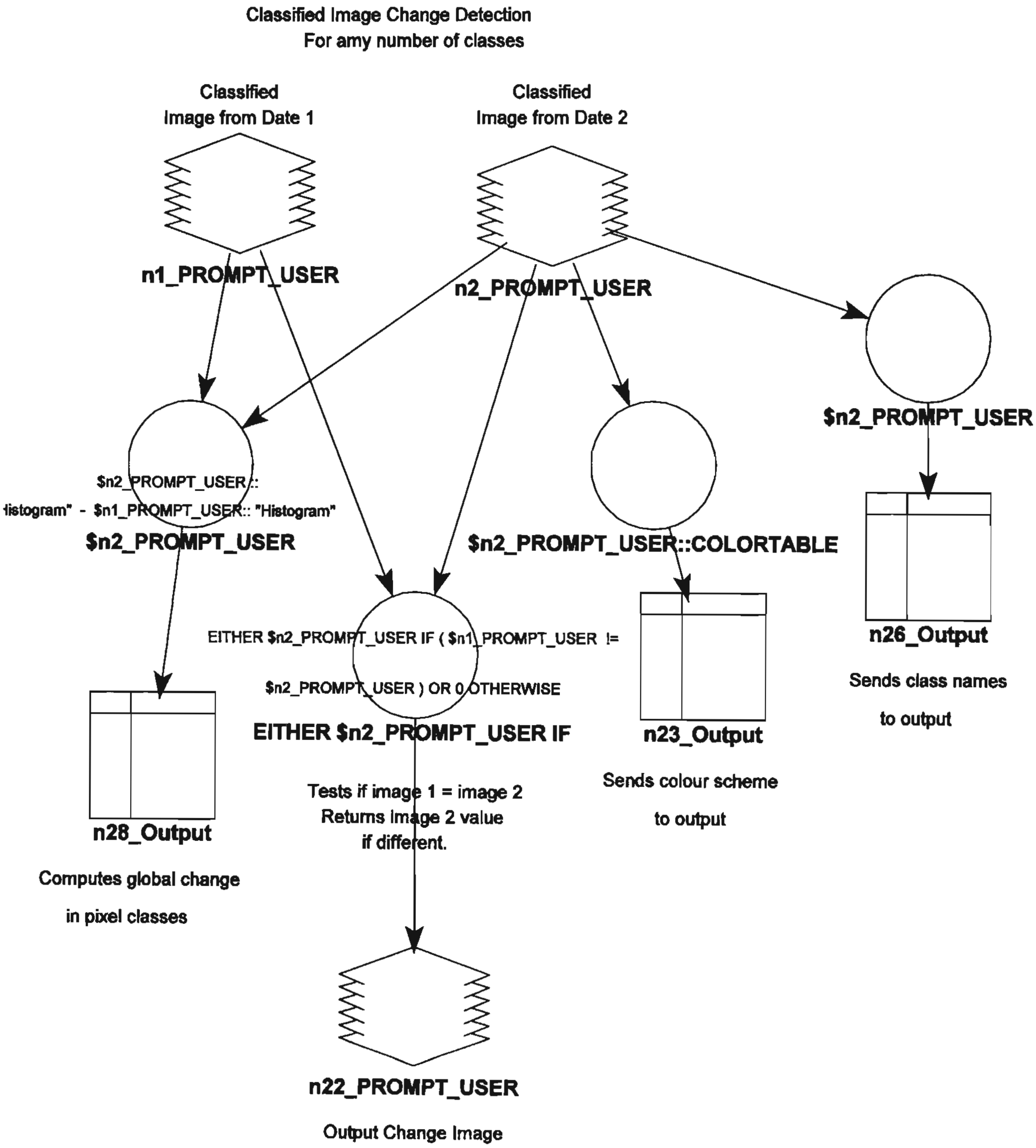
(Jha, 2005)

Appendix 6: Class Break Values: 2-Class Reclassification of Edge Enhanced Imagery

Break Threshold	Image Mean	Image Min	Image Max	Image Range	Image Median	Image Mode
340	330.07	*76*	*616*	*540*	*327.25*	*324.84*
250	236.16	*14*	*675*	*661*	*229.39*	*200.39*
380	372.69	*127*	*721*	*594*	*366.13*	*360.50*
310	283.89	*53*	*555*	*502*	*284.00*	*307.85*
240	255.52	*37*	*589*	*552*	*243.88*	*174.86*
200	249.02	*36*	*617*	*581*	*228.96*	*156.66*
360	325.29	*65*	*578*	*513*	*334.16*	*349.96*
450	351.42	*34*	*887*	*853*	*325.70*	*148.99*
460	399.33	*107*	*661*	*554*	*397.63*	*397.63*
420	360.94	*1*	*726*	*725*	*368.67*	*450.91*
360	313.06	*9*	*633*	*624*	*309.08*	*244.79*
320	287.52	*1*	*819*	*818*	*259.14*	*111.97*
250	244.99	*1*	*2066*	*2065*	*234.04*	*225.97*
250	252.91	*2*	*944*	*942*	*250.75*	*250.75*
350	312.74	*35*	*1078*	*1043*	*324.24*	*336.88*
300	310.99	*1*	*773*	*772*	*298.93*	*307.99*
240	256.36	*3*	*661*	*658*	*247.88*	*234.96*
250	250.98	*1*	*710*	*709*	*241.29*	*232.97*
265	247.55	*4*	*552*	*548*	*256.59*	*260.91*
220	208.26	*39*	*550*	*511*	*208.40*	*216.99*
240	230.69	*6*	*671*	*665*	*228.04*	*230.66*
275	302.13	*65*	*701*	*636*	*295.73*	*287.52*
325	336.11	*2*	*953*	*951*	*331.32*	*331.32*
400	397.73	*114*	*809*	*695*	*388.70*	*372.90*
360	343.06	*1*	*808*	*807*	*347.19*	*340.88*
310	305.70	*1*	*723*	*722*	*307.84*	*321.96*
350	337.38	*37*	*887*	*850*	*329.16*	*280.65*
320	292.58	*102*	*803*	*701*	*276.03*	*250.94*
250	251.23	*16*	*736*	*720*	*247.25*	*247.25*
340	339.09	*117*	*827*	*710*	*335.97*	*335.97*
320	310.78	*6*	*665*	*659*	*306.52*	*290.94*
270	262.87	*1*	*592*	*591*	*261.31*	*265.94*
320	291.38	*22*	*636*	*614*	*285.70*	*285.70*
340	356.15	*49*	*772*	*723*	*343.78*	*328.70*
210	231.12	*10*	*658*	*648*	*223.62*	*197.91*
350	379.83	*44*	*735*	*691*	*378.98*	*370.37*
270	286.09	*16*	*592*	*576*	*286.75*	*293.69*
240	239.81	*30*	*560*	*530*	*229.69*	*207.81*
220	219.89	*1*	*753*	*752*	*188.25*	*91.18*
350	378.62	*90*	*766*	*676*	*377.02*	*385.99*
290	311.90	*83*	*603*	*520*	*301.50*	*244.97*
375	372.26	*155*	*632*	*477*	*372.78*	*367.84*
280	304.33	*36*	*642*	*606*	*310.97*	*348.59*
280	288.94	*35*	*580*	*545*	*287.73*	*348.91*
280	317.66	*19*	*702*	*683*	*309.87*	*205.66*
305	325.51	*146*	*674*	*528*	*323.84*	*318.57*
280	286.79	*22*	*897*	*875*	*280.31*	*276.81*
350	353.60	*140*	*641*	*501*	*345.54*	*330.52*
270	290.70	*14*	*584*	*570*	*292.00*	*307.97*
270	267.07	*29*	*567*	*538*	*263.57*	*256.92*

Break Threshold	Image Mean	Image Min	Image Max	Image Range	Image Median	Image Mode
310	316.88	*136*	*623*	*487*	*313.93*	*313.93*
260	280.09	*25*	*662*	*637*	*271.52*	*258.59*
320	348.99	*64*	*747*	*683*	*338.48*	*320.98*
260	281.54	*41*	*636*	*595*	*280.73*	*265.83*
250	257.50	*30*	*539*	*509*	*250.55*	*218.97*
280	294.07	*1*	*739*	*738*	*271.35*	*199.18*
280	268.35	*114*	*682*	*568*	*266.41*	*258.41*
210	216.16	*27*	*603*	*576*	*209.64*	*204.93*
320	326.03	*128*	*849*	*721*	*311.74*	*301.79*
280	254.10	*1*	*743*	*742*	*246.70*	*243.80*
220	222.30	*10*	*544*	*534*	*214.63*	*201.88*
220	222.05	*1*	*711*	*710*	*194.41*	*80.54*
310	270.76	*116*	*701*	*585*	*262.88*	*240.97*
270	257.51	*129*	*454*	*325*	*253.60*	*248.28*
360	354.81	*123*	*734*	*611*	*344.06*	*338.33*
300	285.09	*75*	*532*	*457*	*280.55*	*263.92*
270	256.90	*85*	*463*	*378*	*253.20*	*240.54*
300	279.60	*51*	*567*	*516*	*270.21*	*205.98*

Appendix 7: Layout of Classified Change Detection Model



(Erdas, 2005)

Appendix 8: Regression Models: Ground Cover Model

Interaction	**Month**	Image	Ground	Predicted (	Bias	% bias	Pred.(inter	Bias	% bias
0.034	1	0.034	0.163	0.142497	0.021	13%	0.159576	0.004	2%
0.268	2	0.134	0.179	0.15542	0.023	13%	0.177312	0.002	1%
0.732	3	0.244	0.196	0.166061	0.030	15%	0.212483	-0.017	-9%
1.098	6	0.183	0.256	0.287183	-0.031	-12%	0.240225	0.016	6%
2.628	9	0.292	0.336	0.369523	-0.034	-10%	0.356196	-0.020	-6%
2.5	10	0.250	0.367	0.414839	-0.047	-13%	0.346494	0.021	6%
4.308	12	0.359	0.440	0.461444	-0.022	-5%	0.483536	-0.044	-10%
4.580333333	13	0.352	0.481	0.4987	-0.017	-4%	0.504179	-0.023	-5%
5.404	14	0.386	0.527	0.526755	0.000	0%	0.566611	-0.040	-8%
4.944	16	0.309	0.631	0.615792	0.015	2%	0.531744	0.099	16%
7.004	17	0.412	0.690	0.62803	0.062	9%	0.687888	0.002	0%
					0.000				

Regression: Predicted Ground Cover (field) Model

SUMMARY OUTPUT

Interaction(GC image*Age) only

Regression Statistics	
Multiple R	0.976859446
R Square	0.954254378
Adjusted R Square	0.949171531
Standard Error	0.041095702
Observations	11

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.31706619	0.31706619	187.7401392	2.4697E-07
Residual	9	0.01519971	0.001688857		
Total	10	0.3322659			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.156998609	0.020913412	7.50707774	3.66543E-05	0.109689184	0.204308033	0.109689184	0.204308033
Interaction	0.075797988	0.005531961	13.70182977	2.4697E-07	0.063283823	0.088312153	0.063283823	0.088312153

Appendix 9: Photographs of Ground-truthed Classes: Medium Resolution Imagery

CLASS 1 – SOIL

Figure 1a. Holmesdale Compt. A07

Figure 1b. Holmesdale Compt. C18

Treatment:	Slash:	Burnt	Planted:	No	Weeded:	No
Veg. Cover	Crop % :		0%			
	Weed %:		<5%			
	Soil % :		>95%			
	Slash % :		<5%			
Crop Ht.:			0m			

CLASS 2 – SLASH

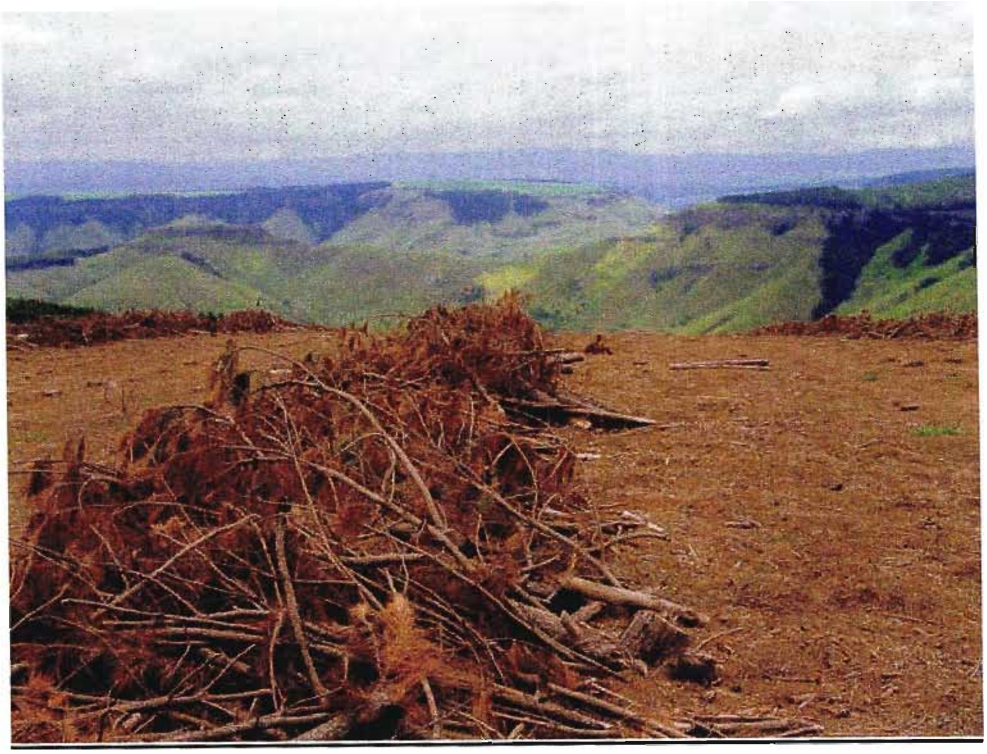


Figure 2a Canema Compt. E14

Figure 2b Holmesdale Compt. B06

Treatment:	Slash:	Spread/Stacked	Planted:	No	Weeded:	No
Veg. Cover	Crop % :		0%			
	Weed %:		<5%			
	Soil % :		<5%			
	Slash % :		>95%			
Crop Ht.:			0m			

CLASS 3 – SLASH/CROP

Figure 3a Holmesdale Compt. C21

Figure 3b Holmesdale Compt E21

Treatment:	Slash:	Spread	Planted:	Yes	Weeded:	No
Veg. Cover	Crop % :		20-30%			
	Weed %:		<5%			
	Soil % :		<5%			
	Slash % :		60-80%			
Crop Ht.:			<1.5m			

CLASS 4 – SOIL/CROP

Figure 4a Mistley Compt. C04

Figure 4b Mistley Compt. C04

Treatment:	Slash:	Burnt	Planted:	Yes	Weeded:	Yes
Veg. Cover	Crop % :		20-30%			
	Weed %:		<5%			
	Soil % :		60-80%			
	Slash % :		<5%			
Crop Ht.:			<1.5m			

CLASS 5 - SLASH/ CROP/WEED

Figure 5a Holmesdale Compt B03

Figure 5b Holmesdale Compt. C23

Treatment:	Slash:	Spread/Stacked	Planted:	Yes	Weeded:	No
Veg. Cover	Crop % :		30-40%			
	Weed %:		40-30%			
	Soil % :		<5%			
	Slash % :		20-40%			
Crop Ht.:			<1.5m			

CLASS 6 – SOIL/CROP/WEED

Figure 6a Holmesdale Compt. H16

Figure 6b Holmesdale Compt. H16

Treatment:	Slash:	Burnt	Planted:	Yes	Weeded:	Yes
Veg. Cover	Crop % :		30-40%			
	Weed %:		40-30%			
	Soil % :		20-40%			
	Slash % :		<5%			
Crop Ht.:			<1.5m			

CLASS 7 – SOIL/SLASH/CROP/WEED

Figure 7a Canema Compt. E15

Figure 7b Canema Compt. E15

Treatment:	Slash:	Burnt/Unburnt	Planted:	Yes	Weeded:	Yes
Veg. Cover	Crop % :		50-70%			
	Weed %:		<10%			
	Soil % :		20-40%			
	Slash % :		20-40%			
Crop Ht.:			<2m			

CLASS 8 – CROP/WEED

Figure 8a Canema Compt. D10A

Figure 8b Canema Compt. D10A

Treatment:	Slash:	Burnt/Unburnt	Planted:	Yes	Weeded:	No
Veg. Cover	Crop % :		50-70%			
	Weed %:		20-40%			
	Soil % :		<10%			
	Slash % :		<10%			
Crop Ht.:			<2m			

CLASS 9 – PRE-CANOPY CLOSURE

Figure 9a Gilboa Compt. C05A

Figure 9b Canema Compt. E11

<table>
<tr><td>Treatment:</td><td>Slash:</td><td></td><td>Planted:</td><td>Yes</td><td>Weeded:</td><td></td></tr>
<tr><td>Veg. Cover</td><td colspan="2">Crop % :</td><td colspan="2">>90%</td><td colspan="2"></td></tr>
<tr><td></td><td colspan="2">Weed %:</td><td colspan="2"><10%</td><td colspan="2"></td></tr>
<tr><td></td><td colspan="2">Soil % :</td><td colspan="2">0%</td><td colspan="2"></td></tr>
<tr><td></td><td colspan="2">Slash % :</td><td colspan="2">0%</td><td colspan="2"></td></tr>
<tr><td>Crop Ht.:</td><td colspan="2"></td><td colspan="2">>3m</td><td colspan="2"></td></tr>
</table>

CLASS 10 – WEED

Figure 10a Canema Compt D10

Figure 10b Holmesdale Compt. H03A

Treatment:	Slash:	Unburnt	Planted:	No	Weeded:	No
Veg. Cover	Crop % :		0%			
	Weed %:		>95%			
	Soil % :		<5%			
	Slash % :		<5%			
Crop Ht.:			0m			

CLASS 11 – SLASH/WEED

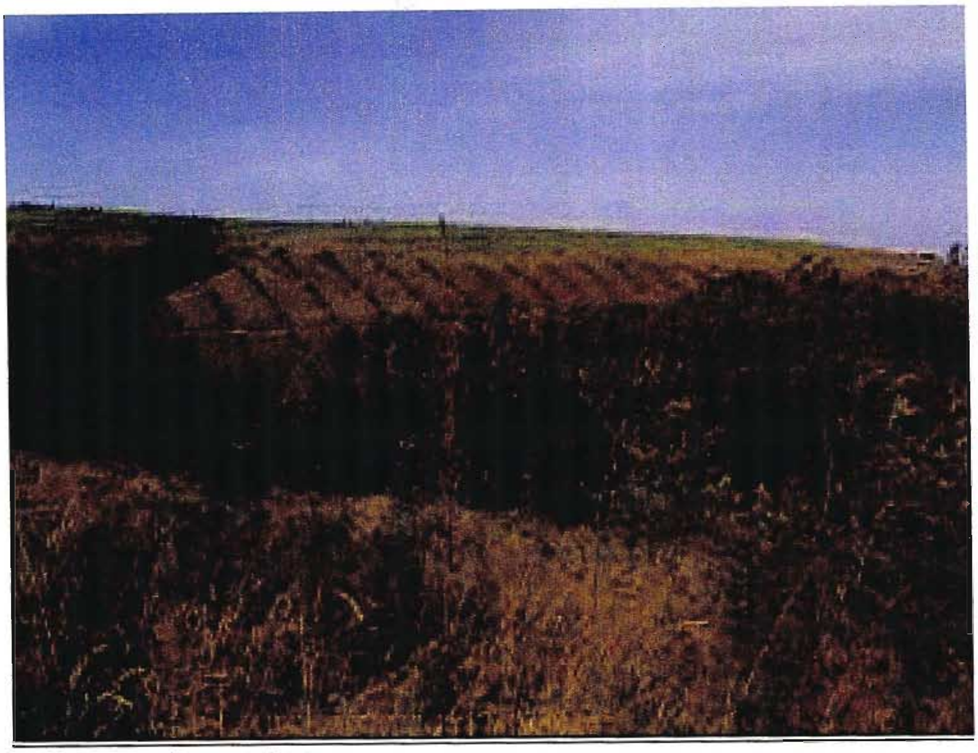


Figure 11a Canema Compt D11

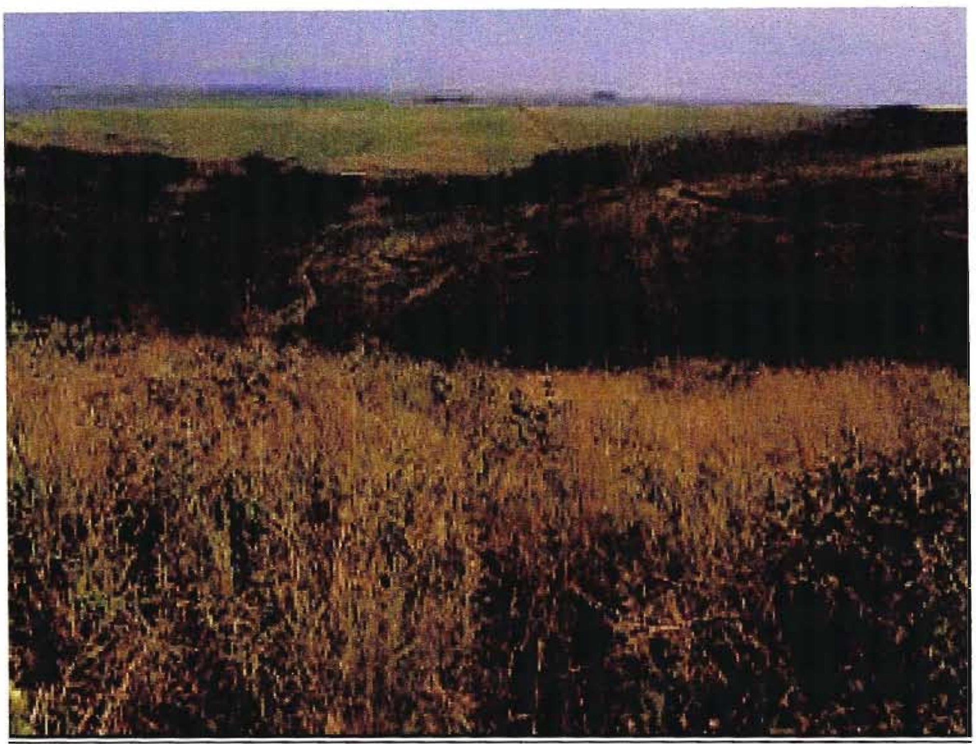


Figure 11b Canema Compt D11

Treatment:	Slash:	Unburnt	Planted:	No	Weeded:	No
Veg. Cover	Crop % :		0%			
	Weed %:		>75%			
	Soil % :		<5%			
	Slash % :		<25%			
Crop Ht.:			0m			

CLASS 12 - CLOSED CANOPY

Figure 12a Gilboa Compt. CC13B

Treatment:	Slash:	N/A	Planted:	No	Weeded:	No
Veg. Cover	Crop % :		>95%			
	Weed %:		<5%			
	Soil % :		<5%			
	Slash % :		<5%			
Crop Ht.:			>10m			

Appendix 10: Photographs of Ground-truthed Classes: High Resolution Imagery

FIRST PHASE:

CLASSES 11/21 – SHADOW/SOIL/SLASH

CLASS 12 – CROP

CLASS 22 – CROP/SOIL

CLASS 31 – LIGHT WEED

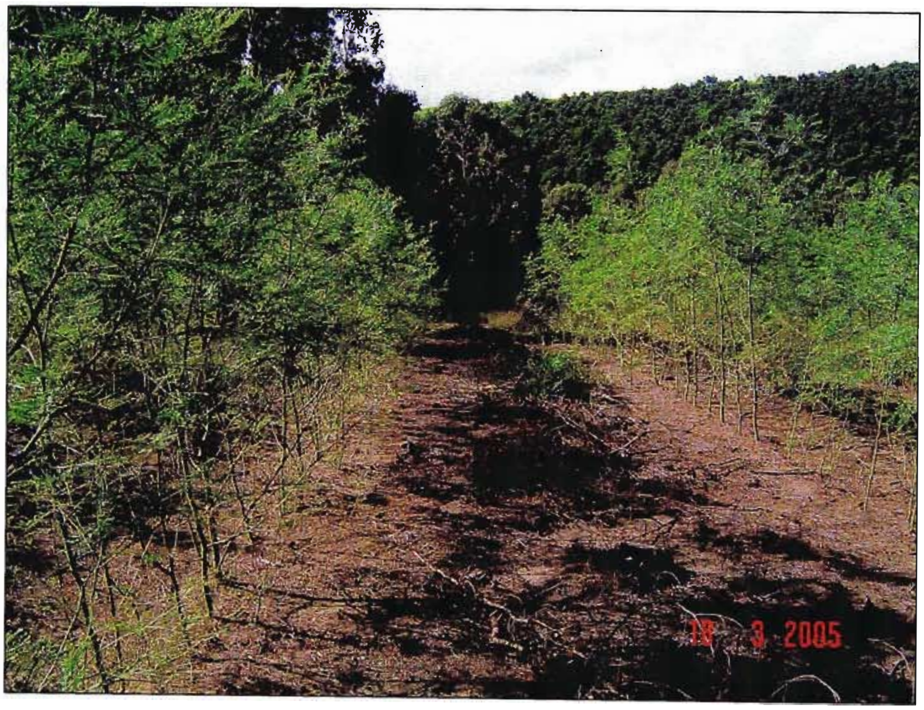
CLASS 32 – CROP/WEED

CLASSES 41/42 – HEAVY WEED

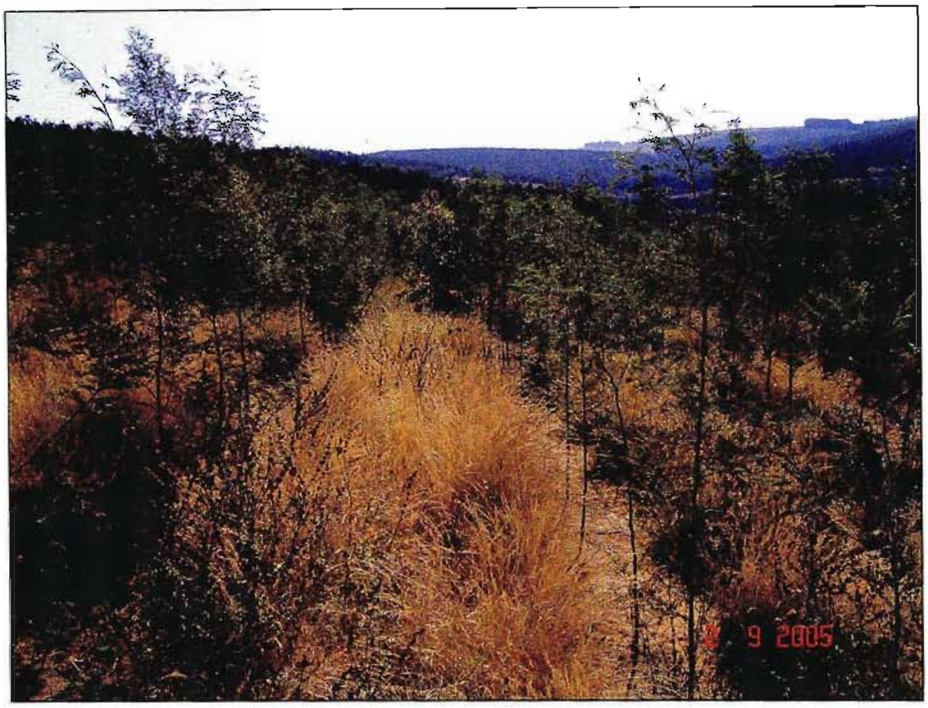
SECOND PHASE:

CLASSES 11/21 – SHADOW/SOIL/SLASH (Inter-row area)

CLASSES 12/22 – CROP



CLASS 31 – LIGHT WEED



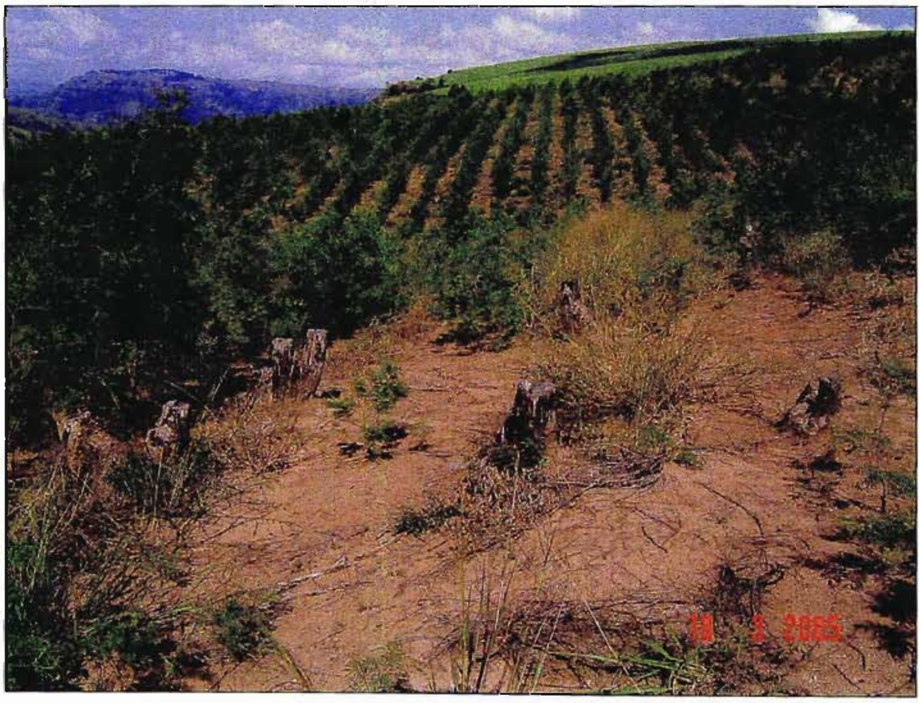
CLASS 32 – CROP/WEED

CLASSES 41/42 – HEAVY WEED

THIRD/FOURTH PHASES:

CLASSES 11/21 – SHADOW/SOIL/SLASH (In Inter-row)

CLASSES 12/22/32 – CROP (Row Delineation in Background)



CLASS 31 – LIGHT WEED

CLASSES 41/42 – HEAVY WEED