ASSESSING DEVELOPMENTAL FOOTPRINT WITHIN AN AGRICULTURAL SYSTEM USING MULTI-TEMPORAL REMOTELY SENSED DATA

A thesis submitted in partial fulfilment of the academic requirements for the degree of Master of Environment and Development: Land Information Management, School of Agricultural, Earth and Environmental Sciences University of KwaZulu-Natal, Pietermaritzburg

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PREFACE

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ABSTRACT

The advent of the new political dispensation in South Africa has seen an exponential growth in the rate of land transformation and encroachment by other land uses into agricultural land in the uMngeni Local Municipality. Accurate evaluation of the rate of transformation is necessary for effective monitoring and management of the natural agricultural resources. In this regard, the use of multi-temporal remote sensing data provides efficient and cost-effective method. The current research assesses the extent to which the development footprint in uMngeni Local Municipality has affected agricultural land categories or zones, using multi-temporal remote sensing data. The study endeavoured to map and quantify the magnitude of change in built-up land cover and other infrastructure by focusing on two time intervals: the periods from 1993 – 2003 and 2003 – 2013. Medium spatial resolution Landsat image data acquired for these periods were analysed to classify and extract the built-up features to appraise the level of change. Results revealed positive change in built-up infrastructure: ~13% increase between 1993 and 2003, ~38% increase from 2003 – 2013, with overall ~32% for the 20 years (1993 – 2013) period under consideration. Next, factors possibly contributing to the encroachment of other land uses into the agricultural landscape and the potential threats to the sustainability of the agricultural system are highlighted.

DEDICATION

This thesis is dedicated to my wife Nozipho and my entire family especially Londiwe, Sibahle, Lwazi and Owenkosi.

ACKNOWLEDGEMENTS

Firstly, I would like to thank God for the opportunity and resources availed for me to complete this work. Secondly, my sincere gratitude to my loving family especially my wife, Nozipho Dlamini, for the prayer, fortitude, encouragement and unwavering support through the process.

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CHAPTER 1: INTRODUCTION

1.1 Background

The expansion of urban development or urbanisation is a global phenomenon transforming the agro-ecological landscapes (Emili and Greene 2014, Konagaya, Morita and Otsubo 2001). Transformation can be a result of increasing demand placed on agricultural land resources for urban settlements and other infrastructure development (Long et al. 2007, Gersh 1996 , Shalaby and Tateishi 2007). Gersh (1996) noted that residential settlements consumes productive farmland and has detrimental impacts on the agro-ecological functions of an area. Shalaby and Tateishi (2007) described the process of urbanization as inevitable due to the demand for economic development and rapid population growth. Urbanisation does not only cause profound changes in the cultural, sociological, and economical landscape but also leads to significant changes in the ecological and environmental condition in an area.

It is important to monitor changes in agricultural land cover in order to maintain a healthy balance between man-induced land uses and ecosystem services and to help establish rational land use policy in favour of sustainable agricultural development (Shalaby and Tateishi 2007). In this regard, effective decision-making hinges on availability of the past and present land cover information. Melendez-Pastor et al (2014) note that understanding of land cover change is important to ensuring sustainable development, especially with the likelihood that land cover change can potentially lead to land use conflicts.

Agricultural land provides for both productive (market) and non-productive (non-market) value (Johnson and Maxwell 2001, Melendez-Pastor et al. 2014). The scenic character espoused by the rural assets has often attracted interest of alternative uses of agricultural land.

Johnson and Maxwell (2001) contend that rural residential developments are a consequence of buyers who are attracted by a mix of amenities acting as pull factors. These include scenic beauty, recreation, opportunity for small business investment, the local small town environment, and personal safety.

Population growth and household formation, combined with growth in income and wealth fuels new housing developments and consumption of land for residential development in formally non-settlement areas. Rail-roads and automobiles allow resources to be transported from points of production, hence, settlements focused on transportation corridors. Moreover, advancement in information technology has enabled goods and services to be shipped at very low costs, thus many people are choosing to live in rural locations with high natural amenities, distant from markets (Gude et al. 2006).

A number of factors influence landowners to take a decision not to remain in agriculture. Such factors may include the reluctance or inability of children to continue the family farming legacy and declining agricultural prices. Johnson and Maxwell (2001) argues that many of the new buyers of rural agricultural land will not continue the agrarian tradition or will shift from intensive agricultural production to less intensive utilisation form of land management such as hobby farming or owning land for its recreational potential.

Prime agricultural land is a scarce, finite, and exhaustible natural resource (Tanrivermis 2003). In the context of South Africa with millions of people vulnerable to food insecurity, impacts of agricultural land transformation cannot be over accentuated. The relationship between land and people is profound; with people's standard of living, wealth, social status and aspirations all closely linked to land (Niroula and Thapa 2005).

In full appreciation that land use is not static but rather a dynamic interacting system, there is increasing recognition that the decisions with potential impacts on agro-ecological system require comprehensive and careful consideration to ensure sustainable development (Fazal 2001). Uncoordinated development can lead to inefficient and undesirable environmental, social, and economic conditions; hence a number of countries have legal requirements for local jurisdictions to prepare comprehensive plans outlining the kinds of land use to be encouraged or discouraged in specific areas (Andersson and Gabrielsson 2012). Against this background, it is highly desirable to implement long-term monitoring and assessment of the trends in human settlement and other infrastructural development within the agricultural system. Remotely sensed data and tools have proved to be the appropriate and cost effective means to map changes in agricultural systems (Shalaby, Ali and Gad 2011).

1.2 Change detection from remote sensing observations

Environmental geographers have historically described changes in land cover features based on temporal alteration of the land-surface components. Change detection process involves identifying differences in the state of an object or phenomenon by observing it at different time intervals (Singh 1989). The conventional methods of mapping changes in land cover of agro-ecological landscapes mostly rely on collection of field data that can be labour intensive, time consuming and lack temporal consistency for very large areas. Moreover in a rapidly changing environment, it is important to generate change maps that are consistent and up to date.

In remote sensing, changes within the natural and man-made land cover are considered as surface component alterations with varying rates. Change detection analysis from remotely sensed data provides useful tool for monitoring changing patterns occurring in for example agricultural, forested, and urban landscapes (Lu et al. 2004). Change detection methodologies and techniques utilizing remotely sensed data have been developed, and newer techniques are still emerging (Hussain et al. 2013). Remote sensing change detection broadly comprises feature extraction techniques to compare differences or ratios, and decision function operation to create change vs. no-change maps.

1.3 Research objectives

The overall aim of the study was to assess extent to which the infrastructure development has impacted on agricultural land categories/zones in uMngeni Local Municipality. The following specific objectives were set:

- to evaluate the utility of a machine learning algorithm for feature classification and extraction using multispectral remote sensing data
- to conduct change detection for built-up infrastructure using post-feature extraction comparison of multi-temporal Landsat images covering the periods 1993–2003, and 2003–2013.
- to relate the change analysis results to factors possibly contributing to the encroachment of other landuse and/or land cover into the agricultural land categories and highlight potential threats to the sustainability of agricultural resources in the uMngeni Local Municipality.

1.4 Research questions

- What was the extent of human settlement and other built-up areas 20 years ago and the degree of change that has characterised the agro-ecological zone of uMngeni Local Municipality?

- Based on literature, what /which factors contribute to development of agricultural land (directly or indirectly) and the potential threats to the agricultural system?

1.5 Study Area

The study area (uMngeni Local Municipality) is located within the Province of KwaZulu-Natal in South Africa under the jurisdiction of uMgungundlovu District. The landscape topography (altitude) ranges between 600 m and 1400 m above mean sea level. UMngeni local Municipality (Figure 1.1) is located approximately 90 Kilometres inland away from the coastline, north-west of Pietermaritzburg. The Local Municipality is predominantly rural in character with a variety of agricultural and tourism related activities. Predominant agricultural enterprises include but not limited to: Horticultural cash crops; Agronomic crops (potatoes, soya beans, maize, etc); Timber plantations; livestock (poultry, and dairy & beef to a limited extent).

Figure 1.1 summarises the demarcation of agricultural land categories for uMngeni Local Municipality. The KwaZulu-Natal Department of Agriculture and Environmental Affairs uses principles of zoning to classify KwaZulu-Natal province into Agro Ecological Zones (AEZ's), a principle developed by the Food and Agriculture Organization of the United Nations (FAO). These zones consist of areas that have similar characteristics in relation to land suitability, production potential as well as environmental impact. Such an AEZ can form the basis for agricultural land use planning. The development of the KwaZulu-Natal Agricultural Land Potential Categories (Collett and Mitchell 2012) is seen against the background of attempting to protect areas called Agricultural Protected Area across varying and diverse natural resources rather than for individual land parcels in isolation. The current research sought to assess development of the built-up land cover within the uMngeni municipality over time.

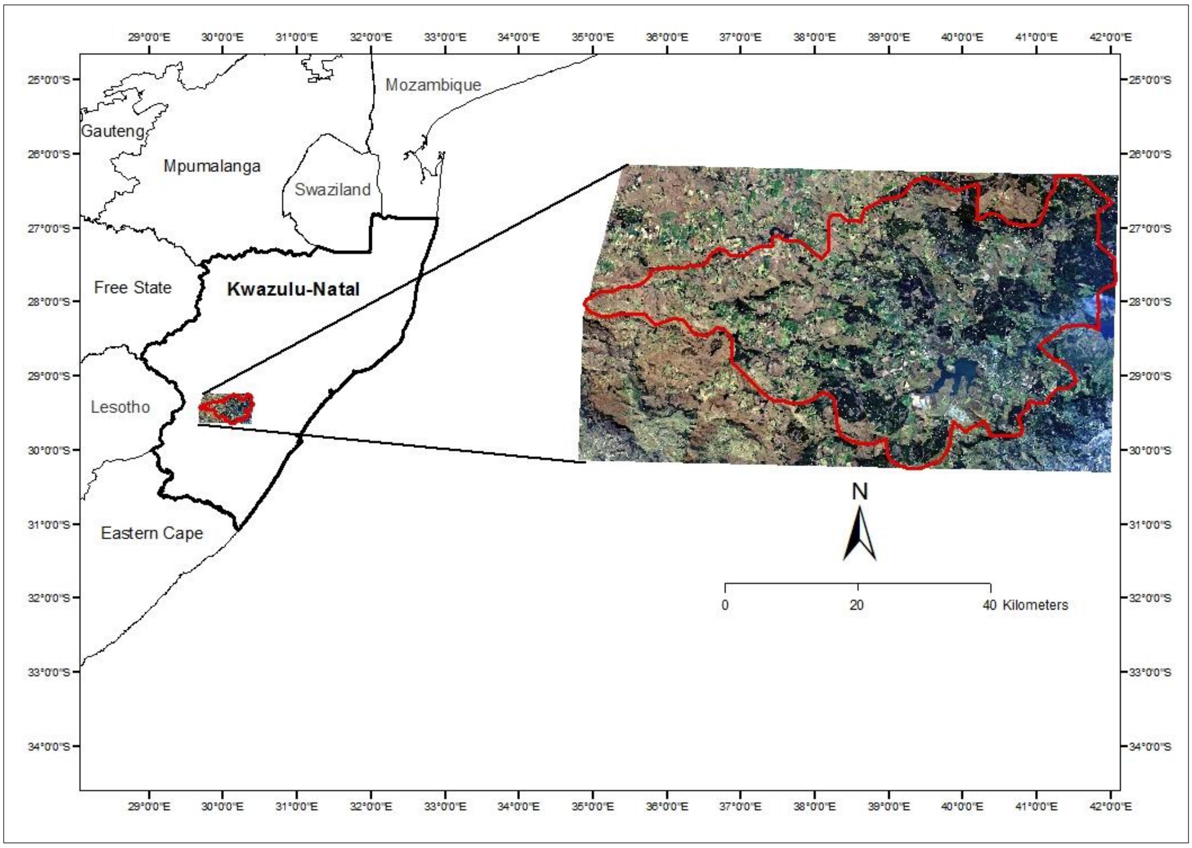


Figure 1.1: Location of uMngeni Local Municipality study area and a summary of agricultural land categorization within the municipality.

1.6 Organisation of the dissertation

The overall organisation of this work is in two major steps. Step one is divided into two parts. Part one involved acquisition and pre-processing of remote sensing images and the appraisal of land cover types from existing land cover base map. The second part was to implement supervised classification using support vector machine (SVM) learning algorithm for each of the multi-temporal Landsat image data.

The second step is modelling change detection using image comparison technique in ENVI framework post-classification analysis to estimate changes in built-up cover in the study area.

Analysis in this section is three fold: the first involves comparison of 1993–2003 Landsat 5 and Landsat 7 ETM images. The second is comparison of 2003–2013 Landsat 7 ETM+ and Landsat 8 images. The final step relates the change analysis results to factors possibly contributed to the encroachment of built-up land cover into the agricultural land categories in the uMngeni Local Municipality. Figure 1.2 illustrates the flow chart for the conceptual framework of the research.

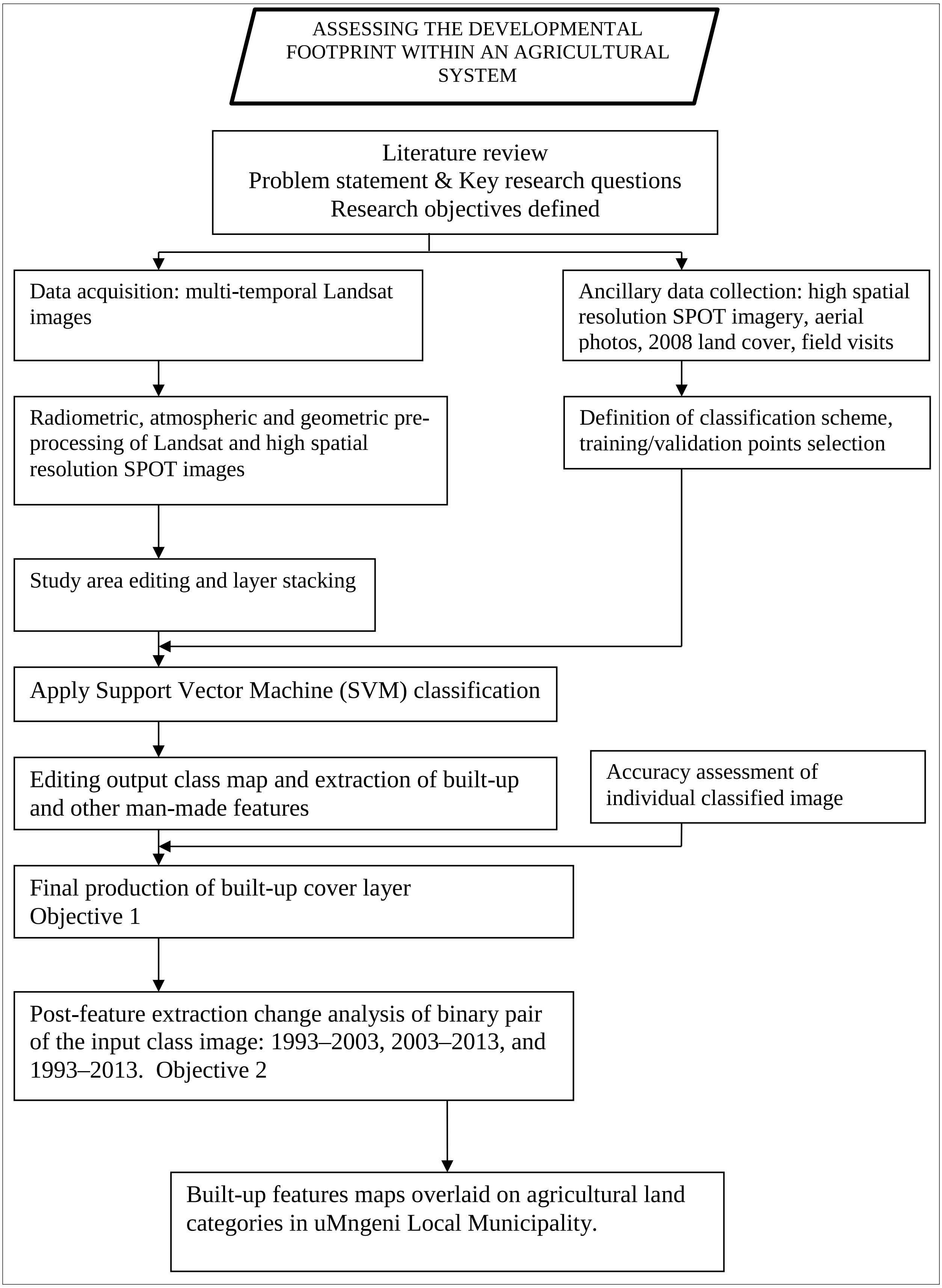


Figure 1.2: The processing scheme for the implementation of the methodology adopted in the current research study

CHAPTER 2: LITIRATURE REVIEW

2.1 Factors contributing to land development

Knowledge of land cover dynamics and driving forces is a fundamental tool for landscape planning and management (Johnson and Maxwell 2001). Land transformation is influenced by a varied number of drivers which could inter-alia be categorised to include economic, policy and institutional, social and cultural, environmental and biophysical considerations (Shrestha et al. 2012). Shrestha et al. postulated that land fragmentation is the result of a combination of biophysical and social processes, particularly urban population dynamics, water provisioning, transportation, institutional factors, and topography. Irrespective of the sector's contribution to the country's economy, there are externalities such as environmental aspects related to the rural landscape, maintenance of drainage systems, prevention of soil erosion and refilling of aquifers which should be taken to account in balancing the total value of the agricultural system (Gal and Hadas 2013).

2.1.1 Urbanization, Industrialization and population growth

Urbanization driven by globalisation is the prime factor producing land use change (Konagaya et al. 2001). Urban sprawl accompanied by the urbanisation degrades natural environments and consumes formerly productive agricultural land and open spaces to provide land for increasing population (Heimlich and Anderson 2001, Wu et al. 2013). Wu et al. concluded that in China economic growth stimulated the demand for more land development, resulting in rapid expansion of built-up land of the city through encroachment of surrounding rural areas.

The majority of land use change (LUC) is a consequent of increasing demand for non-agricultural land from urban and manufacturing development (Long et al. 2007).

Notwithstanding its rural orientation, India is changing and the impact of urbanization is felt even at great distance from the cities (Singh and Mohan 2001). The direct result of urbanisation is the reduction of agricultural land by increasing urban settlements. In China two forms of urbanization have occurred: the growth of the cities following urban economic development and population concentration, and rural urbanization based on the growth of smaller towns in rural areas (Long et al. 2007).

Population growth and household formation combined with growth in income and wealth fuels new housing developments. Invariably, the rate of population growth, coupled with rapid economic development and limited space and natural resources, has generated great pressure on already scarce land and water resources (Gal and Hadas 2013). Population growth and subsequent residential developments in the agricultural areas brings with it a host of detrimental impacts to ecological functions including serving as a pull factor for additional amenities (Johnson and Maxwell 2001). Consequently, with new housing developments new residents realize they need additional services, which then attracts further encroachment in to the agricultural system (Heimlich and Anderson 2001).

2.1.2 Infrastructure and Technology development

Singh and Mahan (2001) states that road infrastructure has greatly enhanced the accessibility of remote rural villages. Investments in infrastructure, such as roads, sewers, and water supplies, can be one of the most important drivers of urbanization, since infrastructure provides the essential framework for development.

The innovation in information and communication technology has the potential to modify the nature of the workplace as far as face to face contacts are concerned. Rail-roads and automobiles allowed resources to be transported from points of production, hence, settlements focused on transportation corridors. However, information technology has enabled goods and services to be shipped at very low costs and many people are choosing to live in rural locations distant from markets, but with high natural amenities (Gude et al. 2006). Johnson and Maxwell (2001), contends that many of the buyers of the rural housing sites are retired or semi-retired or are able to make a living aided by a modern telecommunications network. As a result, they are not fixed to the traditional urban infrastructure for employment.

2.1.3 Land Prices and Profits

The evolving pattern (in India) of urban growth and development is driven by large profits to be made from converting agricultural land to no-farm uses in rural/urban fringe areas (Singh and Mohan 2001). Residential developments on agricultural land have a direct and indirect effect on agricultural land values. When demands for developable land are sufficiently high, the price of land in developed state or use will inevitably exceed the value with which is associated as an agricultural entity.

The pressure posed by developers can lead to high rates of growth in land values, which in turn influences the conversion of farmland to developed uses. Invariably the farmers when faced with the option to either pursue farming or exit farming as a result of increased property prices, may comfortably welcome the increase in farmland values and opt to exit (Heimlich and Anderson 2001).

Plantinga et al (2001) contends that land prices reflect not only the current uses of land, but the potential uses. In a competitive market, the price of land will equal the discounted sum of expected net returns obtained by allocating the land to its most profitable use. Without public intervention the market will allocate land to the use that optimizes economic returns, thus, in the process of urban growth the owners are expected to convert agricultural land to non-agricultural use, since land suitable for development is more valuable (Plantinga, Alig and Cheng 2001, Singh and Mohan 2001, Phuc, Westen and Zoomers 2014). Phuc et al (2014) unpacking the process of land conversion in Central Vietnam, concluded that land conversion from agricultural to urban uses results from profit-seeking by multiple stakeholders.

2.1.4 Legislation/ policy

The absence in clarity of policy from a government perspective could promote the unsustainable transformation of agricultural land to other land uses. Land use policies are known to play a critical role in driving land cover changes, as well as in mitigating land degradation and promoting sustainable development (Zhang et al. 2014). The potential for conflict between different land uses has given rise to 'right-to-farm' policies and the regulation of buffer zones. Financial incentives such as income tax credits and reduced property taxes are provided in order to support continued farming.

In Korea, government imposed various types of land use control policies in both urban and rural areas to provide adequate land resources for economic development, to conserve environments or to stabilize skyrocketing land prices (Hwang 2001). In 2006, the central Chinese government initiated the "red line of 120 million hectares cultivated land" policy, to prohibit further agricultural land transformation beyond this threshold and ultimately ensured the integrity of food security for the growing population (Chen et al. 2014). In Sweden, political and economic pressures have encouraged or enforced changes to more intensive agriculture practices or to other types of land use designed to conserve biodiversity, and preserve ecosystem services, including carbon storage (van Vliet et al. 2012).

2.2 Threats to natural agricultural resources

The transformation of agricultural landscape has a potential to threaten the sustainability of the agricultural system and food security if not monitored. Conversion of cultivated land to non-farm uses such as housing, factories, and infrastructure in combination with growing population poses a serious threat to future food sufficiency (Britz, Verburg and Leip 2011, Gibreel et al. 2014). As more land is converted to urban uses, the question arises as to whether this trend represents a systematic reduction in our ability to produce food by placing infrastructure on the most productive soil resources (Zhang et al. 2007).

Food security is a central issue for agricultural policy in relation to sustainable development. Sustainable development principles establish the foundation for development that “meets the needs of the present without compromising the ability of the future generations to meet their own needs” (Mirkin and Khaziakhmeton 2000). South Africa’s recently approved policy framework on Food and Nutrition Security commits us to conserving scarce agricultural land resources in order to secure the nation’s food supply at both a household and national level.

Johnson et al. (2001) identified negative impacts on the agricultural system as a consequence of land transformation to inter-alia include the following:

- Residents’ complaints about farm odours and chemical spraying may force farmers to turn enterprises that produce fewer negative side effects.
- Conflicts can arise between farmers and new residents over early morning noise, and increased traffic can hinder farmers’ ability to move their equipment along overcrowded rural roads being used as commuter routes.
- Real estate taxes may rise as land prices rise to reflect the potential for non-agricultural development.

- Farmers may face increased pressure from water and land use restrictions.
- Farms may face deteriorating crop yields from urban pollution, theft, and vandalism.

Singh and Mahan, (2001) in a case study of Delhi, India, concluded that transformation of agricultural land from a food grain producer to a totally non-productive permanent land use, in a way deprives the land from being productive and increases the pressure on the remaining agricultural land.

Conversion of agricultural land could potentially undermine rural livelihoods especially rural employment, as most farm labourers are illiterate and unskilled. In Colombo a major consequence of land use changes has been the loss of prime agricultural land and a reduction in agricultural production as well as farming sector employment (Chandrasena 2001).

2.3 Key considerations for Remote Sensing change detection

In general change detection in remote sensing comprises feature extraction and decision function operation to create change vs. no-change image layers. Moreover, the change detection process can broadly be classified into: (a) pre-processing of input image data (b) selection of change detection technique, and (c) accuracy assessment (Hussain et al. 2013). The pre-processing phase deals with image correction step related to radiometric, atmospheric, and random geometric distortions resulting from relief displacement, variations in the satellite altitude and attitude, satellite instrument anomalies, geometrical distortions caused by Earth's eastward spinning motion and curvature and digital image registration. It is important to consider these pre-processing steps to eliminate the effects of sun angle, atmospheric, and topographical effects (Conghe and Woodcock 2003, Fang and Yang 2014, Song et al. 2001). Song et al. (2001) remarked that atmospheric corrections may not be required when single-date image is analysed for classification, but is mandatory when multi-temporal or multisensory data are considered. Post-classification and\or post-feature extraction comparison for change detection approaches are reported not requiring some of these strict pre-processing requirements (Chen et al. 2012).

2.4 Radiometric corrections and image registration

Radiometric corrections of multi-temporal image data and image registration are the key important steps in change detection methods. Accurate geometric registration between multi-temporal images is essential to avoid spurious change results. This is because image displacement causes false change areas in the scene (Gorte and van der Sande 2014). Mean standard error of half a pixel or better level of image registration accuracy is generally required to produce reliable change detection results (Du et al. 2013, Kennedy et al. 2009). Moreover some studies report that very high image registration accuracy requirement is not critical in object-based change detection methods whereby object buffer detection algorithms are applied to compare the extracted features (Deren, Haigang and Ping 2003). Radiometric correction normalizes atmospheric and variation in the optical characteristics of the remote sensing instrument by adjusting the radiometric properties of target images to match a base image (Vicente-Serrano, Pérez-Cabello and Lasanta 2008). Methods such as “empirical estimation approach” for dark object subtraction uses only the image data to remove atmospheric effects, by correcting for atmospheric path radiance which is at-sensor radiance contributed by atmospheric scattering (Mustard, Staid and Fripp 2001).

2.5 Change detection algorithms

The selection of appropriate change technique is dependent on the objective of a study. Change detection techniques such as image differencing provide binary information of change vs no-change maps. Moreover if the objective of a study is to provide detailed time series change matrix, techniques such as post-classification or feature extraction comparison is desirable. It is common practice that the acquisition date of input multi-date images should closely coincide to capture reflectance properties of the land cover feature space under similar measurement conditions. Several change detection algorithms have been developed based on both the pixel-base and object-based approaches (Zhou, Troy and Grove 2008). In some instances the spatial resolution of input image pixel can significantly impact the selection of change detection algorithm. In general, coarser spatial resolution image data (e.g. Advanced Very High Resolution Radiometer–AVHRR, Moderate Resolution Imaging Spectroradiometer–MODIS) are used to analyse changes over very large areas (national and global change mapping). At the local scale studies, medium to high spatial resolution image such as Landsat, worldview or QuickBird data are used. Hussain et al. (2013) summarize different change detection methods that were found to be documented in the literature by 2013. Some of these change detection techniques applied to remotely sensed image are presented in Table 2.1.

Table 2.1: Summary of image classification methods for change detection analysis

Method	Advantages	Limitations	Reference
Image ratioing	Accounts for calibration errors related to sun angle, shadow and topography impacts.	Provides incomplete matrices of change information.	(Rignot and van Zyl 1993)
Image differencing	Simple and easy to interpret outputs	Provides limited matrices of change information. The difference value is absolute. Therefore same value may have different meaning depending on the initial binary class (change vs. no change)	(Coppin and Bauer 1996)
Artificial Neural Network (ANN)	A non-parametric supervised learning algorithm Estimate image data properties based on input training dataset	The hidden layer in the ANN is not known properly; the amount of training data is important in establishing the ANN network; ANN functionalities are not common in image processing software	(Woodcock et al. 2001)

Vegetation index differencing	Reduces impacts of topographic effects and illumination conditions	Constrained by random or coherence noise Binary (change vs. no change)	(Ria et al. 2003)
Regression analysis	accounts for differences in the mean and variance between pixel values for different dates, therefore reduces the confounding effects by atmospheric conditions and sun angles	Regression functions for the selected bands more accurate.	(Coppin et al. 2004)
Support Vector Machine	A non-parametric method that makes no assumption on the distribution of input data Appropriate to handle small training datasets and often produces higher classification accuracy than traditional methods Theoretically can handle larger datasets with higher dimensionality.	Difficulty in optimizing for the best kernel function The computational time for classification and achieving optimization during the learning phase often higher compared to traditional classification methods.	(Melgani and Bruzzone 2004)

Decision Trees (including random forests)	Non-Parametric and makes no assumption on distribution of input data Can provide rule set for change and no-change classes.	Generally sensitive to training data quality and imbalance number of training samples per class,	(Im and Jensen 2005)
Multi-date direct comparison change detection	One classification for stacked data	Less accurate in labeling the change classes Can yield incomplete change matrix.	(Im and Jensen 2005)
Object-based direct comparison based/ Object-based post classification comparison.	Straightforward comparison of objects Image objects have same geometric properties at two times Change by spectral or extracted features(texture) Easy integration into GIS All the available objects could be used for object-based change detection	Dependent on the accuracy of the segmentation Difficulty in searching spatially corresponding objects in multi-temporal images Appropriate threshold selection when comparing objects based on both the geometry and spectral or extracted features Difference in sizes and correspondence of image objects from multi-temporal images because of segmentation	(Miller, Pikaz and Averbuch 2005)

Principal component analysis (PCA)	Data redundancy reduction Emphasizes formation in the derived components	Scene dependent making it difficult to interpret and label for different dates Does not differentiate between change types; rather, it reports on areas that have changed (binary change)	(Deng et al. 2008)
Texture analysis based	Statistical manipulation to the spatial distribution of the image pixels Settlements have higher texture value compared to the non-settlement areas Measures the relative frequency of the spatial adjacency	Dependent on moving window size	(Erener and Düzgün 2009)
Post-classification comparison	Complete matrices of change analysis Minimizes the impact of using images from multi-sensors	Require accurate and pure pixels for complete training dataset Final change detection accuracy is dependent on classification accuracy of input images	(Ghosh, Mishra and Ghosh 2011)

2.6 Accuracy assessment in change detection

The accuracy of change detection relates to several factors, such as the geometric registration of input images, the complexity of the landscape, methods or algorithms used, and image resolution. Accuracy assessment techniques in remote sensing change detection stem from those of images classification. It is possible to extend the accuracy assessment techniques for processing single time image to that of bi-temporal or multi-temporal images. The error matrix for analyzing and evaluating land cover classification is the most efficient and widely-used (Abiden and Abidin 2009).

There are three general approaches to obtain the ground references for bi-temporal change detection, namely, field survey with the assistance of historical GIS data, simultaneous, or within the time proximity, high-resolution images, and visual interpretation. Each of these methods have advantages and disadvantages, depending upon the application. The major challenge is that accuracy assessment of change detection is mainly based on pixel. There is little research done to assess accuracy for feature-level or object-level change detection.

CHAPTER 3: MATERIALS AND METHODS

3.1 Introduction

Materials and methods consisted acquisition of image data, pre-processing (i.e. radiometric, atmospheric and geometric correction of input Landsat images for further analysis), feature classification and extraction, and post-classification comparison for change analysis. The next step in the methods was to classify individual image data using the corrected spectral reflectance image. As part of the classification process, training and validation spectra were collected using the high spatial resolution, pansharpened SPOT images. An accuracy assessment of the classification was done to validate the final results.

3.2 Software and other Materials

The image processing and analysis operations were performed using RSI ENVI (RSI 2010) software version 5.1 and ArcGIS 10.1. Additional data analyses such as calculation of error matrixes were done using Microsoft spreadsheet. Auxiliary data used for this research included KwaZulu-Natal land cover and agricultural land categories maps covering the uMgeni Local Municipality.

3.3 The Landsat program and characterization of Landsat data

The National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS) in the Department of the Interior manage the Landsat program in a joint agency partnership. The Landsat program has provided over 40 years of Earth observation image data (Figure 3.1). The Landsat payload instruments collect image data for multiple spectral bands (Vis/NIR/SWIR/TIR) across ±185 km swath along each path and data are archived for non-discriminatory access to global public, at generate Level 1 data products, and data products are distributed at no cost upon request. The Landsat program provides for acquisition, archiving, and distribution of moderate-resolution multispectral imagery to afford global, synoptic, and repetitive coverage of the earth's land surface. This is at a scale where natural and human-induced changes can be detected, differentiated, characterized, and monitored over time. Figure 3.2 displays the multispectral spectral properties of Landsat 7 ETM+ (analogous with Landsat 5) and the new Landsat 8 (Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) instruments). For all instruments, every Pixel (ground sampling area of 30 m) is a scientific measurement.

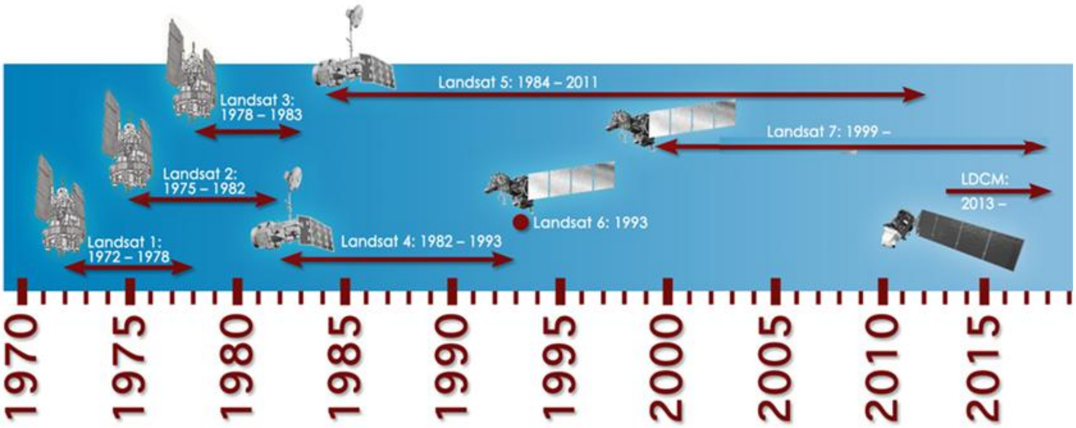


Figure 3.1: Heritage Landsat Earth observing program (source: NASA/USGS, 2013).

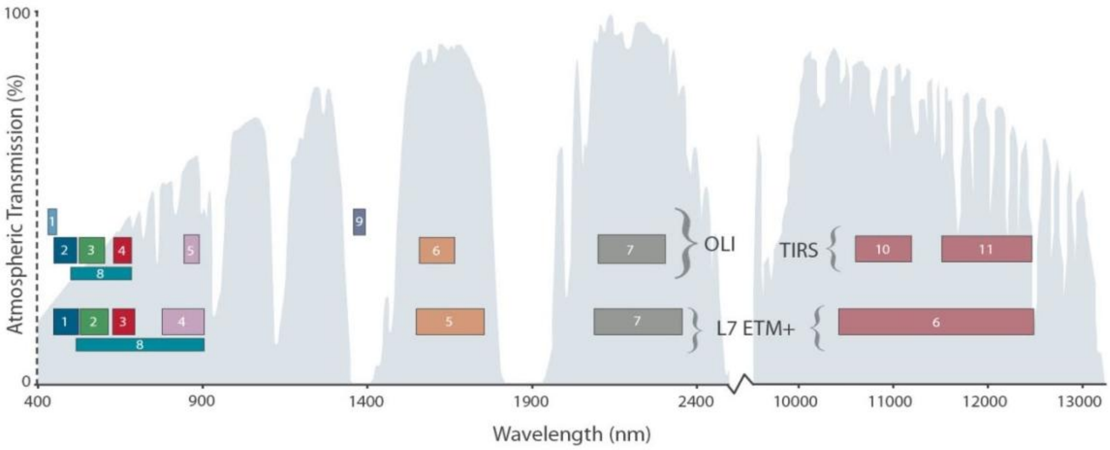


Figure 3.2: Spectral band characteristics of the Landsat Earth observing instruments (source: NASA/USGS, 2013)

3.4 Data acquisition and pre-processing

For the purpose of the current study three dates of Landsat 5, 7 and 8 image data (1993, 2003, and 2013, respectively) for Worldwide Reference System path 80, row 81 were acquired. These multi-sensor Landsat scenes cover the uMgeni local municipality (Figure 3). To reduce scene-to-scene variation due to differences of instrument calibration, geometric and atmospheric conditions, and natural vegetation phenology differences, all data were collected in April. The images had been radiometrically corrected and orthorectified as supplied, by the Earth Observation Directorate of the South African National Space Agency (SANSA). The registration mean error of the images was 0.19 of the input Landsat pixel of 30 m ground sampling distance.

3.5 Correction for the atmospheric effect using FLAASH

The nature of optical remote sensing requires that radiation from the sun pass through the atmosphere before it is incepted by the remote sensing instrument. In that regard, remotely sensed images include information about both the atmosphere and the earth's surface. For application focusing on quantitative analysis of surface radiance or reflectance, removing the influence of the atmosphere is a critical pre-processing step (Yuan et al. 2009). In order to compensate for atmospheric effects, properties such as the amount of water vapour, distribution of aerosols, and scene visibility (including surface topography) must be known or inferred. The atmospheric correction method implemented for the current study is "Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH). This atmospheric correction approach provides accurate compensation for atmospheric effects. The FLAASH method is developed by Spectral Sciences, Inc., U.S.A. The FLAASH atmospheric model is based on MODTRAN 5 code developed for the three Landsat sensors. The model was applied to each georeferenced and rectified Landsat image data, using ENVI 5.1 software.

The digital numbers were converted to surface radiance data, using the absolute radiometric calibration factors and effective bandwidths for specific Landsat bands using the ENVI 5.1 routine. The resultant radiance images were then atmospherically corrected to reduce haze, water vapour and other atmospheric influences.

3.6 Collecting training data

Higher spatial resolution (2.5m) land cover map (developed from 2008 SPOT5 imagery) was used as a reference dataset. Ground truth pixels were collected representing six land cover types in the study area. The resultant data were used to derive a point distribution map of the six land cover types considered in this investigation.

3.7 Separability analysis of ground truth pixels for the target land cover classes

Separability measurement relates to the extent to which patterns can be correctly associated with their target land cover classes using statistical methods. For this research six classes were determined in the study area including the built-up land cover (buildings and other man-made infrastructures such as road), grassland, crop land, plantation forest, water body and, bare-land and other undefined features. Separability of the training data for all class pairs was assessed using the Jeffries Matusita (J–M) distance index (Sousa, Pereira and Silva 2003). The J–M measures the average distance between two class density functions (Schmidt and Skidmore 2003). These values range from 0 to 2.0 and indicate how well the selected pairs can be statistically separated. For this research, a J–M distance greater than 1.90 (≥ 95% of 2) was used as a threshold of spectral separability between group pairs.

3.8 The classification procedure

For the classification of targeted land cover types (i.e. built-up, grassland, crop-land, plantation forest, water body and, bare-land), it was necessary to develop and validate the classification algorithm, and to calculate a change map of the distribution of built-up infrastructure in the area. A supervised learning algorithm, the Support Vector Machines (SVM), was implemented in the ENVI 5.1. The SVM (Vapnik 1998) is non-parametric method which makes no assumption about the underlying data distribution in classifying the multi-date Landsat images. The SVM identifies the class associated with each pixel and employs optimization algorithms to locate the optimal boundaries between classes (Zhang and Ma 2008). The algorithm can be applied to stacked multi-temporal images, to detect change and no-change in a binary classification problem. In this regard the algorithm learns from training data and automatically finds threshold values from the spectral features for classifying change from no-change (Vural et al. 2008). The SVM is known to provide good classification results compared to traditional techniques such as maximum likelihood classifier. For the current research, SVM was used to perform classification analysis independently on each of the multi-date Landsat images acquired for the study area.

3.9 Accuracy assessment

About 30% of the ground truth pixel data was reserved for validation of the accuracy or performance of the support vector machine classification algorithm. A simple random sampling method was used to subset the ground truth pixels across each of the input Landsat images with the aid of ancillary data such as higher spatial resolution SPOT images and aerial photographs covering the study area. A confusion matrix for SVM classifications was computed using the validation ground truth samples. Overall classification accuracy, producers and the user’s accuracies were calculated for each classification. Ancillary data including date of aerial photos acquired were closely to input image dates, and ground truth data collected in the field were used to generate training and validation datasets. In addition, the Cohen's Kappa statistic was calculated for each matrix (Formula 1). The Kappa (KHAT) measures the agreement between the classified map and mutually exclusive categories of the ground truth values (Yang and Chinchilli 2009).

$$\widehat{K} = \frac{N\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi+ * x+i)}{N^2 - \sum_{i=1}^{r}(xi+ * x+i)} \quad [1]$$

Where: $\widehat{K}$= is the KHAT statistic

xii is the number of diagonal entries in row i and column i

xi+ is the sum of row i

x+i is the sum of column i

N is the total number of observations

r is the size of the matrix

3.10 Post-classification feature extraction and comparison

This stage of the methods involves two major steps – (1) independently extracting built-up features from the multi-date images, and (2) comparing the extracted built-up land class pixels for binary pairs of input classification images. The total number of extracted pixels/area from the pairs is calculated to quantify changes in built-up land class, between different time intervals. In this study, only the built-up classes are specified in order to achieve the set objective of estimating the impact of the developmental footprint within the agricultural land categories in uMngeni, using each of the multi-date image analysis.

CHAPTER 4: RESULTS

4.1 Classification of multi-date Landsat imagery

The confusion matrices based on the validation data sets for each classification analysis performed on the multi-temporal Landsat 8, 7, and 5 data are shown in Table 4.1, 4.2, and 4.3, respectively. High overall classification accuracies were achieved for the multi-date images classified individually. All producer's and user's accuracies are high, especially the user's accuracies of the built-up land class of the uMngeni Local Municipality. Figure 4.1, panel b, c, and d summarize the SVM classification results of Landsat 8 (April 2013), 7(April 2003), and 5(April 1993) images respectively. The overall percentage of classification accuracy (OA) and the respective Cohen's Kappa statistic (kappa) obtained for the Landsat 8, April 2013 is OA=83.67% with a kappa=0.82; for Landsat 7, April 2003, the OA=84.18% with a kappa =0.81; and for Landsat 5, April 1993, the OA = 83.33% with a kappa= 0.81.

Table 4.1: Error matrix for SVM classification results of Landsat 8, April 2013 input image. Overall accuracy = 83.67; Kappa = 0.82

Predicted class	Built-up	Grassland	Cropland	Bare-land	Plantation	Water body	reference pixels
Built-up	116	5	0	13	0	0	134
Grassland	12	112	4	2	5	0	135
Cropland	6	8	96	7	6	0	123
Bare-land	3	2	9	77	7	0	98
Plantation	7	0	0	0	65	0	72
Water body	0	0	2	0	0	36	38
Sum of estimation	144	127	111	99	83	36	600
Producer accuracy (%)	80.56	88.19	86.49	77.78	78.31	100	
User accuracy (%)	86.57	82.96	78.05	78.57	90.28	94.74	

Table 4.1: Error matrix for SVM classification results of Landsat 7, April 2003 input image. Overall accuracy = 84.18; Kappa = 0.81

Predicted class	Built-up	Grassland	Cropland	Bare-land	Plantation	Water body	reference pixels
Built-up	66	5	2	7	0	0	80
Grassland	8	54	8	6	3	0	79
Cropland	5	11	111	11	9	0	147
Bare-land	5	6	6	124	0	0	141
Plantation	3	0	0	0	119	0	122
Water body	0	2	0	0	0	42	44
Sum of estimation	87	78	127	148	131	42	613
Producer accuracy (%)	75.86	69.23	87.40	83.78	90.84	100	
User accuracy (%)	82.50	68.35	75.51	87.94	97.54	95.45	

Table 4.2: Error matrix for SVM classification results of Landsat 5, April 1993 input image. Overall accuracy = 83.33; Kappa = 0.81

Predicted class	Built-up	Grassland	Cropland	Bare-land	Plantation	Water body	reference pixels
Built-up	64	9	2	9	0	0	84
Grassland	9	61	6	6	3	6	91
Cropland	2	3	102	4	9	0	120
Bare-land	4	7	12	94	0	0	117
Plantation	0	2	4	0	110	0	116
Water body	0	0	0	4	0	74	78
Sum of estimation	79	82	126	117	122	80	606
Producer accuracy (%)	81.01	74.39	80.95	80.34	90.16	92.50	
User accuracy (%)	76.19	67.03	85.00	80.34	94.83	94.87	

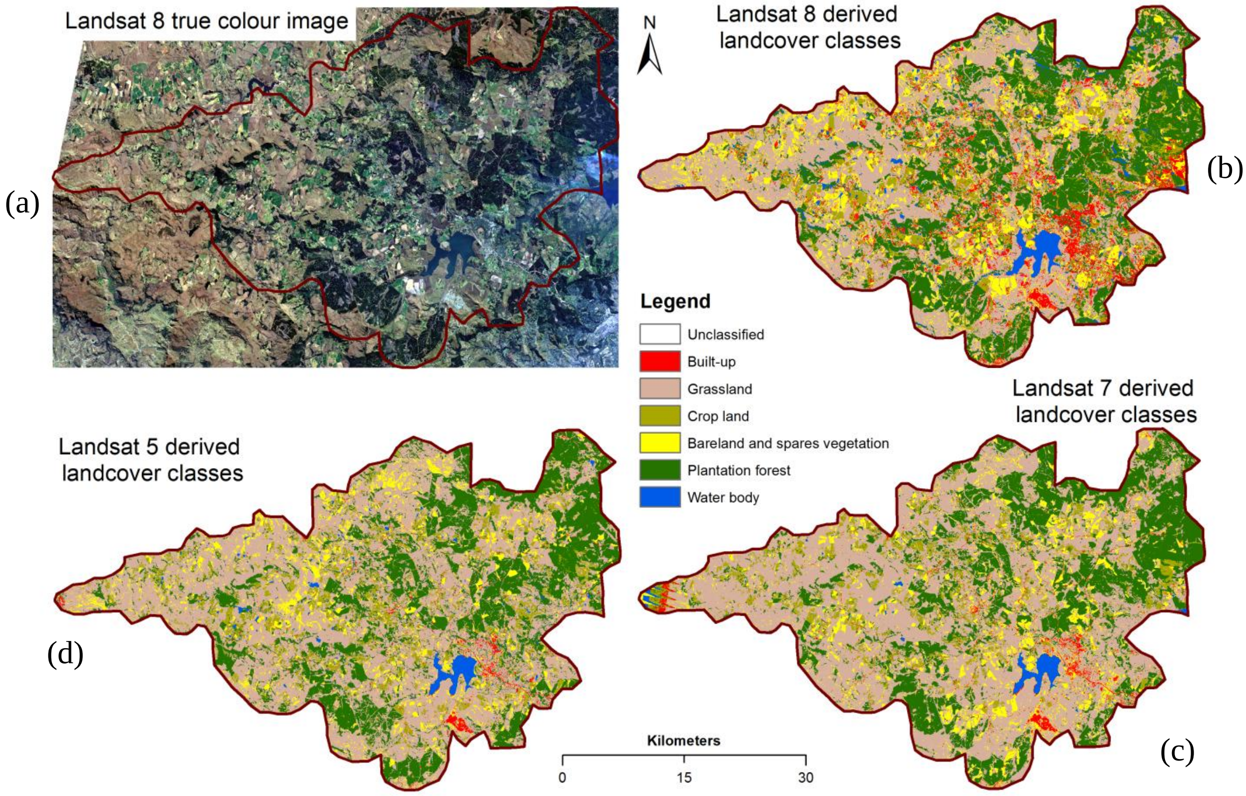


Figure 4.1: SVM classification results of input Landsat image data: panel (b) output classes from analysis of Landsat 8 mage (panel (a) is true colour of the input Landsat 8 image; panels (c) and (d) are respective output class images from analyses of Landsat 7 and Landsat 5.

4.2 Mapping built-up land cover overtime within the agricultural categories

Final products of the research are spatial distribution maps of built-up land cover pixel classified at 30-meter resolution for three multi-date Landsat scenes, and estimates of percentage change at two time periods. Figure 4.2 shows a comparison between classification built-up land cover estimates derived from the multi-date Landsat using SVM algorithm. Overall, the average change of the 1993–2013 land cover prediction by comparing SVM model output images was 38.92%. For Built-up class only, the percentage change detection ranged from 13.07%, 38.37 %, and 32.03% for the period 1993–2003, 2003–2013, and 1993–2013, respectively (Table 4.4).

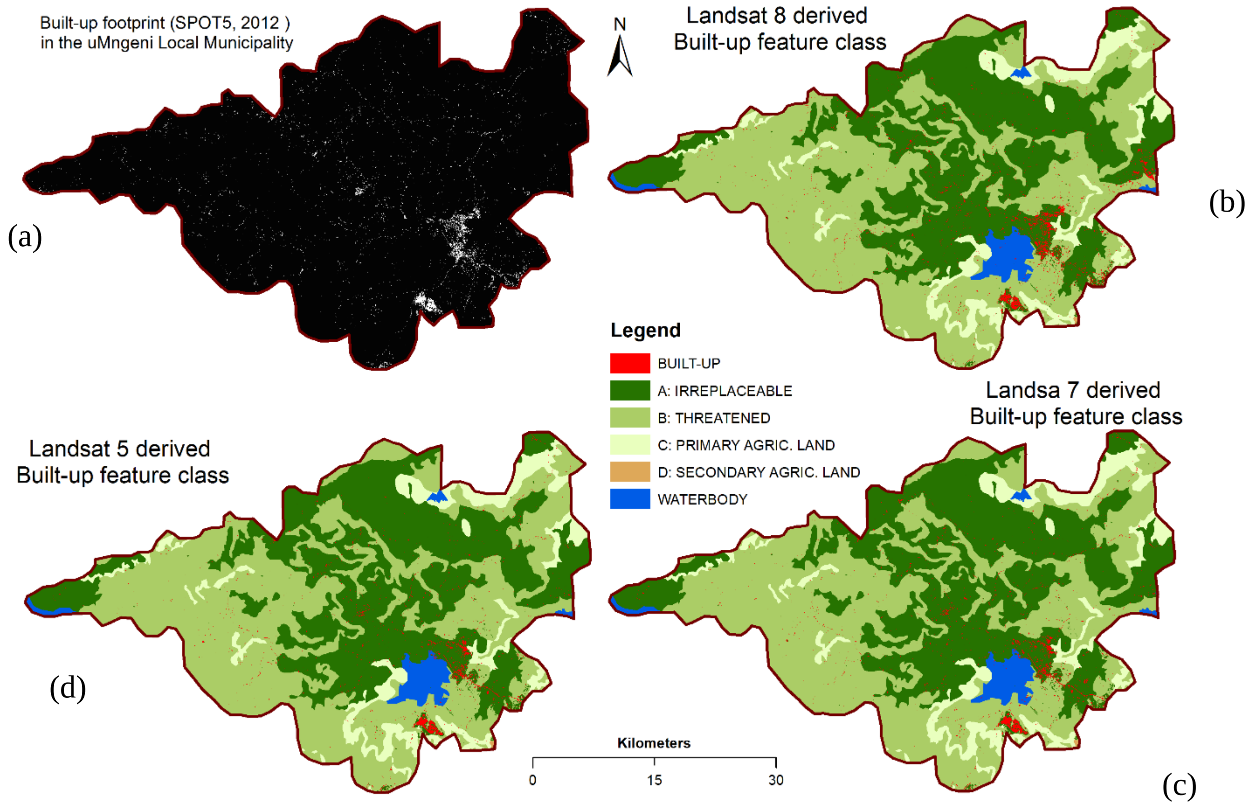


Figure 4.2: Built-up land cover class within agricultural land categories in uMngeni: panel (a) built-up (white pixels) features extracted from high resolution (2.5 m) SPOT5 image; panel (b) shows built-up (red pixels) layer extracted from Landsat 8 mage overlay on the agricultural land categories; panels (c) and (d) are respective output images from analyses of Landsat 7 and Landsat 5.

Table 4.3: Percentage change in land cover classes for different time periods under investigation

Class changes	1993–2003 (%)	2003–2013 (%)	1993–2013 (%)
Unclassified	0	0	0
Built-up	13.07	38.37	32.03
Grassland	19.06	15.18	9.98
Crop Land	2.18	2.83	1.76
Bare-land/spares veg.	42.70	35.96	49.85
Plantation	18.87	4.51	3.47
Water body	4.52	3.15	2.87
Class Total	100	100	100
Class Changes	25.34	47.63	38.92

CHAPTER 5: DISCUSSION

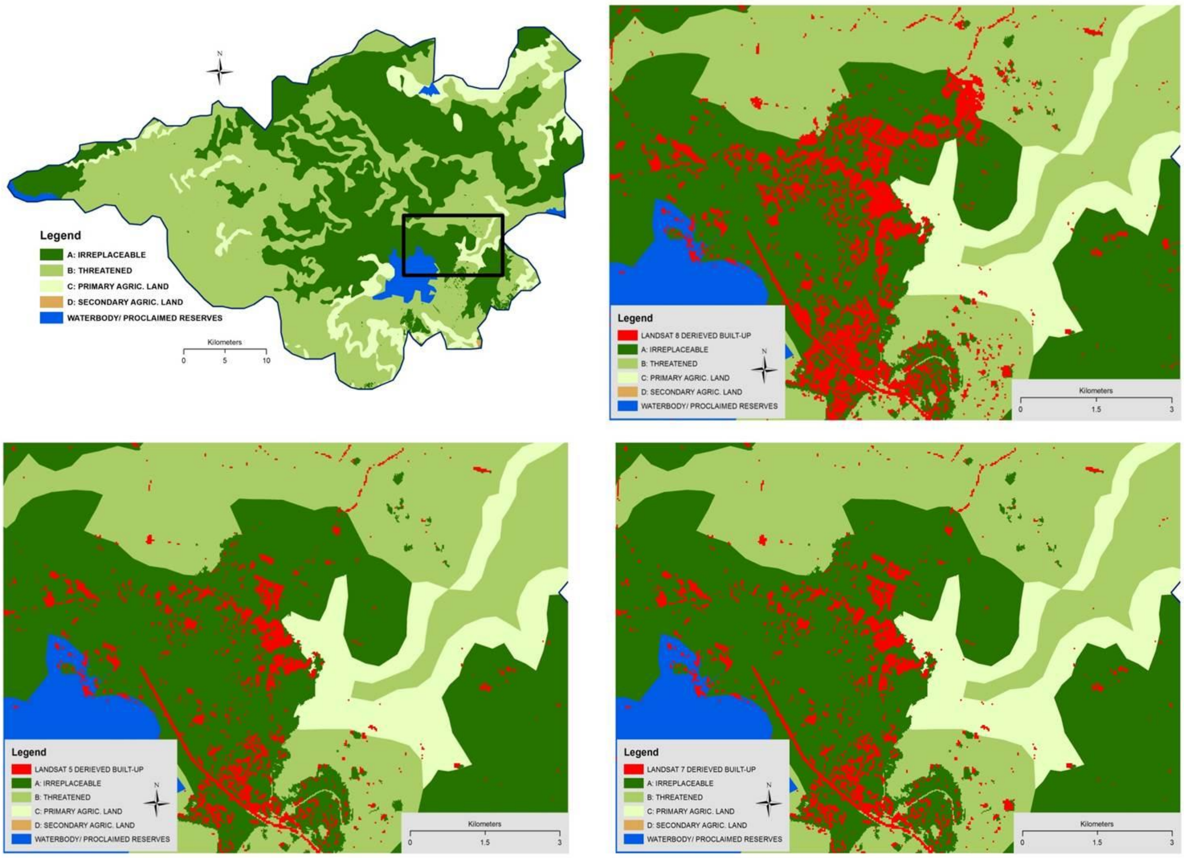
Local municipality-wide land-cover change detection analysis provides a useful tool for the long-term monitoring of agro-ecological systems and for the protection of high value agricultural land. Moreover, monitoring changes in specific land-cover type from a multi-temporal analysis offers historical and recent perspective on landscape dynamics. The increasing availability and accessibility of remote sensing technologies has provided immense opportunities for a wide range of applications such as mapping urban-agricultural landscape. Mapping and monitoring of change occurring in agricultural environments include shifts in land cover/landuse, landscape morphology, urban built-up developments, and analysis of regional impacts – (developmental impacts in agricultural systems). The specific objective of the current research was to appraise issues of loss of agricultural land resource to other landuse options in the study area using multi-temporal remote sensing techniques for change detection in built-up land cover.

Integration of the support vector machine learning algorithm and multi-date Landsat data in this study yielded important information for the time periods investigated. Results obtained from the study helped to identify changes in built-up land-cover that occurred from 1993–2003, 2003–2013, and 1993–2013 in the uMngeni Local Municipality. In general, areas with increased built-up surfaces can be related to known land-use changes or conversion of agricultural land to other uses in this area (Collett and Mitchell 2012). The accuracy of the initial land cover classification analyses and the mapping procedure was repeatable. In the course of this study, great effort was made to the development of good ground truth data for model training and validation from the ancillary sources including high spatial resolution SPOT image, aerial photographs and field survey data. Results of separability analysis for all class pairs showed high Jeffries Matusita distance of 1.65 or greater. However, misclassifications can be explained from the Jeffiries-Matusita separability analysis showed some degree of confusion among class pairs as manifested by the errors of omission and commission between class pairs.

5.1 Monitoring trends in built-up land cover within the uMngeni Local Muicipality

South Africa has a limited amount of high potential agricultural land available for long-term sustainable food production. It is estimated that less than 4% of the national land surface can be regarded as high potential land (Collett and Mitchell 2012). Much of this land, however, has already been lost to non-agricultural land uses such as residential and industrial developments and mining or is currently under severe pressure for non-agricultural development. The use of land for development in both urban as well as rural areas must be viewed against the need to utilize the same land for agricultural production purposes so as to achieve and meet food security requirements for the nation. The scenario of prohibiting development on the one hand, versus allowing development anywhere on the other, is not a feasible option and therefore careful consideration is required to determine the most suitable and sustainable land use option on a given area of land. This poses a serious challenge to land use planners as to the most suitable land use option, as well as ensuring the selected land use matches the natural resource base so as to be both sustainable and viable into the future. Additionally, land use planners and natural agricultural resource managers require critical information regarding patterns in landuse over time and for resource monitoring objectives. Results of SVM classification of multi-date Landsat data revealed significant increases in built-up land cover between the periods 1993 – 2003, and 2003 – 2013. As an example, Figure 5.1, panel a shows high value agricultural land categories in the South-East area in the uMngeni Local Municipality. Using the approach in this study it can be seen from panel b, c, and d the increasing trend in the built-up land cover 20 year period. The results demonstrate impact of development on the Agro Ecological Zones in the area.

(a) (b)



(d) (c)

Figure 5.1: An illustration of increases in built-up land cover with high value agricultural land. Panels: (a) agricultural land categories in uMngeni Local Municipality, (b) built-up extracted from 2013 Landsat 8 image, (c) (built-up extracted from 2003 Landsat 7 image, and (d) built-up extracted from 1993 Landsat 5 image.

5.2 Factors contributing to the encroachment of other landuse and/or land cover into the agricultural land

Transformation of agricultural land to other land uses including built-up infrastructure is influenced by a spectrum of factors. Amongst these include economic, policy and institutional, social and cultural, environmental and biophysical considerations. Notwithstanding the circumscription of the study to independently evaluate the these factors to assess the extent to which they contribute to transformation of agricultural land to other land uses, economic drivers inclusive of growth in the economy driven by industrialisation, urbanisation and the gains in Information Technology are generally considered to have immensely contributed to inordinate transformation of rural land.

In some instances lack of policy clarity serves as an unintended impetus to rural land transformation. Within the context of South Africa in 1995 government promulgated into law the Development Facilitation Act No.67 pursuant to the advancement of the Reconstruction and Development Programme (RDP) imperative following decades of the segregated spatial land development patterns. The significant change of approximately 38% as discovered in this study in built-up area during the period 2003-2013 could be attributed to the inordinate use of this legislation to promote development in uMngeni Municipality.

Globally population is expected to continue to rise, further contributing to an increased demand for the utilisation of already constrained land resources to sustain future human requirements. Population growth remains both an opportunity to increase agricultural food production and a threat to agricultural land in favour of development for human settlement. Agricultural land transformation should be considered within the context of sustainable development without oblivion to other development imperatives. This study advocates for a holistic approach to land development without comparison of land uses against the other.

5.3 Conclusions

The percent temporal changes in built-up surface (30-meter resolution) were mapped for two time periods over uMngeni Local Municipality based on SVM classification. The method was found to be satisfactory based on assessment of the classification error matrices using independent reference data. The change-detection procedure implemented in this study is repeatable and efficient, provided that good training data cover the whole range of spectral variability of all target land cover features.

Change in percent cover over time indicated that some agricultural land resources have been converted into development infrastructure specifically urban land-cover. The rate of increases in built-up land cover often relates to a number of factors including subdivision of agricultural land for alternative use, socio-economic development and legislation. It should be noted that the land cover change product generated using the approach in this study has some limitations. Due to some degree of pixel confusion from the initial SVM classification, a significant percent of built-up land cover may or may not reflect actual changes within the study area. In addition, all accuracy information reported was based on evaluation of SVM classification estimates for each individual time period and therefore there is a degree of compounding error on the final change map. Moreover no direct assessment was made to evaluate the quality of the change product and this should be noted. Consequently, the quality of the change results relates indirectly from the accuracy estimates of each individual time period. It is worthy to note that within-class changes, for example changes due to vegetation growth, soil variation, etc., would potentially impact on the change detection process.

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