Land Use Change Detection of Small Scale Sugarcane:

A Case Study of Umbumbulu, South Africa

by

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Abstract

The aim of this study was to detect spatio-temporal changes in sugarcane land use using satellite imagery for 1991–2006 in Umbumbulu, South Africa. This change detection study will enable quantification of change and the changes between different land use and land cover that has occurred over the study period 1991–2006. This work embarked on a change detection analysis using image-processing software namely ERDAS, IDRISI and ArcGIS to complete the study. Three Landsat TM images from 1991, 2001, and 2006 were used. The images were geometrically corrected to a common map projection, followed by image processing operations namely: radiometric correction, supervised image classification, accuracy assessment and post classification comparison change detection. Each image was separately classified into land cover categories of water, grassland, mix bush/shrub, forestry, sugarcane and built-up land using the supervised classification maximum likelihood algorithm in ERDAS. Final classification accuracy was determined to be 'satisfactory' or 'good' by means of employing standardized accuracy assessment measures, the error matrix. The post-classification comparison technique was applied to compare the classified images to assess for changes in sugarcane land use over time using IDRISI software. The classified images produced were exported into ArcMap GIS software for additional change analysis. The results are displayed as change maps. Change analysis has been executed based on digital interpretation of classification results.

Key words: Land use, change detection, sugarcane

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Declaration

This document describes work undertaken as part of a programme of study at the Centre of Environment, Agriculture and Development. It represents the original work of the author and any work taken from other authors is duly acknowledged within the text and references chapter.

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Abbreviations

ANN	Artificial Neural Network
ASTER	Advanced Space borne-Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CVA	Change vector analysis
ERDAS	Earth Resource Data Analysis System
GIS	Geographical Information System
GPS	Global Positioning System
LULC	Land Use and Land Cover
MODIS	Moderate Resolution Imaging Spectro-radiometer
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
PCA	Principal Component Analysis
RGB	Red, Green and Blue Colour Composite
SMA	Spectral Mixture Analysis
SPOT	Satellite Probatoire d'Observation de la Terre
TM	Thematic Mapper
UTM	Universal Transverse Mercator
WGS	World Grid System

1. Introduction

1.1 Background

Land is the foundation that supports all living organisms, human existence and survival. Most human activities such as food production, shelter, infrastructure development and extraction of natural resources, are performed on land. On a global scale, land resources are however becoming increasingly scarce due to continued exploitation and poor land management. There are two concepts that are closely related to land exploitation; land use and land cover. Inglis-Smith (2006) defines land use as the way in which humans use and modify the land. Typical examples of land uses include agriculture, mining, urban and infrastructure development. In a similar vein, FAO (1995) defines land use as the number of operations performed on land, caused by humans to generate benefits from natural resources. In contrast to land use, Inglis-Smith (2006) defines land cover as the physical state of the land surface. This includes streams, wetlands, bare surface rock, grasslands, forests and human modification such as roads and buildings. Changes in land cover by land use are caused mainly by two factors; conversion and modification (Inglis-Smith, 2006; Briassoulis, 2000). Land conversion involves change from one type of use to another, for example changing from maize to sugarcane cropping. Research, for example by Asubonteng (2007), has shown that landscape conversion can be easily monitored and recorded. Modification, on the other hand, involves the change in the condition within a particular land cover type e.g., change of a suburban forest from its natural state to recreational uses (Briassoulis, 2000).

According to Briassoulis (2000), there are a variety of driving forces of land use/land cover change, namely urbanization, population growth and economic factors, which relate differently in different spatio-temporal settings. It is a well-established fact that land use change can lead to major environmental problems such as biodiversity loss, water pollution, desertification and soil erosion. In addition, land use change also has a profound impact on food security and increased human vulnerability especially in Africa (Bottomley, 1998). Recently, South Africa has been facing unprecedented price increases on essential food items and globally, food prices in 2008 escalated significantly due to scarcity. To survive this harsh reality, many rural and suburban people have resorted to cultivation of both food and cash crops on their land. However, some studies, for example Makhanya (1997), have established that farmers are converting land previously used for food crops to cash crops such as sugarcane. How much of such land has been converted remains unknown in most cases. To manage land and its resources effectively, there is need for information on land use activities, and their resulting land cover alterations. Too fully, understand the complex relationship between land use and land cover changes for future of natural resource distribution, Read and Lam (2002) and Asubonteng (2007) suggest information is needed on what change occurs, where and when and the rate at which they occur. Over the last two decades, earth-sensing satellites, viewing the earth and its phenomena from space, have assisted scientists and planners in detecting environmental change. Several authors (Bottomley, 1998; Srivastava & Gupta, 2003) have acknowledged the acquiring of up to date information on human utilization of the landscape as of paramount importance for future planning, management and monitoring of natural resources. Through remote sensing and GIS, (Gilbert, 1998; Bottomley, 1998) suggest that it is possible to map and monitor land use and land cover.

1.2 Problem statement

Numerous studies that seek to analyze land use changes have been conducted. However, some works (e.g. Makhanya, 1997) have tended to focus on 'why' land use changes have occurred and mainly from a socio-economic perspective. In particular, studies conducted in South Africa that assess the spatial changes in land use using remote sensing and GIS techniques particularly in small-scale farming situations are rather few. Unlike large scale farming operations, small-scale farming is often viewed as insignificant in most developing countries. Despite this lack of attention, small-scale farmers in rural areas are converting current land uses/cover to other uses like cash cropping. In most cases, the spatial extent of the land converted towards such uses is often unknown. Lack of knowledge about the spatial changes in land use over time can make the planning of interventions and development of strategies for sustainable land and resource management rather difficult. This study seeks to determine spatially how much of land use/cover has been converted from one use to another in a small scale farming area, in order to help with such initiatives.

1.3 Main objective

The main objective of the study is to analyze spatially, the amount of land that has been converted from one land use/land cover type to another over time. The focus is particularly on the conversion to small-scale sugarcane of land that was previously used for other purposes. The Umbumbulu region in KwaZulu-Natal, South Africa, is used as a case study.

1.4 Research questions

How has land use changed between 1991, 2001 and 2006 (in space) for the selected area (Umbumbulu, Kwa Zulu- Natal as illustrated in Figure1)?

(1) What are the present land use types in the study area?

(2) What were the previous land uses before sugarcane cultivation?

1.5 Study area

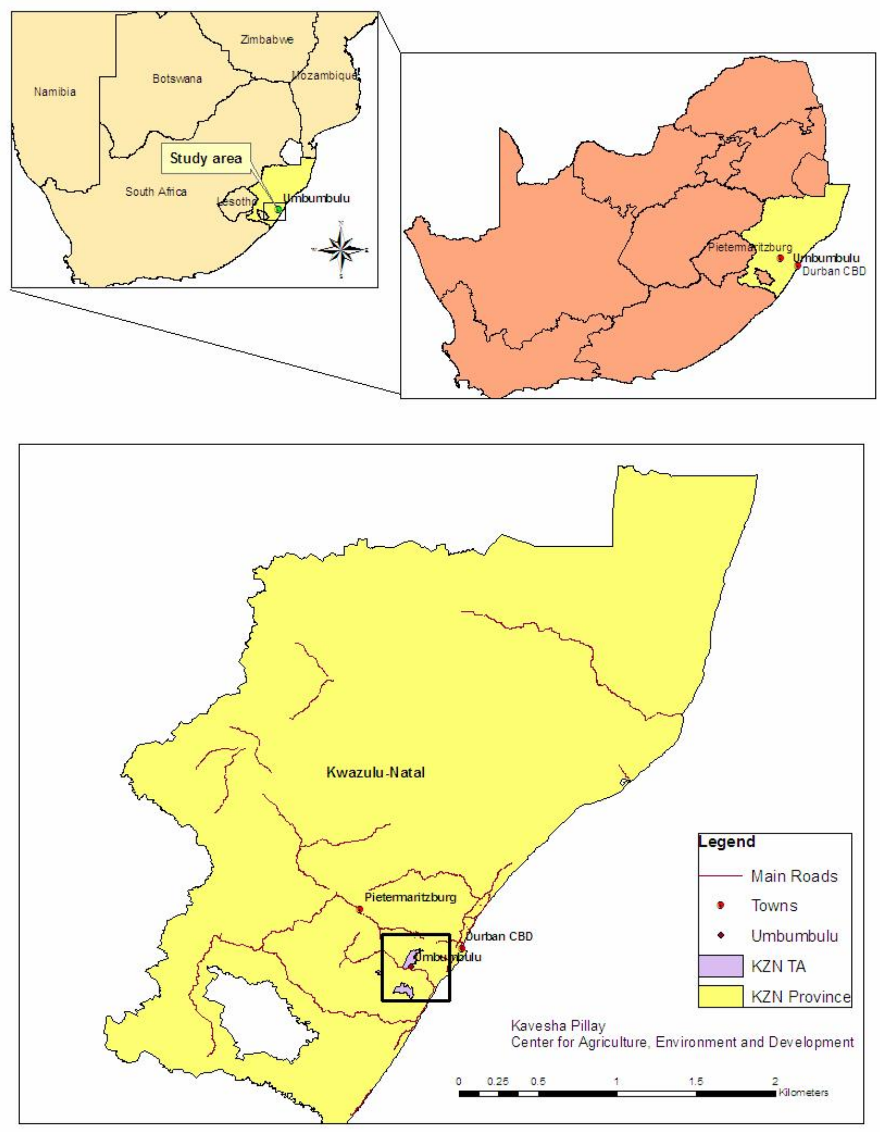

Figure 1: The geographic location of the study area

Umbumbulu is located in KwaZulu-Natal, South Africa, approximately 30 km south of Durban and about 12 km from the Indian Ocean (Makhanya, 1997). The area measures about 22, 65 km x 22, 9 km^2, and is located between latitude 29º 59’ 0” S and longitude 30º 42’ 0” E. Its altitude is 593 m above sea level. The area was selected mainly due its proximity, familiarity and because of the several observed changes in agricultural land use towards sugarcane. Umbumbulu encompasses a variety of land uses that range from agriculture, settlement and infrastructure as well as land covers such as; water bodies, grassland, mix bush/shrub, forestry, sugarcane and built-up land.

1.6 Organization of the thesis

This thesis consists of five chapters. Chapter 1 presents the background to the study, the research problem and a brief discussion of the study area. Chapter 2 examines existing literature on change detection techniques and the application areas where the different techniques have been applied. A summary of these techniques and application areas is provided in a table. In Chapter 3, materials and methodology used to achieve the objective of the study are presented while in Chapter 4, the results as well as discussion of the findings of the study are presented. Chapter 5 concludes the study and highlights some limitations and recommendations.

2. Literature Review

This chapter reviews literature pertinent to change detection particularly for sugarcane. A discussion of selected change detection techniques and their application is presented first followed by a summary of each technique, key characteristics, advantages, disadvantages and application areas. A discussion on satellite imagery that can be used in sugar cane change detection is then presented. The chapter concludes with a summary.

2.1 Change detection and its importance

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time periods (Singh, 1989). Hsiung Huang and Ju Hsiao (2000) define change detection as the comparison and contrast of multi temporal images of the same geographical area. This is achieved by using image-handling techniques to analyze the changed areas of the landscape over different time periods. Change detection is important for the monitoring of the earth's natural resources through the analysis of the spatial distribution of the population of interest. Aspects of change detection that are essential for monitoring natural resources are; detecting changes that have occurred, identifying the nature of the change, measuring the magnitude of the change, and assessing the spatial pattern of the change (Macleod & Congalton, 1998). Change detection is useful for a wide range of applications namely; land use analysis, monitoring cultivation patterns, assessment of deforestation, natural disaster e.g. real time floods, environmental monitoring, and urban change (Bottomley, 1998; Inglis-Smith, 2006).

2.2 Change detection techniques

Various change detection techniques have been developed over the last two decades. Lu *et al.* (2004) classified change detection techniques into seven categories namely: (1) Algebra, (2) Transformation, (3) Classification, (4) Advanced models, (5) Geographic Information Systems (GIS), (6) Visual analysis and (7) other techniques (see Table 1). An elaborate discussion of these is presented in the same study. Ernani and Gabriels (2006) point out that change detection analysis encompasses a broad range of techniques used to identify, describe, and quantify differences between images of the same scene at different times or under different conditions. Lu *et al.* (2004) highlighted the importance of selecting a suitable change detection technique to be used in a specific application area. The most common change detection techniques are; image differencing, principal component analysis and post classification comparison. Image differencing and principal component analysis can provide change/non-change information whereas post-classification comparison provides detailed ‘from–to’ change information. These techniques and their application areas are discussed below.

Table 1: Summary of change detection techniques categories (Lu *et al*. 2004).

Categories	Techniques
(1) Algebra	Image differencing Image regression Image rationing Change vector analysis Vegetation index differencing
(2) Transformation	Principal component analysis Tasselled cap (KT) Gramm–Schmidt (GS)
(3) Classification	Post classification comparison Spectral change pattern analysis Hybrid change detection Expectation Maximization detection Unsupervised change detection Artificial neural network
(4) Advanced Models	Spectral Mixture analysis Li–Strahler reflectance model
(5) Geographic Information Systems	Integrated GIS and remote sensing method GIS approach
(6) Visual Analysis	Visual Interpretation
(7) Other	Regression analysis Knowledge-based expert systems

2.2.1 Image differencing

Singh (1989) and Lu *et al*. (2004) defined image differencing as the subtraction of one date imagery from a second date that has been precisely registered to the first as illustrated in figure 2. This is achieved pixel by pixel. Bottomley (1998) conducted a study to detect prior forest conversion to pasture lands in Arkansas County from 1984–1999 using the image differencing technique on Landsat TM imagery. His research builds on previous work by Maus *et al.,(*1992); Doak & Lackey,(1993); Green *et al.,(*1994), who were able to detect, delineate, and classify forest canopy changes using image differencing with multi-temporal Landsat TM images.

Date 1

8	10	6	11
220	11	8	20
205	210	201	50
220	90	82	45

Date 2

5	7	5	5
95	9	8	22
99	101	202	222
102	97	250	210

3	3	1	6
125	2	0	-2
106	109	1	172
118	-7	-168	-165

Difference Image
= Image1 - Image 2

Figure 2: Illustration of an image differencing technique adapted from Kennedy (date unknown).

In addition, Green *et al*. (1994), who demonstrated that Landsat band 7 is better for identifying vegetation loss than Landsat bands 3 and 4, found that image differencing using band 7 subtraction was suitable for vegetation identification and discrimination. The band 7 difference file and land use and land cover maps depicted areas which had experienced the conversion of forest to agricultural pastures and the regeneration of successional forests from fallow pastures in Carroll County. Image differencing has the advantage that it is very simple and data is easily interpreted. Its disadvantages are that the technique cannot provide a detailed change matrix and it requires selection of thresholds.

2.2.2 Principal component analysis

Inglis-Smith (2006) defines principal component analysis (PCA) as a statistical procedure of data compression of multi date imagery. It assumes that multi temporal data can be linked; thereby change information can be determined in the new components. Lu *et al*. (2004) points out that PCA is performed in one of two ways; (1) by merging two or more date images as a single data file, and then running the PCA to analyze small component images for change information, or (2) by running the PCA separately, then subtract second date principal component image from the rest. Becerra and Celia Dos Santos Alvala (2006) find PCA particularly useful for image data transformation, information compression and change detection analysis. Aldakheel and Al-Hussaini (2005) conducted a study on the use of multi temporal Landsat TM imagery to detect land use and land cover changes in Al-Hassa, Saudi Arabia. Three change detection techniques were used, namely; image differencing, image overlay and PCA. Though the PCA technique was found to be complex, involving more multi-spectral imaging of combined multi-date data sets than the other techniques used in the study, it was considered the preferred choice to highlight differences that contributed to change in the physical environment. Inglis-Smith (2006) conducted a study to determine change on land use along the West Virginia Corridor Urban development using PCA. The study also found that principal components images provided a better basis for classification. The main advantage of PCA is the reduction of data redundancy between bands and the focus on different information in the given components. Its shortcomings are that; (1) it cannot provide a complete matrix of change information and (2) it is scene dependent; thereby change detection results between different dates are sometimes very difficult to interpret and label (Lu *et al*., 2004). Another limitation of PCA is that it is based on the statistical properties of the data and therefore is confined in its application to different times and areas (Rogan & Chen, 2004).

2.2.3 Spectral mixture analysis

Adams *et al*. (1986, 1993), Gillespie and Inglis-Smith (1990) and Roberts *et al*. (1997) define spectral mixture analysis (SMA) as a model based on the linear mixing of two or more pure spectral end members. Palaniswami *et al*. (2006) further discusses spectral mixture analysis as the operation that assumes the reflectance spectrum measured by a sensor is a linear combination of the spectra of different components within the pixel known as end members. The end members are derived from the image data based on specific image characteristics. Research by Palaniswami *et al*. (2006) on sub-pixel classification of coconut in the Kasaragod district, Kerala, found fraction image of end members to be important for identifying coconut land cover type. In addition, the study found that SMA as a sub-pixel technique is capable of mapping coconut land cover in the study area. The results, though, are shown to be more accurate in homogenous coconut land cover portions than in other areas. Löhnertz *et al*. (2006) conducted a study on land use/land cover (LULC) on crop classification using multi temporal high resolution SPOT images. The SMA technique was employed on every SPOT image to ensure that crop types can be separated by using image end members, vegetation, soil and shadow (Löhnertz, *et al*., 2006: 80). The advantage of the fraction images extracted by this technique is that they contain different land cover components within a pixel (Palaniswami *et al*., 2006). The results are found to be accurate, consistent and repeatable (Lu *et al*., 2004: 2378). Settle and Drake (1993) found SMA to be suitable for classifying successional forest types and forest types with varying carbon-sink strengths. However, Palaniswami *et al*. (2006) argue that the SMA technique has limitations in the classification of species type and age class. In addition, SMA is found to be, time consuming and difficult to convert image reflectance values to biophysical parameters. It is considered an advanced image processing technique, which is rather complex (Lu *et al*., 2004).

2.2.4 Artificial neural network

Artificial neural network (ANN) is defined as a non-linear mathematical model to process information. It is also further described as a replica of the human brain as it operates similarly and is able to interpret graphical information. The input used to train ANN is the spectral data of the period of change. ANN does not require hypothesis a priori about distribution functions or another statistical assumptions. The ANN approach can probably provide better change detection results when the land-cover classes are not normally distributed. Allan (2007) conducted a study on land cover classification in a heterogeneous savanna environment to investigate the performance of an artificial neural network and the effect of image resolution. To improve the accuracy of the maximum likelihood classifier, an artificial neural network was trained using ancillary data and SPOT 5 image. The results of the study show an increase in the classification accuracy of the ANN. In addition, specific classes were easily identified. The advantage of ANN is that it is a non-parametric supervised method that has the ability to estimate the properties of data based on the training samples (Lu *et al*., 2004). Neural networks are able to learn from a set of parameters for the classification, and it is possible to perform classifications of complex data (Linderman *et al*., 2004). Its disadvantages are that hidden layers are poorly known, and training of imagery is time consuming. In addition, ANN is sensitive to the amount of training data used and its functions are rarely available in image processing software (Lu *et al*., 2004).

2.2.5 Post classification comparison

The post-classification comparison (PCC) technique classifies date 1 and date 2 images separately and compares class values on a pixel–by-pixel basis between the dates (Ernani & Gabriels, 2006). This results in the production of a change detection matrix as illustrated in Figure 3.

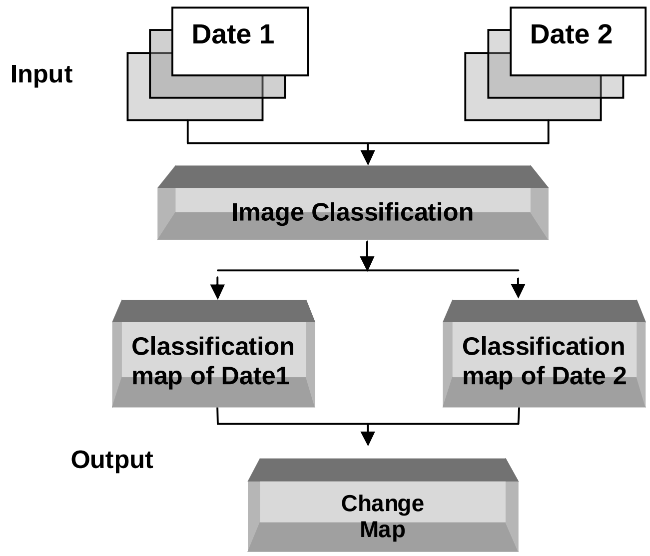

Figure 3: A flowchart of post-classification change detection technique.

Post classification comparison provides detailed ‘from–to’ change class information that is important for landscape monitoring. Asubonteng (2007) points out that PCC is a commonly used quantitative technique for change detection though challenges can arise when classifying historical image data. Hurskainen and Pellikka (2004) applied post classification comparison technique on classified multi temporal aerial images, to detect spatio temporal changes of built-up and non-built-up areas of informal settlements. This study, in the small village of Voi in Kenya, investigated how the informal settlements had grown and changed for the period 1984–2004. Hurskainen and Pellikka (2004) found that post classification comparison technique had limitations as it was unable to detect the changes for example; if a building established in 1993 was demolished and a new building was built on the same plot or an extension to an existing building was made. Shalaby and Tateishi (2007) applied post classification comparison on supervised maximum likelihood classification of Landsat imagery, of 1987 to 2001, in an attempt to map land cover changes in the Northwestern coast of Egypt. The study found that severe land cover changes occurred due to agriculture and tourism projects resulting in vegetation degradation and water logging in the study area. Feleke (2003) used post classification comparison on a supervised maximum likelihood classification of ASTER imagery in an attempt to map *Chromolaena odorata* distribution in the St. Lucia wetland area, South Africa. It was found that the land cover and land use of the area has changed and the infestation of *Chromolaena odorata* was observed. The advantages of post classification comparison are, (1) the technique avoids the need for strict radiometric calibration and minimizes impacts of atmospheric, sensor and environmental differences between multi temporal images, and (2) the technique provides a complete matrix of change directions unlike image differencing. Macleod and Congalton (1998) have highlighted that post classification comparisons has significant limitations because the comparison of land cover classifications for different dates does not allow the detection of slight changes within land cover categories. In addition, Stow *et al*. (1980) and Mas (1999) found that the change-map output of two classifications, often display accuracies similar to the product of multiplying the accuracies of each individual classification. Further limitations exhibited are; requires knowledge, expertise, and time to create classification products (Lu *et al*., 2004).

Table 2 below provides a summary of the aforementioned change detection techniques, their key characteristics, advantages, disadvantages as well as application areas and studies that have used them. It can be concluded that the post-classification comparison technique is widely used in land use and land cover applications, and hence was selected for use in this study.

Table 2: Summary of change detection techniques (adapted from Lu *et al*., 2004).

Techniques	Characteristics	Advantages	Disadvantages	Application areas
Image Differencing	Subtract date 1 from date 2, Picks a threshold for change.	Simple and easy to interpret data.	Cannot complete matrices of change information.	Land use and land cover (Bottomley, 1998).
Principal Component Analysis	Assumes multi temporal data are linked and change information can be derived in the new components.	Reduces data redundancy between bands and the focus of change information in the given components..	PCA is scene dependent. Change detection results between different dates difficult to interpret and label. Cannot complete matrices of change information.	Multi temporal Landsat TM imagery to detect LULC changes in Al-Hassa, Saudi Arabia (Aldakheel & Al-Hussaini, 2005).
Spectral Mixture Analysis	Model based on the assumption of linear mixing of two or more pure spectra different components within a pixel known as end members.	Fraction images extracted by this technique contain different land cover components within a pixel (Palaniswami *et al*., 2006). The results are found to be accurate, consistent and repeatable (Lu *et al*., 2004).	Time consuming, difficult to convert image reflectance values to biophysical parameters, considered an advanced technique and is seen to be complex (Lu *et al*., 2004).	SMA for sub-pixel classification of coconut (Palaniswami *et al*., 2006). LULC on crop classification using Multi temporal high resolution spot images (Löhnertz, *et al*., 2006).
Artificial Neural Network	The input used to train ANN is the spectral data of the period of change.	Reduces data redundancy between bands.	Hidden layers are poorly known; Time is required for training data and ANN is sensitive to the amount of training data used. ANN functions rarely found in image processing software.	Land cover classifications in a heterogeneous savanna environment (Allan, 2007).
Post Classification Comparison	Classifies date 1 and date 2 imagery and compares the classified imagery pixel by pixel.	Minimizes impacts of atmospheric, sensor, environmental differences between multi temporal images. Complete matrices of change information.	Require knowledge, expertise, and time to create classified result.	Informal urban settlement; (Hurskainen & Pellikka, 2004), Land use and cover, (Shalaby & Tateishi, 2007) and (Feleke, 2003).

2.2.6 Hybrid change detection techniques

In addition to the single techniques, hybrid approaches are often used. Hybrid change detection involves the combination of two or more techniques. It is useful especially for generating higher accuracies in change maps. For example a study conducted by Petit *et al.* (2001) used image differencing and post classification to detect detailed 'from–to' land cover change in south-eastern Zambia. The study found that the combination of such hybrid techniques yielded better accuracies than using a single post-classification comparison technique. Silapaswan *et al*. (2001) used change vector analysis (CVA) technique, and unsupervised classification method, followed by aerial photographs to detect land cover change. It was also found that the combination of CVA and unsupervised classification method provided better results of change information than a single method. Due to the time limitations in the current study, the option of using hybrid techniques could not be explored.

2.3 Satellite imagery used in change detection of sugarcane

There are many satellite sensors that can potentially be used for land use and land cover mapping and change detection. These include; IKONOS, Quick bird Advanced Very High Resolution Radiometer (AVHRR), Advanced Space Borne Thermal Emission and Reflection Radiometer (ASTER), Satellite Pour l' Observation de la Terre (SPOT), Landsat Thematic Mapper (Landsat TM), and Moderate Resolution Imaging Spectrometer (MODIS). Each satellite sensor has different spatial, temporal and spectral characteristics. Briassoulis (1998) suggests that the detection and measurement of change depends on the spatial scale. For example, the higher the spatial level of detail, the larger the changes in the areal extent of land use and land cover which can be detected and recorded. Satellite sensors that have a higher spatial resolution include IKONOS and Quick bird, while Landsat TM and SPOT can be viewed as medium spatial resolution sensors and Modis, as lower resolution. SPOT and Landsat are the most commonly used satellite sensors for agricultural purposes. Gers and Schmidt (2001), for example, used Spot 4 satellite imagery to monitor sugarcane-harvested areas cultivated by small-scale growers at Umfolozi, South Africa. The supervised classification method was used to distinguish between standing sugarcane and harvested plots. Lee-Lovick and Kirchner (1991) studied the spectral signature of sugarcane in Bundaberg, Australia, using data from the Landsat TM sensor and found that bands 1, 2 and 3 (blue, green, and red) had a lower reflectance range and would therefore be more useful in sugarcane crop identification rather than assessing crop condition. Narciso and Schmidt (1999) used Landsat TM for the identification, classification, and estimation of sugarcane areas in Eston district, South Africa. The results showed that it is feasible to use Landsat TM for identifying and classifying sugarcane. A study conducted by Hadsarang and Sukmuang (2000) used Landsat TM imagery to map and estimate sugarcane growing areas in Thailand. It was possible to separate sugarcane from other crops and delineate the areas covered by cane, using false composite colour in the district at 1:50 000 map scale.

This research used post-classification comparison change detection technique due to its previous uses by Hurskainen and Pellikka (2004), Shalaby and Tateishi (2007) and Feleke (2003). The technique was chosen based on its popularity and was found to have the ability to complete a matrix of change information over other techniques. The Landsat TM sensor was chosen due to its availability, feasibility and suitability for identifying, classifying and mapping sugarcane.

2.4 Summary

The review of literature presented above has outlined the various change detection techniques used for different application areas. Following the review, a brief summary of the commonly used techniques has been provided. In addition, a discussion of satellite imagery used in sugarcane mapping has also been explored. The next chapter presents the methodology used to execute the study.

3. Materials and Methods

This chapter describes the materials and equipment used for data collection as well as the specific image processing steps used for the change detection process, namely geo-corrections of Landsat TM 5, radiometric correction, image classification, accuracy assessment and post classification comparison. These steps were performed using ArcMap GIS software, ERDAS Imagine 9.1 and IDRISI Andes image processing systems.

3.1 Materials

3.1.1 Research Material

The following materials and equipment were used in this study.

1. **Remotely sensed data**: Landsat TM 5 images for 1991, 2001 and 2006 covering Umbumbulu area
2. **Ancillary data**: 1: 50 000 topographical map (1993); aerial photo map (2000)
3. **Hand held trimble Global Positioning System (GPS)** unit
4. **Software used:** ArcGIS 9.2, ERDAS Imagine 9.1 and IDRISI Andes

3.2 Methods

The following steps were employed within the scope of this study (figure 4):-

1. Acquiring of satellite imagery
2. Gathering ground truthing information
3. Image processing (geometric corrections, radiometric correction, and image classification of the Landsat TM images.)
4. Accuracy assessment
5. Change detection

The section below gives a detailed description of each of the steps.

3.2.1 Acquiring satellite imagery

The first step in the process of mapping sugarcane areas was the identification of a suitable sensor appropriate for sugarcane change detection.

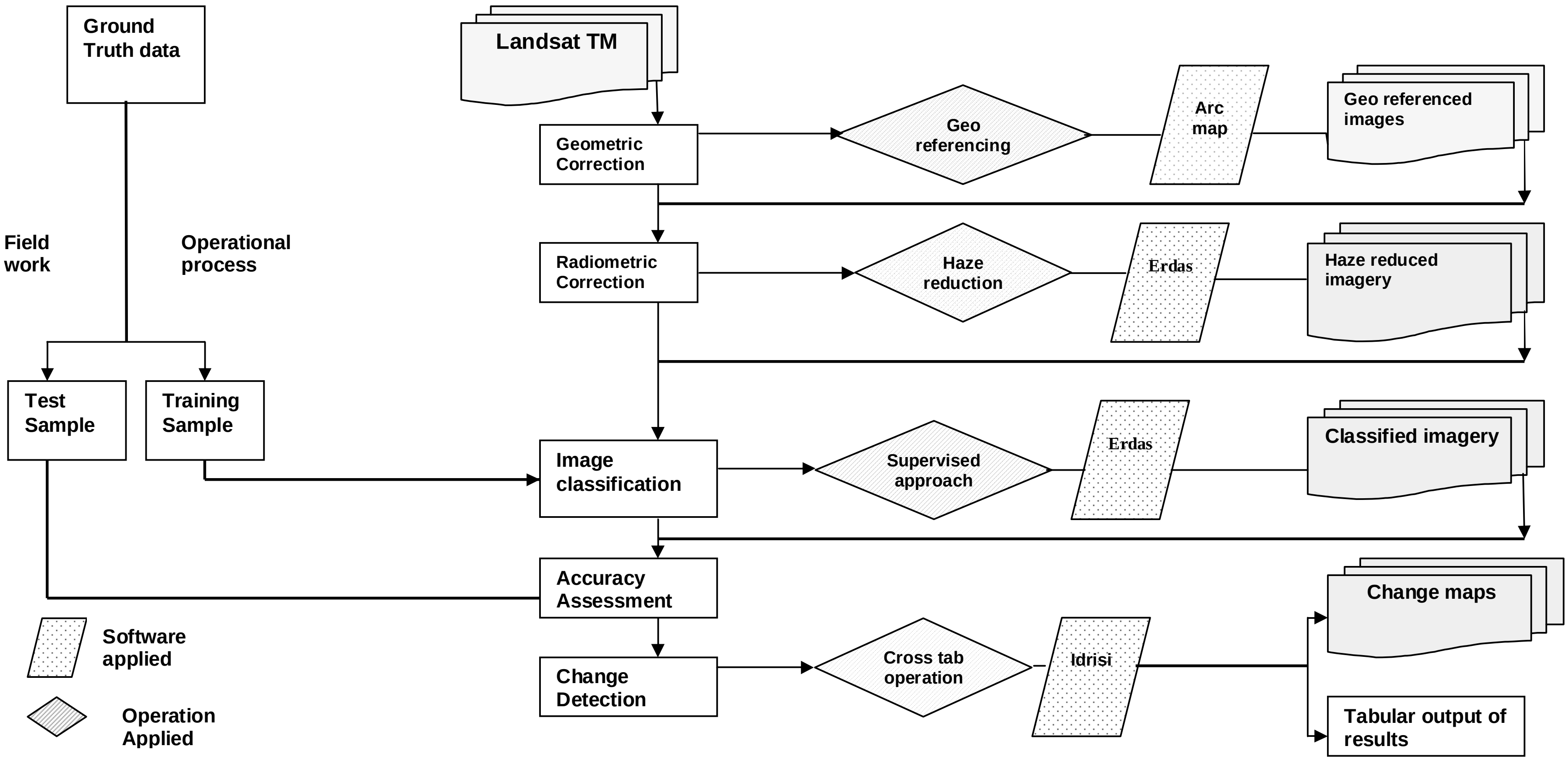

Figure 4: Flow chart illustrating the methodology of the study.

Studies, for example, by Lee-Lovick and Kirchner (1991), Narciso and Schmidt (1999) and Hadsarang and Sukmuang (2000) recommend the use of Landsat TM for sugarcane identification and mapping. In the present study, 3, Landsat TM 5 images were used. Scenes covering Umbumbulu, for the periods 1991, 2001 and 2006 (Table 3), were acquired from archives. The images were selected due to their availability. In order for the satellite images to fit perfectly when overlaid, it was necessary to ensure that they had the same projection. The 1991 and 2006 satellite images were geo-rectified to the 2001 image, whose map projections were correct when received. The red (1), green (2) and (3) blue bands of the Landsat TM images, considered most appropriate for vegetation identification, were used for all images.

Table 3: Characteristics of Landsat TM imagery made available for this study (Munyati, 2000; Pereira, 2004).

Acquisition Date	Landsat Sensor	Spatial Resolution	Pre-processing level
*1991	TM 5	30m	Geo-referencing Radiometric correction
February 2001	TM 5	30m	Geo-referenced Radiometric correction
September 2006	TM 5	30m	Geo-referencing Radiometric correction

* Not available

3.2.2 Gathering ground-truthing information

Ground–truthing was conducted to gather field data useful for the classification and verification of the satellite imagery. Whilst it is possible to collect ground reference information for up to date satellite imagery, it is almost impossible to collect the same for historical imagery, Jensen *et al*. (1995). In this study, the first step was to collect GPS points to be used for training for the 2006 imagery. The 1993 topographical map was overlaid with the 1991-landsat tm image similarly; the 2000 aerial photo map was overlaid with the 2001 landsat tm image. This was performed to determine the land use and land cover classes for the image classification process for the above-mentioned imagery. 41 GPS points were recorded in the field. The geo statistical analyst module in Arc Map was then used to create subsets of sample points for training and accuracy assessment. It was decided to use 34 of the 41 points collected because 7 points recorded (scarp, banana, and fallow land) - land cover classes considered to be inappropriate for the study.17 of the GPS points were used as training samples and the other 17 as test samples (Table 4).

Table 4: Number of training and test samples for the classification of Landsat TM 5 image.

	Training Samples (50%)	**Test Samples (50%)**
Land cover classes		
Water	1	1
Grassland	4	4
Mix bush/shrub	3	3
Forestry	3	3
Sugarcane	5	5
Built-up land	2	2
Total (34)	**17**	**17**

3.2.3 Image processing

According to Jensen (1996) and Munyati (2000), the important considerations that one needs to take into account when processing images for change detection, include:

(1) The sensor system, namely, spatial, spectral, temporal and radiometric resolution and geometry.

(2) Environmental variables, namely, time of year, time of day and atmospheric composition at image acquisition time (Lillesand & Kiefer, 2004; Edgar, 2004).

In order to improve the results of a change detection analysis, the sensor and environmental variables should be minimized as much as possible (Munyati, 2000). For greater accuracy, results largely depend on the geo-referencing of the images to be used and the relation between the spatial resolution and spatial size of the changes (Munyati, 2000). The choice of the appropriate image processing operations to apply was made based on the procedures tabulated in Table 5.

Table 5: Image processing operations applied to the satellite images used in this study (Pereira, 2004).

Group of operations	**Type of operations**	**Operation applied**	**LANDSAT TM 1991**	**LANDSAT TM 2001**	**LANDSAT TM 2006**
GIS	Geometric correction	Geo-referencing	✓	*	✓
Image rectification and restoration	Radiometric correction	Haze reduction	✓	✓	✓
Image classification	Classification	Supervised classification	✓	✓	✓
	Accuracy assessment	Accuracy assessment	✓	✓	✓

*Geo-referenced when received.

3.2.4 Geo-corrections of Landsat TM

Geo-referencing is a process in which raw remotely sensed imagery, that are highly distorted with inaccuracies when retrieved, is corrected in terms of its geographical co-ordinates (latitude/longitude) to a known map projection. It requires a set of ground control points to produce a geo-referenced image (Lillesand & Kiefer, 2004). The imagery for 1991 and 2006 were geo-referenced in Arc Map. The 2001 image was used as the base image. The geo-referencing was performed according to the following procedures:-

(1) The satellite imagery was imported to the ArcGIS 9.2 software. Each image included a set of control points based on the respective satellite position and a base geometric correction. In this study, UTM projection was used as it is a commonly used and preferred projected co ordinate system, whilst the WGS 1984 datum was used, because it is the reference coordinate system used by the Global Positioning System.

(2) A minimum of 4 ground control points were used. The ground control points used were mainly river bends and junctions.

3.2.5 Radiometric correction

Radiometric correction is a process used to remove unwanted noise and atmospheric abnormalities on image brightness values. Lillesand and Kiefer (2004) state that the process is important due to variations in scene illumination, atmospheric conditions, sensor noise and responses. The haze reduction operation was performed in ERDAS on all 3 geo-rectified images. Compared to the 1991 and 2001 images, more haze was visible on the 2006 image.

3.2.6 Image Classification

Image classification is defined as the process of automatically categorizing all pixels based on their spectral properties into land cover classes (Navalgund *et al*., 2007; Lillesand & Kiefer, 2004). Similarly, Palaniswami *et al*. (2006) define image classification as the process of creating thematic maps from satellite imagery. The two primary methods of image classification are; supervised and unsupervised. Jensen (1996) highlighted that supervised classification is dependent on the input from the user and informational classes or types known a priori. In addition, Edgar (2004) agues that training data from the field and maps form the basis of the supervised classification approach. Supervised classification identifies homogenous areas or samples of known land use/cover types.

This means the pixels are assigned to known informational classes Jensen *et al*. (1996). These areas are known as samples or training sites containing numerical properties that are used to train the classification algorithm. Training is the process of defining the criteria by which these patterns are recognized. The outcome of training is a set of signatures, which form the criteria for a set of proposed classes (Jovanovic *et al*., 2007). With the supervised approach, calibration pixels are selected and statistics are produced for the classes of interest. There are three different calibration strategies for supervised classification; single pixel, seed, and polygon (Chen and Stow, 2002). The seed calibration strategy was chosen for this study, because it selects spectrally similar pixels and is an effective way of selecting homogenous training data. Algorithms commonly used in supervised image classification include *parallelepiped* classification, *minimum distance* classification and *maximum likelihood* classification. The maximum likelihood is, however, the most widely used per-pixel algorithm. This research used the maximum likelihood, as it is a preferred algorithm especially in land cover and land use monitoring approaches, because it assumes that (1) image data are normally distributed and (2) pixels are composed of a single land cover or land use type. Franklin *et al*. (2003) point out that the maximum likelihood algorithm classifies data according to the highest probability. The advantage of this method is that the result of a classified image is more accurate due to validation through ground-truthing.

3.2.6.1 Signature Creation

Signature creation was performed on all 3 images. The class vector files, for each image was imported into ERDAS Imagine 9.1. These vector files formed the base for the classification process (Allan, 2007). Using the vector files overlaid on the image, polygons were created around the points for the creation of signatures from which the classification would be made. The region grows properties tool was used to select pixels that have similar spectral characteristics to assign to a class based on the user defined class codes for each land use and land cover present (table 6). Six signature classes were created using signature editor of ERDAS. This process was performed on all three images.

Table 6: The user defined class codes and classes used for creating the signatures in ERDAS.

Class Code	Class Name	Class Code	Class Name
1	Water	6	Built-up land
2	Grassland		
3	Mix bush/shrub		
4	Forestry		
5	Sugarcane		

To increase the level of accuracy of results, a number of classification trials were performed on all three Landsat TM imagery. At least 3 trials were performed on 1991 imagery, aided by a 1993 topographical map, to establish the actual land use and cover on ground surface, 1 classification trial was performed on the 2001 image aided by an aerial map and 4 classifications trials on the 2006 image. More trials were done on the 2006 image, because it had significant spectral mixing of classes (water bodies, grasslands and mix bush/shrub). By the fourth attempt, the image appeared more realistic. The quality of the 2006 image was overally considered poor.

3.2.7 Land Use and Land Cover Class Definition

Land covers for the study were created based on the South Africa National Land Cover Data-base project (Thompson, 1999; CSIR, 2002; Anderson *et al.,* 1976). Six, land use and land cover types were identified (table 7).

Table 7: Land use and Land cover class definition (Anderson *et al*., 1976; Thompson, 1999; CSIR, 2002).

Water	All open bodies of water, including streams and rivers.
Grassland	Area less than 10% tree or shrub cover, containing grass as the dominant species, included plant grass types.
Mix Bush/Shrub	Dense natural vegetation, consisting of shrubbery and natural forest.
Forestry	This land use includes timber, pulpwood, firewood, charcoal and pole wood.
Cane	Sugarcane plantations.
Built-up land	An area where there is permanent concentration of people, buildings and man-made structures and activities, from large village to city scale.

3.2.8 Accuracy Assessment

Once the classifications are completed, it is necessary to determine the accuracy of the final image. Jensen (1996) argues that if through remote sensing, land use and land cover maps are produced and statistical results are to be useful, then it is important to perform a quantitative assessment of the classification accuracy. This is important for post-classification change detection analysis. Accuracy assessment involves the comparison of classified map and the reference test information. This information can be presented in an error matrix where columns represent the referenced data while rows represent the classified data. The overall accuracy is shown by the number of sample/pixels in each class, for example, the sum of all samples on the diagonal divided by the total number of samples (Feleke, 2003). The accuracy is a measure of how many ground truth pixels were classified correctly (Bottomley, 1998). This study adapted the error matrix accuracy method. From the field data collected, not all GPS points were used for training in image classification and testing in accuracy assessment. As previously mentioned, some GPS points were insufficient for creating land use and land cover classes of the area. A random stratified sampling method, using the geo statistical analyst operation in Arc Map, was employed. This method was used to create subsets (train/test) of the vector shape files of each class for classification and accuracy assessment. In order to increase the accuracy of historic data, the classified imagery for 1991 and 2001 was overlaid with a topographical map (1993) and an aerial photo map (2000) in ERDAS. This was done to achieve verification and accuracy of land cover for the classified imagery. The system compares the classified image with these known points to determine the accuracy of the original image and the classified image.

3.2.9 Change Detection

As defined by Edgar (2004), change detection involves pixel-by-pixel comparison to detect changes. The output is in the form of a change detection matrix. In this study, post-classification change detection technique was applied to detect and quantify the extent of change in sugarcane land use and produce change image (s). Post classification is the most commonly used technique of change detection, which requires the comparison of independently produced classified images of different dates. This method provides ‘from–to’ classes that can be calculated for each changed pixel (Ernani & Gabriels, 2006). Therefore, change information can be extracted to determine how much of change has resulted from different land covers over time. Change detection was done for 1991–2006 to get ‘from–to’ information of changes in land use and land cover in the study area. Post-classification comparison proved to be the most effective technique, because data from three dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates (Lu *et al.*, 2004). The cross operation allows the analyst to know the extent and nature of changes observed. In other words, the transition between different land use and land cover classes and the correspondent area of change (Pereira, 2004). Post-classification change detection method is carried out, through cross-tabulation. The land use change detection was assessed using the post-classification cross-tabulation approach in IDRISI software.

3.2.10 Analysis using ERDAS, IDRISI ANDES and GIS

ERDAS was found to be a more suitable image processing software for performing image classification than IDRISI. This is because the user can automatically create signature files or training sites in ERDAS. This software gives the user the option of the number of pixels in a class, using the region grows seed operation whilst it is difficult to create signature files in IDRISI, as the user would have to manually digitize pixels of specific land use and land cover to assign to specific class. This method was found to be time consuming. However, IDRISI was found to be better in performing time series analysis using the cross tabulation operation than ERDAS. Cross-classification images of 1991, 2001 and 2006 were produced in ERDAS. These final land use and land cover change maps show the conversion of land use and land cover from one type to another in Umbumbulu, from 1991 to 2006.

3.2.11 Data Analysis

Some data was organized using a Microsoft Excel spreadsheet (tabular output of results) which was useful for change detection analysis and in revealing quantitatively the change dynamics in sugarcane areas.

3.2.12 Summary

This chapter outlined the materials and equipment used and gave an elaborate explanation of the various steps used to execute the change detection study. Reference was also made to the software: ArcGIS, ERDAS and IDRISI Andes, used for image processing and performing time series change analysis. The next chapter presents the results and a discussion of the findings.

4. Results and Discussion

This chapter presents the results and a discussion of the findings. First, the results are presented in the form of tables, bar charts and land use and land cover (LULC) change maps. Next, a discussion, that attempts to explain the findings, follows.

4.1 Results

4.1.1 Accuracy assessment

The accuracy assessment, to determine the correctness of the classifications, was performed using error matrix tabulations. Tables 8, 9 and 10 show the error matrices for the 3 sets of Landsat TM images. The results show an accuracy of 100% for the 2001 image, 88.8% for 2006 and 83.3% for the 1991 image.

Table 8: Error Matrix for the classification of the Landsat TM for 1991.

		REFERENCE DATA							
		S	**MB/S**	**G**	**F**	**BL**	**W**	**Total**	**User Accuracy (%)**
CLASSIFICATION DATA	**S**	5	0	0	0	0	0	4	**125**
	MB/S	0	2	1	0	0	0	4	**50.0**
	G	0	1	3	0	0	0	4	**75.0**
	F	0	1	0	2	0	0	3	**66.66**
	BL	0	0	0	0	2	0	2	**100.00**
	W	0	0	0	0	0	1	1	**100.00**
	Total	5	5	4	2	2	1	18	
Producers accuracy (%)		**100**	**60**	**75**	**100**	**100**	**100**		**Overall accuracy = 83.3%**

Legend: S–Sugarcane; MB/S–Mix bush/shrub; G–Grassland; F–Forestry; BL–Built-up land; W–Water

Table 9: Error Matrix for the classification of the Landsat TM for 2001.

		REFERENCE DATA							
		S	**MB/S**	**G**	**F**	**BL**	**W**	**Total**	**User Accuracy (%)**
CLASSIFCATION DATA	**S**	5	0	0	0	0	0	5	**100.00**
	MB/S	0	3	0	0	0	0	3	**100.00**
	G	0	0	4	0	0	0	4	**100.00**
	F	0	0	0	3	0	0	3	**100.00**
	BL	0	0	0	0	2	0	2	**100.00**
	W	0	0	0	0	0	1	1	**100.00**
	Total	5	3	4	3	2	1	18	
Producers accuracy (%)		**100**	**100**	**100**	**100**	**100**	**100**		**Overall accuracy = 100%**

Legend: S–Sugarcane; MB/S–Mix bush/shrub; G–Grassland; F–Forestry; BL–Built-up land; W–Water.

Table 10: Error Matrix for the classification of the Landsat TM for 2006.

		REFERENCE DATA							
		S	**MB/S**	**G**	**F**	**BL**	**W**	**Total**	**User Accuracy (%)**
CLASSIFICATION DATA	**S**	5	0	0	0	0	0	5	**100.00**
	MB/S	0	3	0	0	0	0	3	**100.00**
	G	0	1	2	0	0	0	4	**50.00**
	F	0	0	0	3	0	0	3	**100.00**
	BL	0	0	0	0	2	0	2	**100.00**
	W	0	0	0	0	0	1	1	**100.00**
	Total	5	4	4	3	2	1	18	
Producers accuracy (%)		**100**	**75**	**100**	**100**	**100**	**100**		**Overall accuracy = 88.8%**

Legend: S–Sugarcane; MB/S–Mix bush/shrub; G–Grassland; F–Forestry; BL–Built-up land; W–Water.

4.1.2 Land Use and Land Cover Change

The LULC changes were assessed using post classification cross-tabulations. Possible change and no change were identified, with no change presented in shaded colour along the diagonals. Tables 11, 13 and 15 indicate the LULC change of one land use/land cover type against another. Figures 8 A, B and C show the LULC classifications for 1991, 2001 and 2006 while the change maps for 1991 to 2001, 1991 to 2006 and 2001 to 2006 are presented in figures 9, 10 and 11, respectively.

Table 11: Cross tabulation of land use and land cover classes between 1991 and 2001 (area in ha).

	1991						
2001	**Water**	**Grassland**	**Mix bush/ shrub**	**Forestry**	**Sugarcane**	**Built-up land**	**Total**
Water	597	18	60	7	1	4	687
Grassland	14	41 398	27 910	1 294	11 712	14 157	96 485
Mix bush/shrub	753	75 190	37 767	17 978	39 083	47 361	218 132
Forestry	141	10 177	1 703	3 452	1111	1 721	18 305
Sugarcane	2	8 754	9 097	1 200	14 709	11 122	44 884
Built-up land	97	55 638	69 590	4 956	31 771	52 308	214 360
Total	**1 604**	**191 175**	**146 127**	**28 887**	**98 387**	**126 673**	**592 853**

4.1.2..1 Changes between 1991 and 2001

The changes between different LULC classes for the period 1991 to 2001 can be derived from Table 11. For example, sugarcane covered 98 387 ha in 1991 and 44 884 ha in 2001. Out of the 98 387 ha that was sugarcane in 1991, 14 709 ha remained sugarcane in 2001, but 11 712ha was converted to grassland, 39 083 ha was converted to mix bush/shrub and 31 771 ha was converted to built-up land. At the same time, the increase of sugarcane from 1991 to 2001, was attributed to 8 754 ha from grassland, 9 097 ha from mix bush/shrub and 11 122 ha from built-up land. Table 12 presents a summary of the major LULC types of the study area between 1991 and 2001 while figure 5 shows the net area increase or decrease for the different LULC categories in hectares, for the same period.

Table 12: Summary of Land use and land cover types 1991 and 2001.

Land use/cover type	Area 1991 (ha)	Area 2001 (ha)	Code
Water	1 604	687	W
Grassland	191 175	96 485	GL
Mix bush/shrub	146 127	218 132	MB/S
Forestry	28 887	18 305	F
Sugarcane	98 387	44 884	S
Built-up land	126 673	214 360	BL

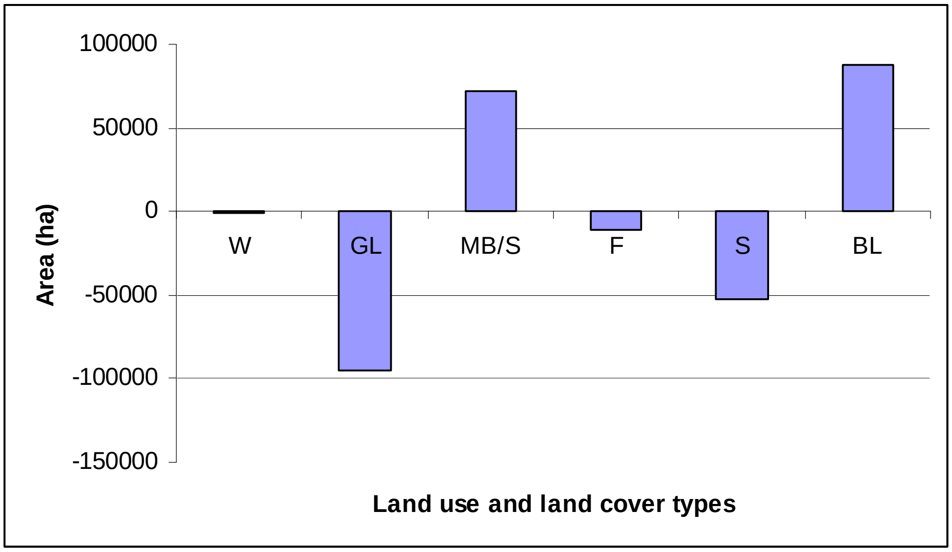

Figure 5: Land cover increases/decreases from 1991 to 2001.

4.1.2..2 Changes between 1991 and 2006

The nature of changes of different LULC for 1991 to 2006 can be derived from Table 13. For example, sugarcane covered 89 039 ha in 1991 compared to 80 776 ha in 2006. Out of the 89 039 ha that was sugarcane in 1991, 19 538 ha remained sugarcane in 2006, but 22 651 ha was converted to grassland, 39 201 ha was converted to built-up land. At the same time the increase of sugarcane from 1991 to 2006, was 25 332 ha from grassland, 14 508 ha from mix bush/shrub and 17 390 ha from built-up land. Table 14 shows the summary of the major LULC types of the study area for the period 1991 and 2006. The net area increase/decrease for the different LULC categories for the same period are presented in figure 6.

Table 13: Cross tabulation of land use and land cover classes between 1991 and 2006 (area in ha).

	1991						
2006	**Water**	**Grassland**	**Mix bush/ shrub**	**Forestry**	**Sugarcane**	**Built-up land**	**Total**
Water	443	2 984	918	515	918	1 002	6 780
Grassland	258	57 303	31 341	8 516	22 651	32 618	152 687
Mix bush/shrub	85	3 103	1 340	677	1 296	1 435	7 936
Forestry	311	14 028	4 032	3 901	5 435	6 044	33 751
Sugarcane	90	25 332	14 508	3 918	19 538	17 390	80 776
Built-up land	211	69 104	82 395	8 257	39 201	56 308	255 476
Total	**1 398**	**171 854**	**134 534**	**25 784**	**89 039**	**114 797**	**537 406**

Table 14: Summary of Land use and land cover types 1991 and 2006.

Land use/cover type	Area 1991 (ha)	Area 2006 (ha)	Code
Water	1 398	6 780	W
Grassland	171 854	152 687	GL
Mix bush/shrub	134 534	7 936	MB/S
Forestry	25 784	33 751	F
Sugarcane	89 039	80 776	S
Built-up land	114 797	255 476	BL

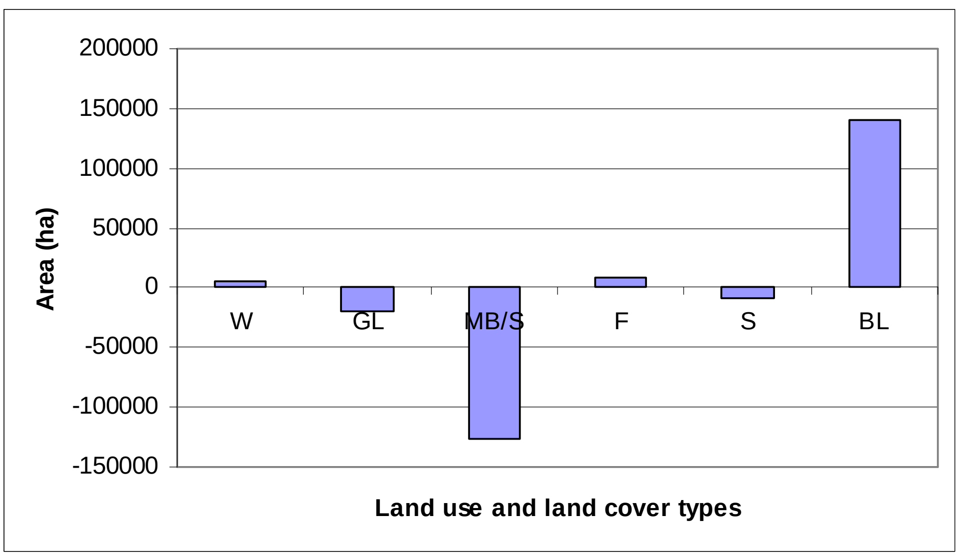

Figure 6: Land cover increases/decreases from 1991 to 2006.

4.1.2..3 Changes between 2001 and 2006

Table 15 shows the changes in the different LULC classes for the period 2001 to 2006. For example, sugarcane covered 40 493 ha in 2001 and 80 795 ha in 2006. Out of the 40 493 ha that was sugarcane in 2001, 10 438 ha remained sugarcane in 2006, but 10 187 ha was converted to grassland, 17 452 ha was converted to built-up land. At the same time the increase of sugarcane, from 2001 to 2006, was 14 131 ha from grassland, 29 489 ha from mix bush/shrub and 24 848 ha from built-up land. A summary of the major land use and land cover types of the study area in 2001 and 2006 is given in table 16, while figure 7 represents the net area (in hectares) increase or decrease for different LULC categories, for the same period.

Table 15: Cross tabulation of land use and land cover classes between 2001 and 2006 (area in ha).

	2001						
2006	**Water**	**Grassland**	**Mix bush/ shrub**	**Forestry**	**Sugarcane**	**Built-up land**	**Total**
Water	332	693	3 655	506	354	1 245	6 785
Grassland	60	23 705	67 027	6 538	101 87	45 240	152 757
Mix bush/shrub	44	723	4 276	565	460	1 877	7 945
Forestry	72	2 155	21 244	3 305	1 602	5 405	33 783
Sugarcane	32	14 131	29 489	1 857	104 38	24 848	80 795
Built-up land	63	46967	69 166	3 531	17 452	118 477	25 5656
Total	**603**	**88 374**	**194 857**	**16 302**	**40 493**	**197 092**	**537 721**

Table 16: Summary of Land use and land cover types for 2001 and 2006.

Land use/cover type	**Area 2001 (ha)**	**Area 2006 (ha)**	**Code**
Water	603	6 785	W
Grassland	88 374	152 757	GL
Mix bush/shrub	194 857	7 945	MB/S
Forestry	163 02	33 783	F
Sugarcane	40 493	80 795	S
Built-up land	197 092	255 656	BL

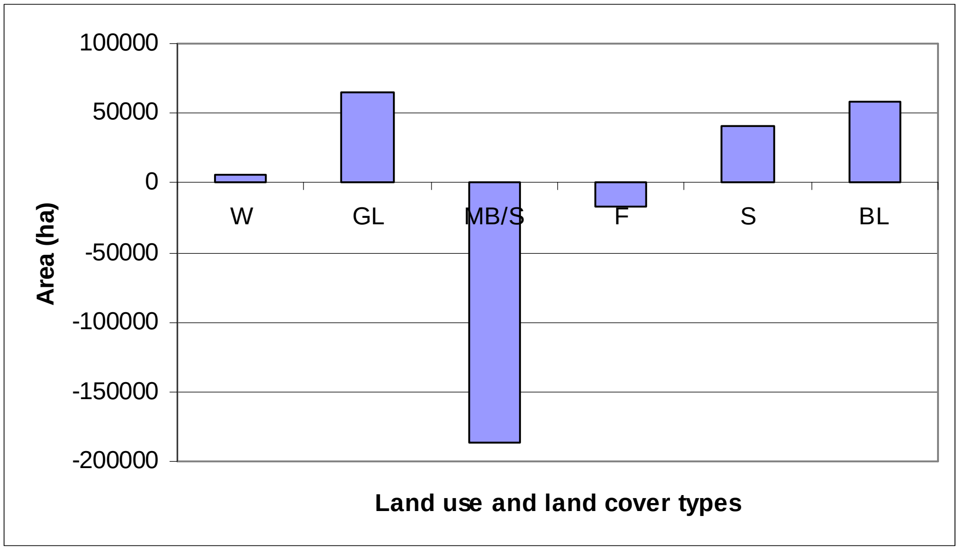

Figure 7: Land cover increases/decreases from 2001 to 2006.

4.1.3 Land Use and Land Cover 2006

There are six LULC identified in the study area in 2006 namely: Water, grassland, mix bush/shrub, forestry, sugarcane and built up land. The current LULC types are presented in table 17.

Table 17: Current land use and land cover types with area extent in (ha) and percentage (%).

Land use/cover type	Area 2006 (ha)	Area %
Water	6 785	1.26
Grassland	152 757	28.4
Mix bush/shrub	7 945	1.5
Forestry	33 783	6.3
Sugarcane	80 795	15.0
Built-up land	255 656	47.5
Total area	**537 721**	**100**

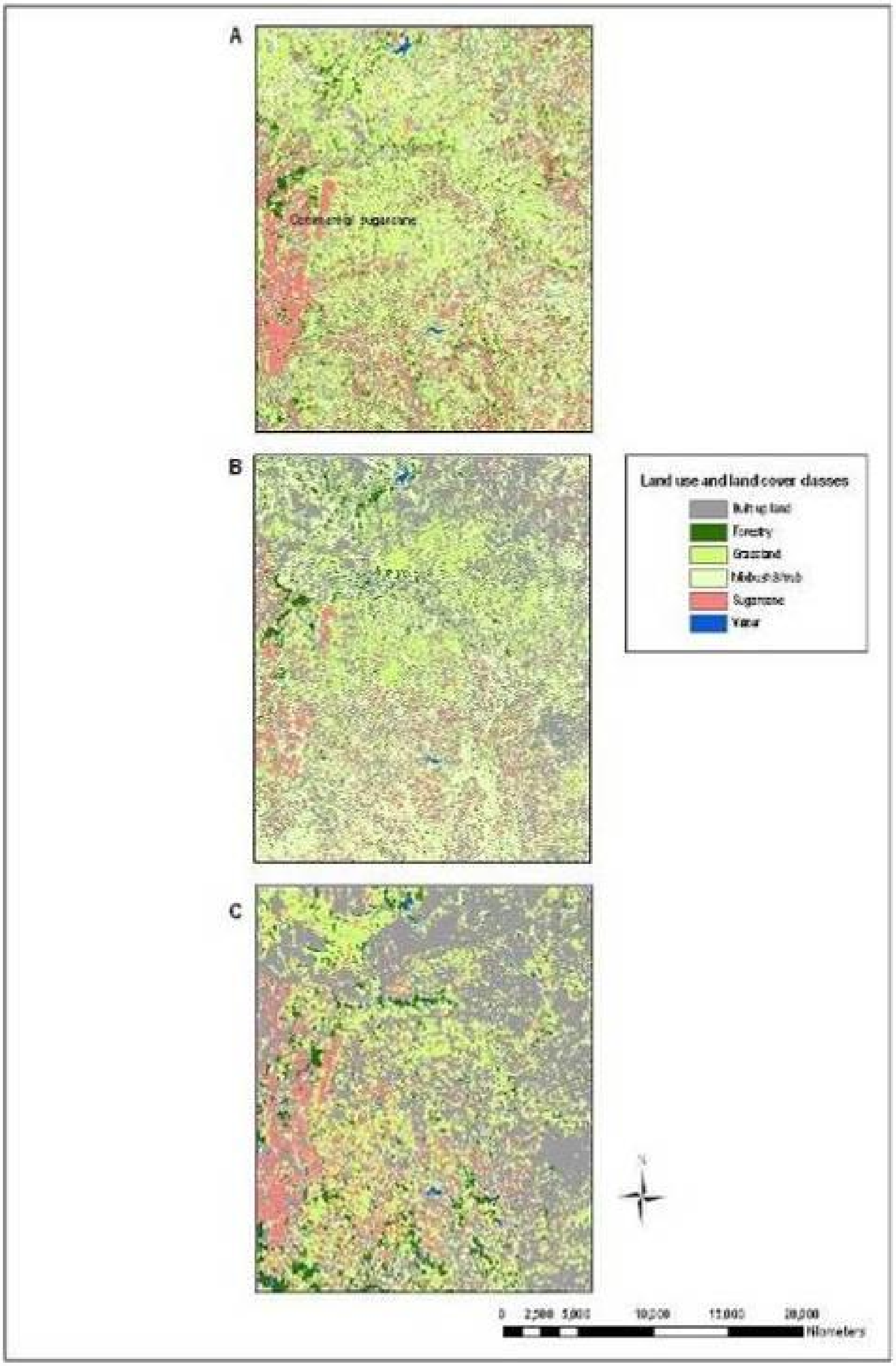

Figure 8: A, B and C: Land use and land cover classes of 1991, 2001 and 2006.

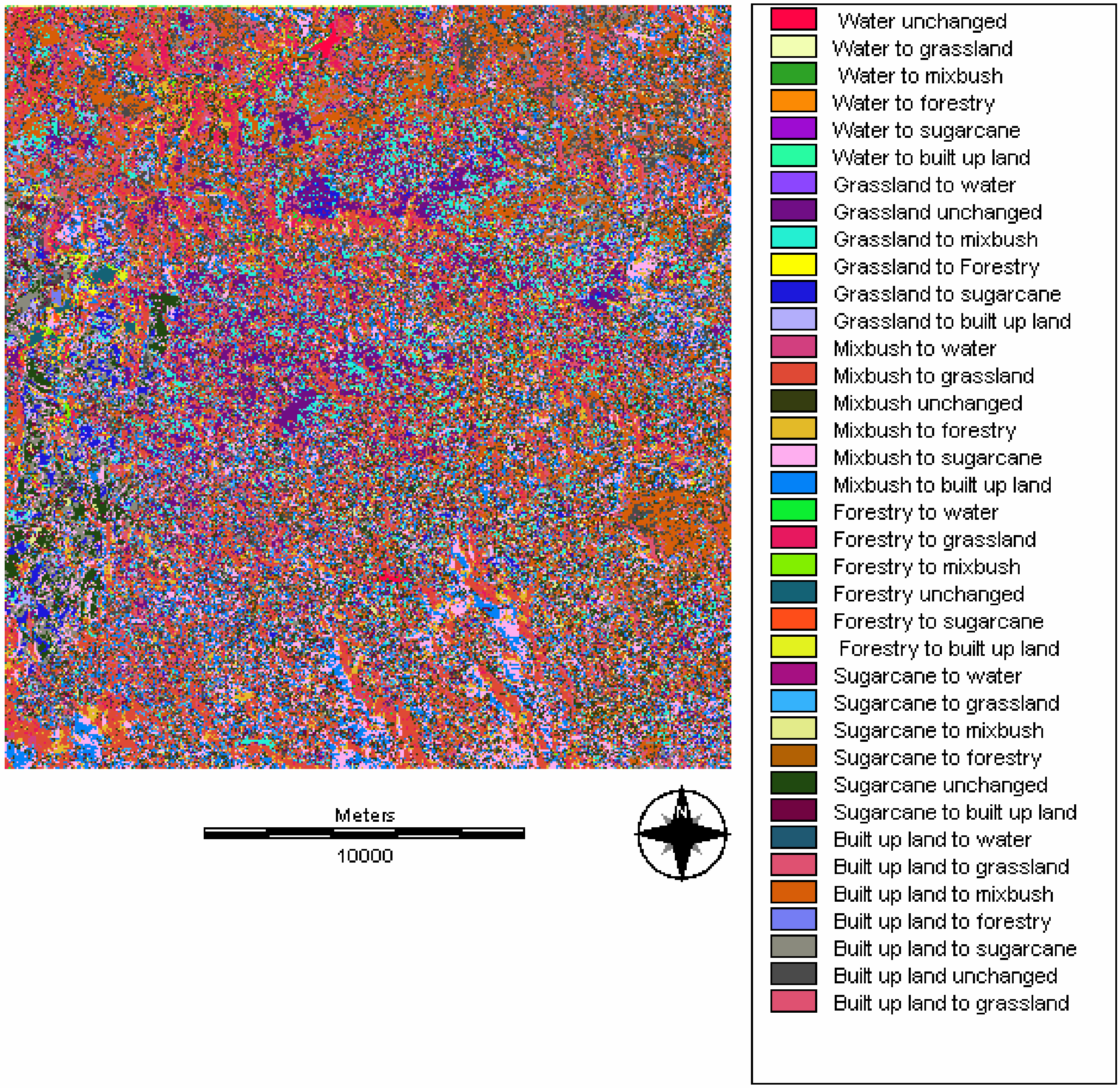

Figure 9: Land use and land cover change map for 1991–2001.

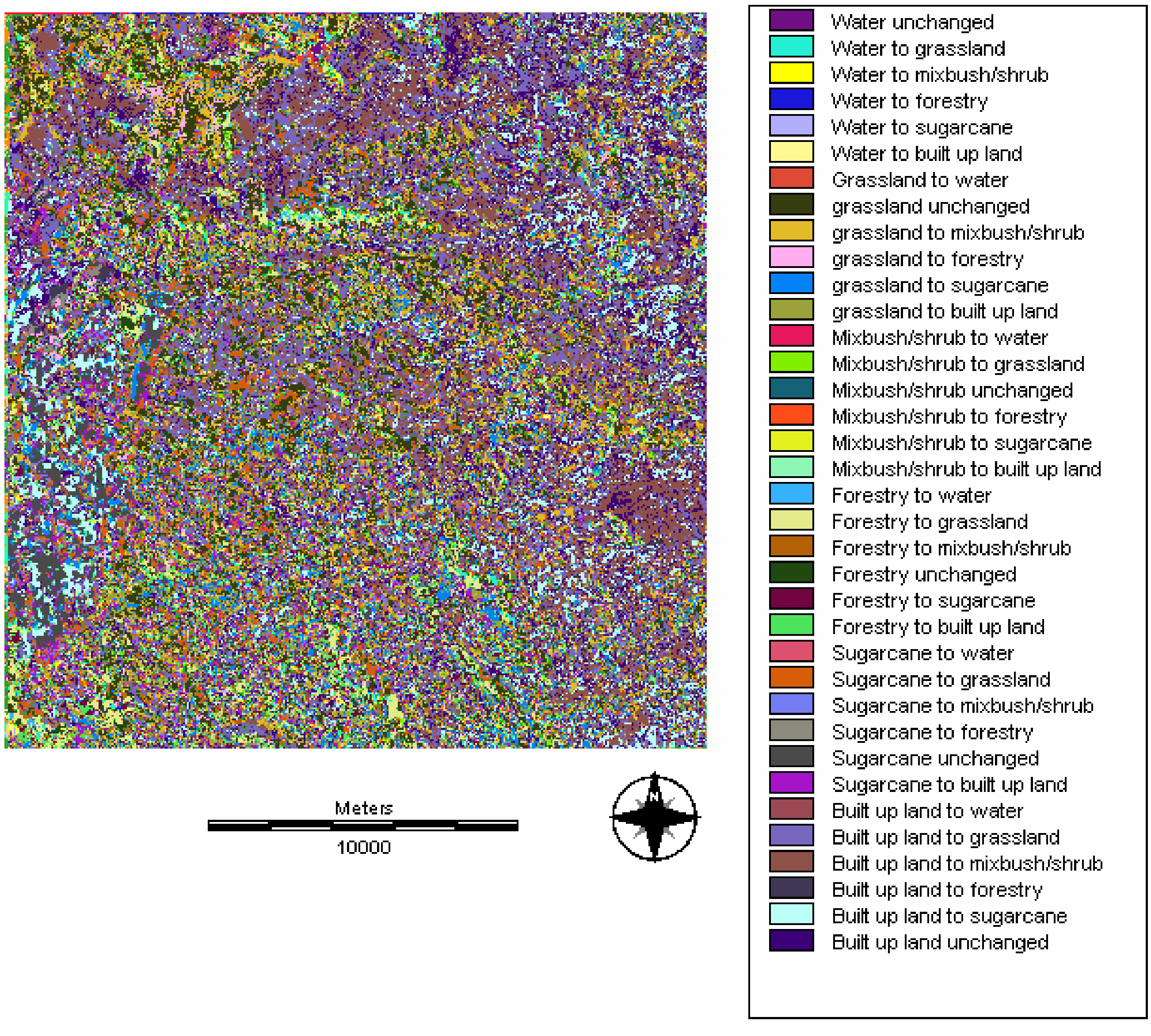

Figure 10: Land use and land cover change map for 1991–2006.

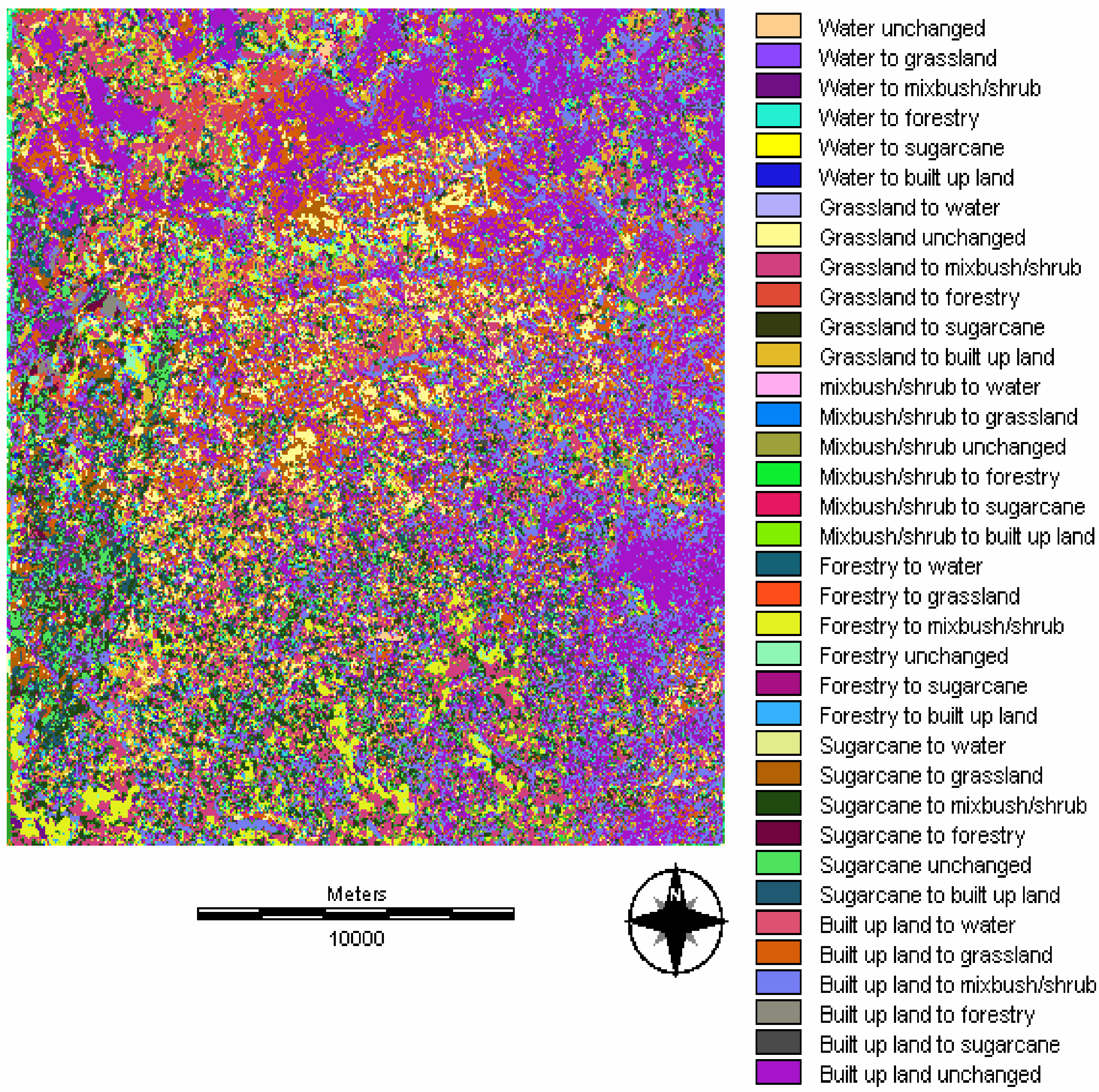

Figure 11: Land use and land cover change map for 2001–2006.

4.2 Discussion

The post-classification comparison change detection technique was employed. This method involved the comparison of three independently classified images of land use and land cover as presented in tables 11, 13 and 15. Six land use and land cover classes of; water, grassland, mix bush/shrub, forestry, sugarcane and built-up land, were identified in the study area (see table17).

Overally, between 1991 and 2001, land use/cover changes occurred in all land use/cover classes as shown in the cross tabulation matrix presented in table 12. Based on the bar graph (figure 5) and the classification maps (figures 8 A and B), a rapid decline of grassland, forestry and sugarcane is visible. To the contrary, mix bush/shrub and built-up land increased during the same period. The cumulative changes in LULC, between the various land use/cover classes during the same period are shown in table 12, with grassland decreasing from 191 175 ha in 1991 to 96 485 ha in 2001 (a decrease of 94 690 ha). The results as presented in table 11 show at least 75 190 ha of grassland in 1991 was converted to mix bush by 2001. The decline in grassland may have encouraged mix bush/shrub encroachment into the Umbumbulu area. Another reason for the decline in grassland may have been a result of conversion toward sugarcane as illustrated in figure 9. From table 12, built-up land, showed an increase of 87 687 ha from 126 673 ha in 1991 to 214 360 ha in 2001. This could have been due to increase in the human population of the area. Historically, the Umbumbulu area experienced some unrest from the early 1990s up to 1994, which resulted in significant population movement as residents moved out due to violence. After 1994, the population numbers began to increase again. Increase in built up area (and population) may have also contributed to the significant decline in grassland. Another significant change was observed in forestry which declined from 28 887 ha in 1991 to 18 305 ha in 2001. This may be a result of conversion toward mix bush and built-up land, as illustrated in figure 9. In particular, sugarcane decreased from 98 387 ha in 1991 to 44 884 ha in 2001 (table 12). The rapid decline in sugarcane between 1991 and 2001 may be attributed to the conversion to grassland and built-up land.

However, from figure 6 and the classifications presented between 1991–2006 in figure 8 A and C, a significant decline in grassland, mix bush/shrub and sugarcane is noted in the study area. To the contrary, an increase in forestry and built-up land is observed. Table 14 shows a decrease in grassland from 171 854 ha in 1991 to 152 687 ha in 2006, a decrease of 19 167 ha. The decline of grassland can be attributed to land conversion toward sugarcane and built-up land as presented in figure 10. Sugarcane decreased from 89 039 ha in 1991 to 80 776 ha in 2006. The sudden decline in sugarcane may be a result of land conversion toward grassland and mix bush/shrub. However, within the fifteen-year time span, built-up land was converted to sugarcane (see figure 10) and this may be a result of conversion of land around rural households of Umbumbulu to sugarcane. Mix bush/shrub have decreased from 134 534 ha in 1991 to 7 936 ha in 2006. A decrease in mix bush/shrub may be a result of the land conversion toward grassland and built-up land (see figure 10), whilst an increase in built-up land (from 114 797 ha in 1991 to 255 476 ha in 2006) may be a result of increased human population within the study area. It was also found that forestry increased to 33 751 ha in 2006 from 25 784 ha in 1991. Such an increase in forestry coverage may be due to expansion of timber production, wood and fuel or implementation of conservation measures. Prior to sugarcane farming, from 1991 to 2006, the dominant land uses was forestry and built-up land.

A steady increase in sugarcane, built-up land and grassland was observed for the period 2001–2006 as presented in figure 7. In contrast, a rapid decline of mix bush and forestry is clearly evident. Mix bush/shrub have decreased from 194 857 ha in 2001 to 7 945 ha in 2006, a decrease of 186 912 ha. This rapid decline of mix bush/shrub may be largely attributed to land conversion toward built-up land. As reflected in table 16, built-up land still remained on the increase from 197 092 ha in 2001 to 255 656 ha in 2006. This steady increase of built-up land may be a result of increased human population of Umbumbulu area. Grassland increased from 88 374 ha in 2001 to 152 757 ha in 2006 and sugarcane increased from 40 493 ha in 2001 to 80 795 ha in 2006, a total increase of 40 302 ha. This increase suggests that sugarcane could have doubled within the last five years. The increase could be due to the local cane growers cultivating sugarcane around their local homesteads for an economic benefit. As Machen (2009) points out that sugarcane is increasingly being cultivated by local people and sold to private companies in the area. This in turn has the potential to improve the standard of living of the local population by enabling them to buy food and basic commodities.

4.3 Summary

This chapter presented the results in the form of tables and maps followed by a discussion and interpretation of the results. The results for 1991, 2001 and 2006 were provided in error matrix tabulations, classified maps, cross tabulations of land use and land cover as quantitative data for change analysis and change maps detect for ‘from–to’ change. The discussion provided an interpretation of the possible meanings of the results.

5. Conclusions

This chapter provides a summary of the findings of the study. The Chapter relates to the main objective and research questions presented in Chapter 1.

5.1 Summary

This study has demonstrated the utilization of Landsat TM satellite imagery, GIS and remote sensing techniques in the spatial mapping of the distribution and quantification of land use and land cover changes from 1991 to 2006. Information of present land use and land cover and its changing patterns over time is very important especially for the management of resources in the study area. The main objective of the study was to detect spatio-temporal land use changes with satellite imagery. The research questions posed to meet the main objective were:

(1) How has land use changed between 1991, 2001 and 2006 of the selected area?

(2) What are the present land use types of the study area?

(3) What were the previous land uses before sugar cultivation?

Indeed, between the periods from 1991 to 2006, the results showed significant changes of LULC changes between all LULC classes. It was observed that there was a significant decline in grassland, mix bush/shrub and sugarcane, whilst an increase in forestry and built-up land. The rapid decline of grassland can be attributed to the land conversion toward sugarcane and built-up land. The increase in built-up land may be a result of an increase in population growth in the study area. However, within the fifteen-year time span, built-up land was converted to sugarcane. For the time period 1991 to 2001, sugarcane had decreased whilst there was a significant increase in built-up land. The result of a decline in sugarcane within the ten-year time span would therefore suggest that there may have been an increase in the human population of the area. The land conversion is from sugarcane to built-up land. However, over the past five years from 2001 to 2006, the results showed an increase in built-up land and in sugarcane cultivation within the study area. This suggests that there could be a shift towards sugarcane production in Umbumbulu which appears to be driven by economic benefits.

Although, sugarcane is an important economic resource in the Umbumbulu area and in South Africa, the spatial dynamics of the changes in land use regarding sugarcane expansion have often remained unknown and unexplored. As shown in this study, understanding the changes in the use of land resources is critically important for land management and planning for the future. Remote sensing and GIS techniques are effective tools that have made it possible to extract information of features on the physical landscape for monitoring, assessing, managing and planning our earth's natural resources.

This sub-section below outlines a few of the limitations of certain aspects of this study. Some recommendations have also been made in order to correct the identified problem areas.

5.2 Limitations

5.2.1 Image resolution

Some limitations have been encountered using Landsat TM imagery. Since it has a medium spatial resolution (pixel size) of 30 m x 30 m, it records the value of the majority of classes found within a given pixel. The Landsat TM imagery of 2006 was seen as unsatisfactory, as it was difficult to identify and classify vegetation namely; mix bush/shrub and grassland on the ground surface due to spectral mixing of land use/cover classes.

5.2.2 Challenges with image classification techniques

Lillesand and Kiefer (2004) found that the Landsat TM has a medium spatial resolution of 30 m x 30 m, therefore the identification of land use and land cover classes within these images were challenging. Bands (1, 2, and 3) were used for the classification for all three imagery. Some problems occurred during signature creation of classes whereby the classifier was incorrectly mixing pixels that had similar spectral characteristics. In this study, for example, mix bush/shrub land, grassland and water bodies had similar spectral signatures, therefore making it difficult for the classifier to detect the spectral difference between these classes. Aerial photos and topographical maps of the study area were used to aid signature creation of historical data. Classification trials were performed for all classified Landsat TM imagery for 1991, 2001 and 2006. Particularly, the classified 2006 Landsat TM imagery had to be run several times to increase the level of accuracy of the classification results. It was clearly visible that there was spectral mixing of classes as mentioned above.

5.3 Recommendations

As previously stated, there were limitations encountered during the study, both in the imagery and in the techniques adopted for the study. Some recommendations are presented below that may minimize the effect of these limitations on further analysis that may be done in similar investigations.

5.3.1 Improvement of digital satellite imagery

The use of higher spatial resolution imagery could have easily improved the identification of land use and land cover classes. SPOT is recommended since it is a higher spatial resolution satellite sensor and is found suitable for vegetation identification on ground surface.

5.3.2 Image classification: Landsat TM

Although Landsat TM imagery was employed in this study, it is recommended to use the NDVI (Normalized Differential Vegetation Index) method with Landsat TM imagery, however NDVI cannot solve all problems of land cover classifications as it suffers some limitations too. However, it will assist in the following:

a) Achieving better vegetation discrimination,
b) Producing an increase in classification accuracies, and
c) Reducing spectral mixing at the boundaries within the imagery.

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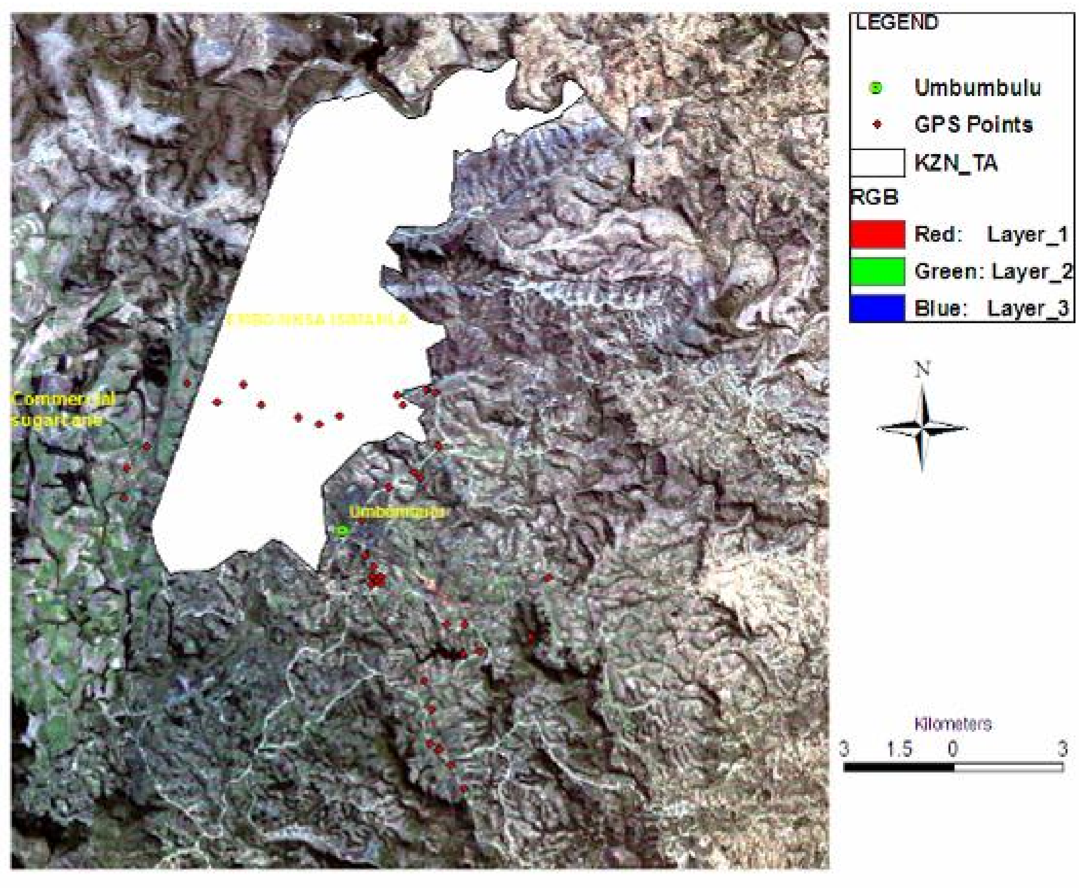
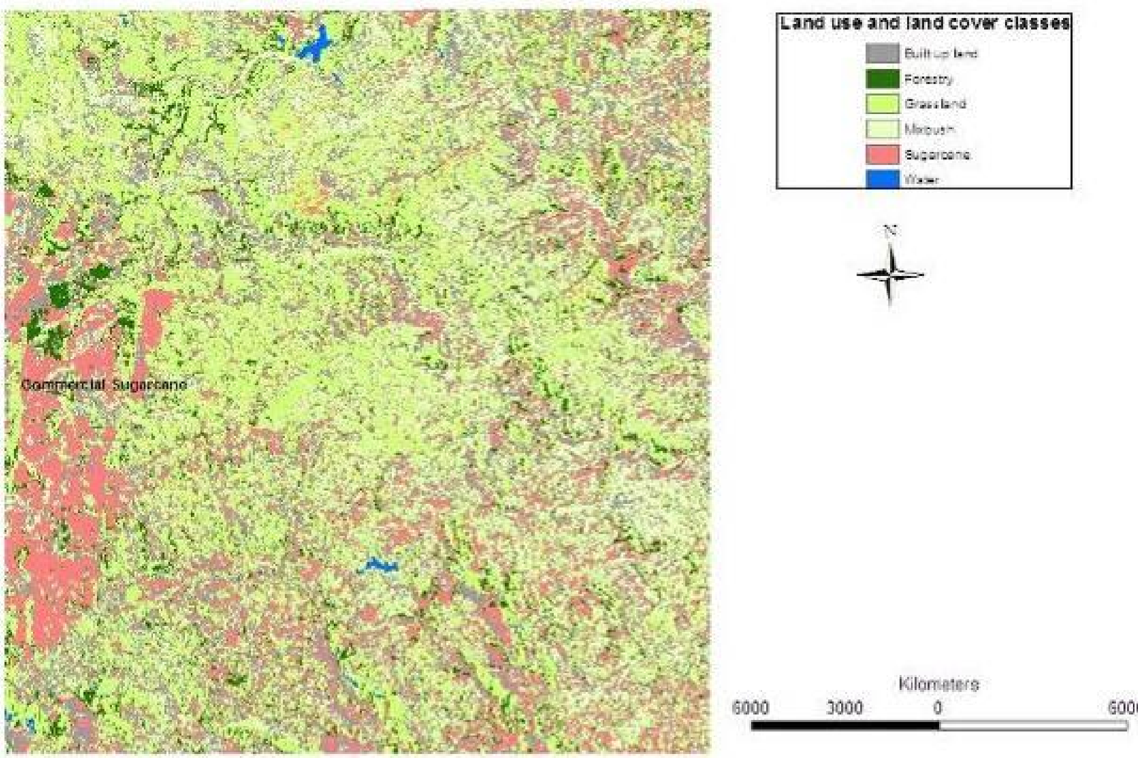
Appendices

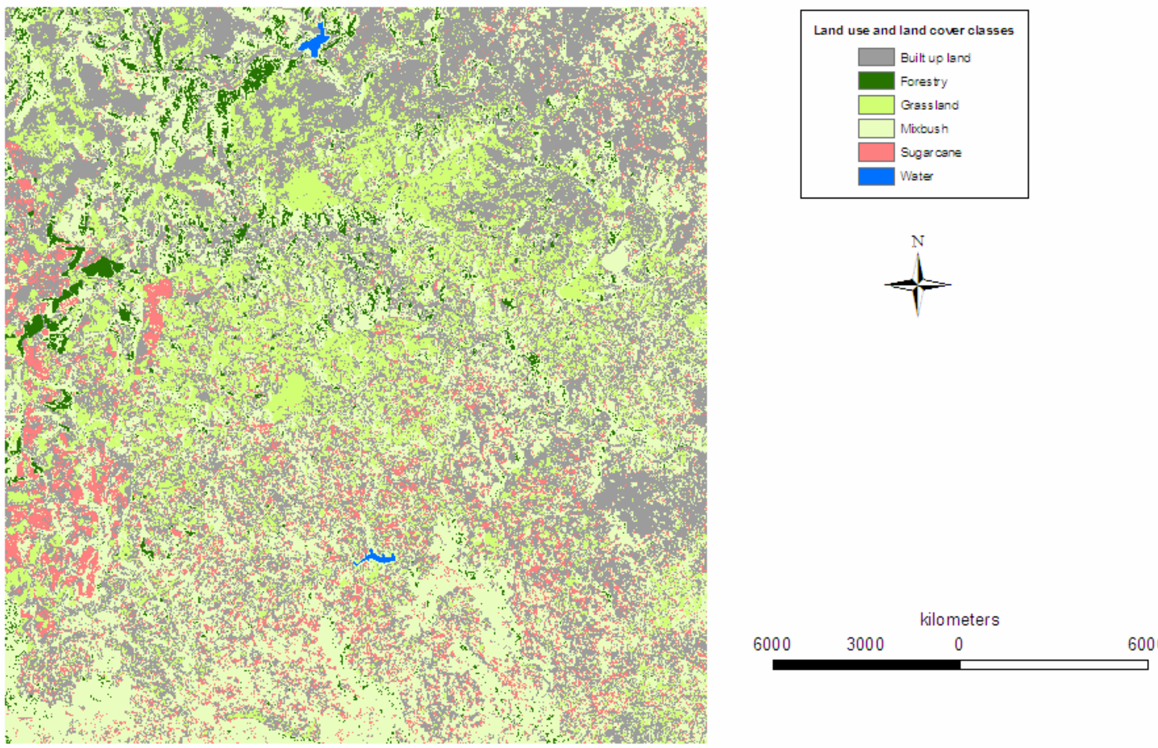
Appendix A: Landsat TM 5 satellite scene of 2006



Appendix B: Land use and land cover classification map of 1991



Appendix C: Land use and land cover classification map of 2001



Appendix D: Land use and land cover classification map of 2006