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Developing an optimised remote sensing and GIS methodology for monitoring urban growth in major towns in North West Province, South Africa

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Thesis submitted in fulfilment of the requirements for the degree Doctor *of Philosophy in Geography* at the North-West University

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DECLARATION

I declare that this thesis "Developing an Optimised Remote Sensing and GIS Methodology for Monitoring Urban Growth in Major Towns in the North West Province, South Africa" has been composed solely by myself, that the work contained herein is my own except where explicitly stated otherwise in the text. Other assistance received has been acknowledged. I have not knowingly copied or used the words or ideas of others without such acknowledgement. This work has not been submitted for any other degree or professional qualification except as specified.

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This thesis has been submitted with my approval as a university supervisor and I hereby certify that the requirements for the degree Doctor of Philosophy in Geography have been fulfilled.

Signed...

Prof C. MUNYATI

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DEDICATION

It is virtually impossible to undertake a study of any magnitude without the cooperation and assistance of people who are generous not only with their time but who make the conscious decision of laying on the line deeply personal vestiges of themselves.

I am dedicating this thesis to my late baby brother Joshua K. Bett who meant so much to me and continues to. Although no longer in this world, and gone forever from our loving eyes, you left a void in our lives that can never be filled. Though your life was short in this system of things, I will make sure your memory lives on as long as I shall live. His memory continues to regulate and inspire my life. Until we meet in Paradise.

ACKNOWLEDGMENTS

First of all, and above all things, Honour, Power and Glory to the Almighty GOD Jehovah. I am forever grateful, without his spiritual guidance and mercy that he has shown me throughout my life and the duration of my study, this work would not have been possible.

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Unfortunately, I cannot thank everyone else by name. Nevertheless, I want you all to know that you count so much. If it had not been for all your prayers and blessings; if it were not for your sincere love and help, I would never have accomplished this thesis. *Kwa hiyo asante nyote na Bwana awezaye kukubariki nyote.*

At the end of all this, I say that LIFE IS NOT A RACE, THE JOURNEY THAT COUNTS.

ABSTRACT

In the North West Province of South Africa, as well as in South Africa in general, there is a rapid rate of urban expansion. The rapid rate requires techniques that can effectively detect and quantify the rate of change. The aim of the study was to establish an optimised Remote Sensing and GIS methodology for monitoring urban growth in major towns in the North West Province. The study was conducted in the province's four main towns, namely Mahikeng, Rustenburg, Klerksdorp and Potchefstroom. SPOT images of the towns from dry season dates in 1999, 2013 and 2017 were acquired from the South African Space Agency (SANSA).

Processing of the images to map multitemporal urban sprawl established a methodology for monitoring urban sprawl in the province, given the unique characteristics of the urban metrics. The images were processed using the combination of ERDAS Imagine 2016 and eCognition Developer 9 software. The recommended methodology consists of establishing similar image data units if there are differences in radiometric resolution, as well as common pixel size and projection. Following a comparison with the widely used, parametric and accurate Maximum Likelihood Classifier (MLC), the nonparametric approach of Random Forest (RF) classification was established as more accurate in discriminating the urban land in the four towns studied. The RF classifier is an Object-Based Image Analysis (OBIA) approach. The generation of objects was optimised using the multiresolution segmentation algorithm. Segmentation level 3 at the scale parameter of 160 gave ideal segmentation results from the multiresolution segmentation. Boolean GIS overlay analysis using the built up area class from each image then enabled mapping and quantification of the urban sprawl. It is concluded that the nonparametric classification approach using a nonparametric classifier like Random Forest is more accurate for delineating the urban metrics of the towns in the North West Province of South Africa, whose urban land is characterised by a mixture of formal built up areas and the scantly built informal settlements with gravel roads, bare land and small dwellings ('shacks') made from iron roofing sheets. The methodology is recommended for use in spatial assessments of urban growth in the towns of the North West Province of South Africa as well as other towns in the country or in other countries with similar urban metrics.

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LIST OF ACRONYMS

ANNs	:	Artificial Neural Networks
BHUs	:	Broad Habitat Units
CBD	:	Central Business District
CFR	:	Cape Floristic Region
CVA	:	Change Vector Analysis
DEM	:	Digital Elevation Model
ESP	:	Estimation of Scale Parameter
ETM+	:	Enhanced Thematic Mapper Plus
FCC	:	False Colour Composite
GCPs	:	Ground Control Points
GGP	:	Gross Geographical Product
GIS	:	Geographical Information System
GPS	:	Global Positioning System
HELM	:	Historical Empirical Line Method
IHS	:	Intensity, Hue, and Saturation
ISODAT	:	Self-Organising Data Analysis Techniques
MLC	:	Maximum Likelihood Classifier
MSS	:	Multi-Spectral Scanner
NIR	:	Near Infrared
NOAA	:	National Oceanic and Atmospheric Administration
NWP	:	North West Province
OBIA	:	Object-Based Image Analysis Methods
PCA	:	Principal Component Analysis
RMS	:	Root Mean Square
SANSA	:	South African National Space Agency
SDGs	:	Sustainable Development Goals

SECHO	:	Supervised Extraction and Classification of Homogeneous Objects
SPOT	:	*Systéme Pour l'Observation de la Terre*
TBS	:	Thicket, bush-land, and Scrub forest land
UTM	:	Universal Transverse Mercator
TM	:	Thematic Mapper

Chapter 1

INTRODUCTION

1.1. Background and problem statement

1.1.1. Background

The need for monitoring urban development has become imperative in South Africa to help curb environmental problems. Although there are many Remote Sensing and Geographical Information Systems (GIS) methods that have been applied to study land use (Schowengerdt, 2012; Lillesand *et al.*, 2015), there remains a gap in developing a method which can be used in differentiating urban land use from rural land use, in the developing world context where built up structures are different from those in the developed world. Specifically, there still remains a paucity in the literature on the optimum image classification algorithm to accurately discriminate the urban growth characteristics within the South African context. Urban growth varies in degrees and attributes between the developed and the developing world and, subsequently, needs different algorithmic approaches in the use of Remote Sensing and GIS to monitor the phenomenon.

There are two terms that are encompassed by the phenomenon of urban growth: urban sprawl and urban expansion (Sun *et al.*, 2013). According to Jacquin *et al.* (2008), urban sprawl is the extension of metropolitan areas into adjacent rural landscapes. A more encompassing definition by Ewing *et al.* (2003) is that urban sprawl consists of (1) a population widely dispersed in low-density residential development; (2) rigid separation of homes, shops, and workplaces; (3) a lack of distinct, thriving activity centres, such as strong downtowns or suburban town centres; and (4) a network of roads marked by large blocks size and poor access from one place to another. Tsai (2005), on the other hand, summarily defines urban sprawl as low-density, leapfrog, commercial strip development and discontinuity. While urban expansion has no specific meaning yet, it takes place in substantially different forms such as in places with the same densities (persons per square kilometre) as those prevailing in existing built up areas, through the redevelopment of built up areas of higher densities, through infill of the remaining open spaces, or through new "greenfield" development areas previously in non-urban use. Wilson *et al.* (2003) are of the opinion that the sprawl phenomenon seeks to describe rather than define. "Sprawl typically moves away from an existing settlement in a 'leap-frog' pattern, as widely spaced developments initially occur several kilometres from the central business district and later become connected by infill development" (Robinson *et al.*, 2005).

Urban sprawl or growth are alternative words for urbanisation, which refers to the migration of population from populated towns and cities to low-density residential areas, and further to the rural land and beyond (Bett *et al.*, 2013). However, the concept is strongly controversial, with no neutral point about sprawl: there are antagonists (Commission, 2002; Kasanko *et al.*, 2005) and advocates (Bruegmann, 2005; Echenique *et al.*, 2012). On the other hand, urban sprawl remains a diffuse and elusive concept. After the democratic transition in South Africa in 1994, there has been a great shift in terms of rural-urban migration. Munyati and Motholo (2014) asserted that there had been large migration from the former homelands during the apartheid system, to urban centres after 1994. For instance, the discovery of platinum mine in Rustenburg became a pull factor for rural migrants to relocate to urban centres to work as unskilled labourers (Kleynhans, 2006).

Urban sprawl is a phenomenon that has several drastic consequences. It often happens very quickly, as opposed to gradually. Another key characteristic of urban sprawl is low-density land use, where the amount of land consumed per capita is much higher than in more densely populated city areas. Its concern is simply not on the increase of urban lands in a given area but in the rate of its increase relative to population growth. It could be said that sprawl is a pattern and pace of land development in which the rate of land consumed for urban purposes exceeds the rate of population growth for a given area over a specified period, which results in inefficient and consumptive use of land and its associated resources.

Regardless of increasing awareness of the need for rigorous definition and systematic measuring of sprawl (Angel *et al.*, 2005; Galster *et al.*, 2001; Tsai, 2005), the term is used ambiguously and is equivalent to expansion (Angel *et al.*, 2005; Galster *et al.*, 2001). Galster *et al.* (2001) stated that there is no general agreement on what sprawl means, or how to measure it empirically and compare its occurrence across different cities. Sun *et al.* (2013), however, consider urban expansion as a neutral concept which refers to the increases of cities in size and surface into adjacent land areas without qualitative implications. As cities expand as a result of demographic and economic growth, sprawl is an unavoidable fact.

Around the world, many environmental impacts of urban growth have been observed. Johnson (2001) states that to identify environmental impacts of urban growth, one needs to focus on those communities whose development is the source of the sprawl phenomenon. South Africa is no exception to the environmental issues that the world is experiencing concerning urban growth and urban land use. According to Bett *et al.* (2011), the current urban growth problems being experienced in North West Province of South Africa could be attributed to population growth and increased economic development. Urban sprawl causes negative environmental concerns and demands on natural resources, most notably the conversion of land and the accompanying impacts on air and water quality (Long *et al.*, 2014; Güneralp and Seto, 2008). The environmental impacts include, among others, air pollution resulting from automobiles, water pollution caused in part by increases in impervious surfaces, the loss or disruption of environmentally sensitive areas such as critical natural habitats (e.g., wetlands, wildlife corridors), reductions in open space, increased flood risks, and overall reductions in quality of life (Kahn, 2000; Hirschhorn, 2001). The rapid development also negatively affects wildlife by tearing down, clearing, or building over habitats, potentially threatening survival.

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Urban growth results in an increase in consumption of resources to cater for growing demands of urban populations and industry, leading to the generation of large amounts of waste in cities. It also results in the emergence of informal settlements, which usually lack service provision, in terms of sanitation, water, and waste management. This is more evident in urban areas in South Africa where the rate at which informal housing springs up is high, due to migrants having little to no formal income and being only able to afford to construct the informal dwellings called shacks. An increase in informal dwellings, in turn, outstrips the abilities of the local authorities to provide services such as running water, refuse collection, and refuse disposal.

The use of Remote Sensing has gained wide adoption in monitoring urban growth. It mainly in determining the type, amount and the location of land being converted and in planning future uses of the land (Gandhi *et al.*, 2011). Owing to being cost-effective and technologically sound, in recent years Remote Sensing is increasingly being used for the analysis of urban growth (Haack and Rafter, 2006; Sudhira *et al.*, 2004; Yang and Liu, 2005). Many researchers (Gomarasca *et al.*, 1993; Green *et al.*, 1994; Haack and Rafter, 2006; Yang and Lo, 2003; Li and Yeh, 2002) have used it for nearly three decades in urban change research. However, there is the gap that, according to Epstein *et al.* (2002), the impervious (built up) area is generally considered as a criterion for quantifying urban growth. Impervious area refers to the area consisting of residential, commercial and industrial complexes including paved ways, roads, markets, and so on. Urban growth has been quantified by considering the impervious area as the key feature of urban growth. In some areas the impervious area is not discernible on imagery.

Jat *et al.* (2008) stated that without Remote Sensing data, one may not be able to monitor and estimate urban growth effectively over a time period, especially for the earliest time period. There are a variety of techniques used to measure or estimate the area of impervious surfaces (Greenberg and Bradley 1997; Lu and Weng, 2006; Mundia and Aniya, 2005; Stefanov *et al.*, 2001; Stuckens *et al.*, 2000; Sugumaran *et al.*, 2003; Vogelmann *et al.*, 1998). It is, however, time-consuming and costly, yet the most accurate use in manual extraction of impervious surface features from Remote Sensing images is through heads-up digitising (Jat *et al.*, 2008). Nonetheless, point sampling can be used as an alternative to digitising, despite being time-consuming and less accurate. Remote Sensing pattern recognition approaches, such as supervised, unsupervised and knowledge-based expert system approaches have been used in the recent past to measure impervious area and urban growth (Lu and Weng, 2006; Mundia and Aniya, 2005; Sugumaran *et al.*, 2003). They require both moderate to high-resolution Remote Sensing data as well as the ability to process and analyse.

One approach to studying this urban growth phenomenon is through manual counting of urban features. In the study by Munyati and Motholo (2014) manual interpretation techniques appeared workable. On the other hand, manual counting may only be possible for certain spatial resolutions, but those resolutions are not available for all time periods, such as prior to 2013. For the newer sensors with a spatial resolution higher than 5 m, manual counting is possible. There is this technical capability advancement, but for older sensors, it is impossible to use manual counting, hence an automated approach is needed. One such method is the Gray-Level Co-occurrence Matrix (GLCM) variance to distinguish between slums and formal built up areas using very high spatial and spectral resolution satellite imagery (Kuffer *et al.*, 2016). This approach worked for the slum areas in three different cities (Ahmedabad, Mumbai and Kigali) that were tested. The reason that the GLCM variance method worked well is that the slums are well differentiated from the surroundings (caused by the contrast of the buildings) for different urban environments due to the close proximity of the structures within those areas as opposed to the ones in the North West Province that are 20 to 30 m apart. This study, therefore, developed a method for use in the scattered-buildings urban setting.

1.1.2. Problem statement

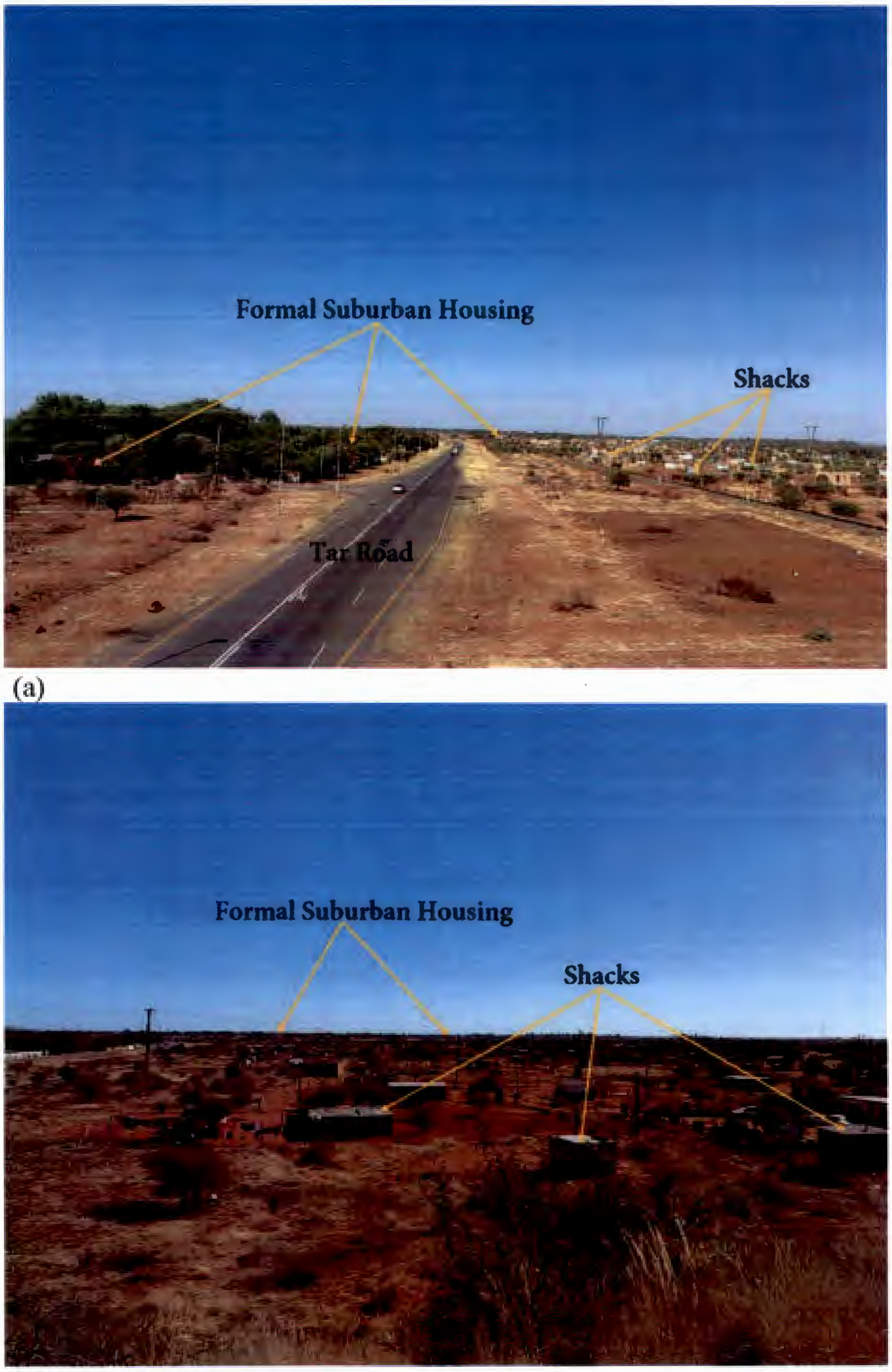
Scale has been a long-term major problem in the utility of multispectral data for discriminating and automatically generating thematic maps of spatial features (Marceau and Hay, 1999; Kim *et al.*, 2011). According to Marceau and Hay (1999) the concern emerged in the mid-seventies when "scientists became concerned over the choice of spatial resolution and data processing techniques that were producing poor automated classification results" (p. 358). Despite recent improvements in image classification algorithms and spatial resolution of multispectral sensors, there remains the problem that some spatial phenomena are too fragmented or dispersed to be automatically aggregated into thematic products (Schneider, 2012). Urban land in the developing world context has, in general, proved to be difficult to classify on multispectral imagery due to fragmentation, lack of pattern, and diversity of material used for buildings or lack of paving (Dewan and Yamaguchi, 2009; Scheneider, 2012; Kuffer *et al.*, 2016). These attributes have made pattern recognition using image classification algorithms difficult. Urban land in the North West Province is one such phenomenon, which makes monitoring it through the use of multitemporal imagery problematic.

Due to migration, some of the households in the North West Province are informal dwellings known as "shacks" (Figure 1), which are built using corrugated iron and walls made of tin-sheet material as opposed to bricks as is the case in high-income neighbourhoods (Munyati and Motholo, 2014). The building up of informal settlements occurs very rapidly and without monitoring them using special data and purpose-specific image classification protocols, they become very difficult to characterise. Hence, the nature of the characteristics of urban development in South Africa makes it difficult to monitor urban growth by multitemporal image classification. Therefore, there is a need to develop image classification protocols which are specifically suitable for the phenomenon on multispectral imagery.

1.2. Aim and objectives

The aim of this study is to establish an optimised Remote Sensing and GIS methodology for monitoring urban growth in major towns in the North West Province. The specific objectives formulated to achieve the principal aim of the study are as follows:

1) To establish the spatial scale of the field features that constitutes urban growth in the North West Province.



(a)

(b)

Figure 1: Illustration of the characteristics of urban sprawl on the eastern fringes of Mahikeng. The photos show that what constitutes 'urban' includes formal suburban housing (background) and informal dwellings called 'shacks' (foreground in photo (b)). Date of photography: 28 July 2018, at coordinates (25° 51' 04.55" S; 25° 40' 44.49" E), facing west.

2) To determine the appropriate digital image processing algorithm that can detect the spatial elements of urban growth.
3) To operationalise the identified algorithm in change detection for monitoring urban growth using common optical satellite imagery and GIS.
4) To determine the overall suitability of Remote Sensing for monitoring urban growth in towns of the North West Province of South Africa.

1.3. Justification of the study

Studies have discussed and emphasised the need to accurately and consistently monitor urban growth with the use of GIS and Remote Sensing as tools for informed decision making (Araya and Cabral, 2010; Bett *et al.*, 2013; Sivakumar, 2014). However, shortfalls brought about by current urban growth monitoring systems demand that there be an exploration of an alternative and reliable monitoring system which provides a better prediction of urban growth and expansion. Therefore, this study seeks to fill this gap by determining the spatial and temporal dynamics of urban growth through exploring a range of techniques that might be used to quantify sprawl. Consequently, the study is important in providing insights to academics, planners and policymakers in addressing problems related to monitoring urban growth.

Given the driving factors, behind urban growth any city in the world can experience negative effects of urban growth. It, therefore, becomes necessary to understand these changes, when using the appropriate digital image processing algorithm technique that can detect the spatial elements of urban growth, to be used as an effective monitoring tool in the province. In South Africa, there have not been any studies attempting to establish such an approach to identify an optimised algorithm for change detection in monitoring urban growth using common optical satellite imagery. This is because the characteristics that constitute urban growth in South Africa are unique. Urban growth in South Africa mostly occurs through informal settlements that constitute small built up structures like shacks that are emerging on the urban fringe due to continued migration into the urban area.

1.4. Conceptual framework for analysis

In developing countries, rapid urbanisation and urban growth continue to be one of the main issues of global change in the 21st century affecting the physical dimensions of towns. Hence, this study makes use of GIS and Remote Sensing as well as spatial metrics methods to get an understanding of spatiotemporal urban growth processes and the underlying patterns. Figure 2 shows the conceptual framework of the study which consists of three major elements (Remote Sensing, urban growth and spatial metrics) interacting at different stages of the research. To quantify urban growth, the potential use of classified temporal Remote Sensing images is indicated by the arrow at point A. Likewise, the interaction between urban Remote Sensing and Spatial metrics, are indicated by the arrows at points B and C, respectively. The output of a classified Remote Sensing image will be used as an input for the spatial metrics computation to quantify urban landscape fragmentation processes and patterns for selected metrics.

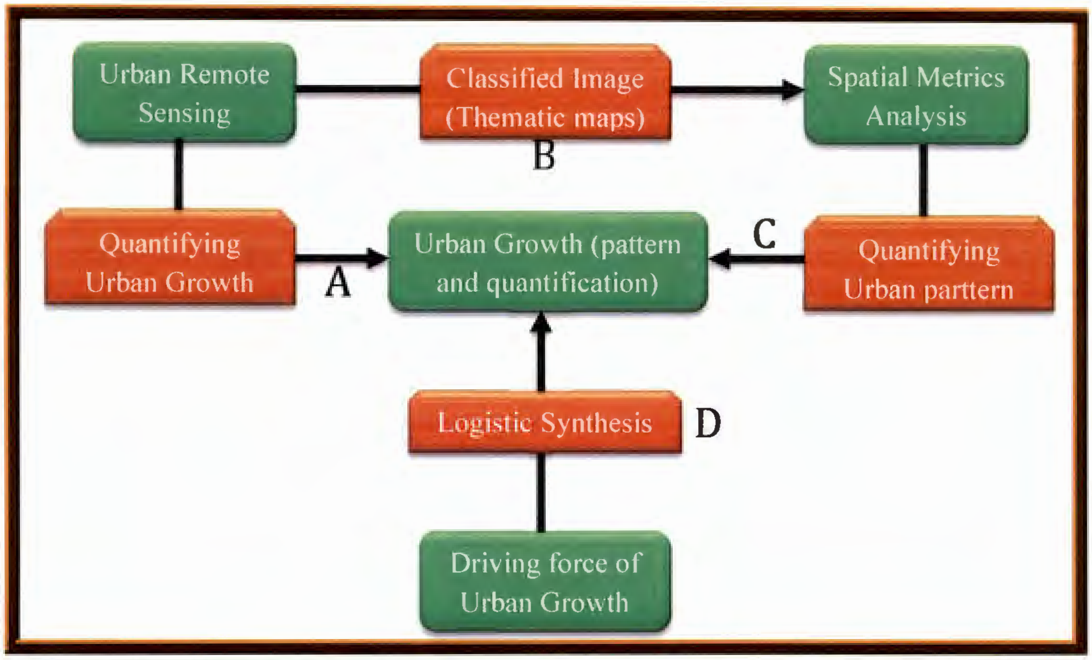


Figure 2: Conceptual framework for the analysis of urban growth (adapted from Herold *et al.* 2005).

The spatial configuration of the urban landscape and its composition are measured using selected metrics (Gustafson, 1998). To identify factors responsible for the changing patterns of urban landscape, driving forces of urban growth are used to conclude the analysis at point D. In the end, a discussion based on the results of the entire analysis is utilised to indicate how the methods can improve the understanding of urban growth processes and patterns by helping the policy makers and urban planners to put forward informed decisions.

1.5. Outline of the thesis

This thesis is divided into seven chapters. The first chapter is the introduction to the research. It sets the background, presents the problem statement, identifies the investigation approach, and stipulates the purpose, objectives and the justification of the study as well as the conceptual framework for analysis. The second chapter gives the description, background and location of the study areas, as well as the settings of the towns used in the study, in the North West Province of South Africa. The third chapter identifies gaps in current research about urban growth and situates the study within these loopholes using existing literature. It also discusses some of the causes and consequences, which are essential for the analysis of urban growth and to evaluate the appropriate algorithm for monitoring growth. The fourth chapter provides the research design, data analysis, and the Remote Sensing and GIS methods used. Chapter four also reports the fieldwork methods that were used to determine urban sprawl metrics in the towns in the study.

The fifth chapter describes the data used and assessment procedures for urban growth, gives results obtained from the digital satellite image analysis and illustrates the environmental changes identified. The results are used in the succeeding chapter. The sixth chapter analyses results from the preceding chapter by outlining the optimised change detection protocol through urban expansion and examination of land cover changes within the study areas. The adopted change detection methods quantitatively reveal the major changes that have occurred in the towns. The seventh chapter concludes the thesis by presenting empirical findings, the conclusions from the study and giving suggestions for further work as well as recommendations on sustainable strategies for managing sprawl. This is achieved by providing policy suggestions based on the obtained results from the overall research.

Chapter 2

DESCRIPTION OF THE STUDY AREAS IN THE NORTH WEST PROVINCE

2.1. General characteristics of the North West Province

The North West Province (NWP) is located towards the northern part of South Africa (Figure 3(a)). The spatial extent of North West Province is 106 512 km^2 with a population of 3.7 million according to StatsSA (2012). The towns chosen for the study are Mahikeng, Rustenburg, Klerksdorp, and Potchefstroom (Figure 3(b)). These towns were ideal for the study because they are the fastest urbanising towns in the North West Province (NWP), according to Walmsley and Walmsley (2002). The province is divided into four district municipalities, namely Dr Ruth Segomotsi Mompati, Ngaka Modiri Molema, Bojanala and Dr Kenneth Kaunda, as shown in Figure 3(b). The NWP shares borders with four other South African Provinces: Northern Cape to the West, Free State to the south, and Gauteng and Limpopo to the east. North West Province also shares an international border with Botswana to the north (Figure 3(a)). There are five airports in the province; Mafikeng International Airport, Pilanesberg International Airport and three minor airports (Rustenburg, Klerksdorp and Potchefstroom). In 1994 after the political changes, NWP was established by the merger of Bophuthatswana, one of the former Bantustans (black homelands) and the western part of Transvaal, one of the four former South African Provinces (READ, 2014).

The landscape of the NWP varies from plains in the west to mountains in the east. The northwestern and western portions of the province are dominated by plains, with scattered hills running in an arc from the Northern Cape Province (READ, 2014). The central and southern portions feature mostly plains with pans. The north-eastern portion is characterised by plains and undulating plains with the widespread occurrence of hills and lowlands and parallel hills. The province has a continental climate characterised by the high variance between a minimum and maximum temperatures, as per the South African Weather Service (SAWS). Thus the daily maximum temperatures range from 17 to 31°C in the summer and from 4 to 20°C in the winter with dry, sunny days and chilly nights.

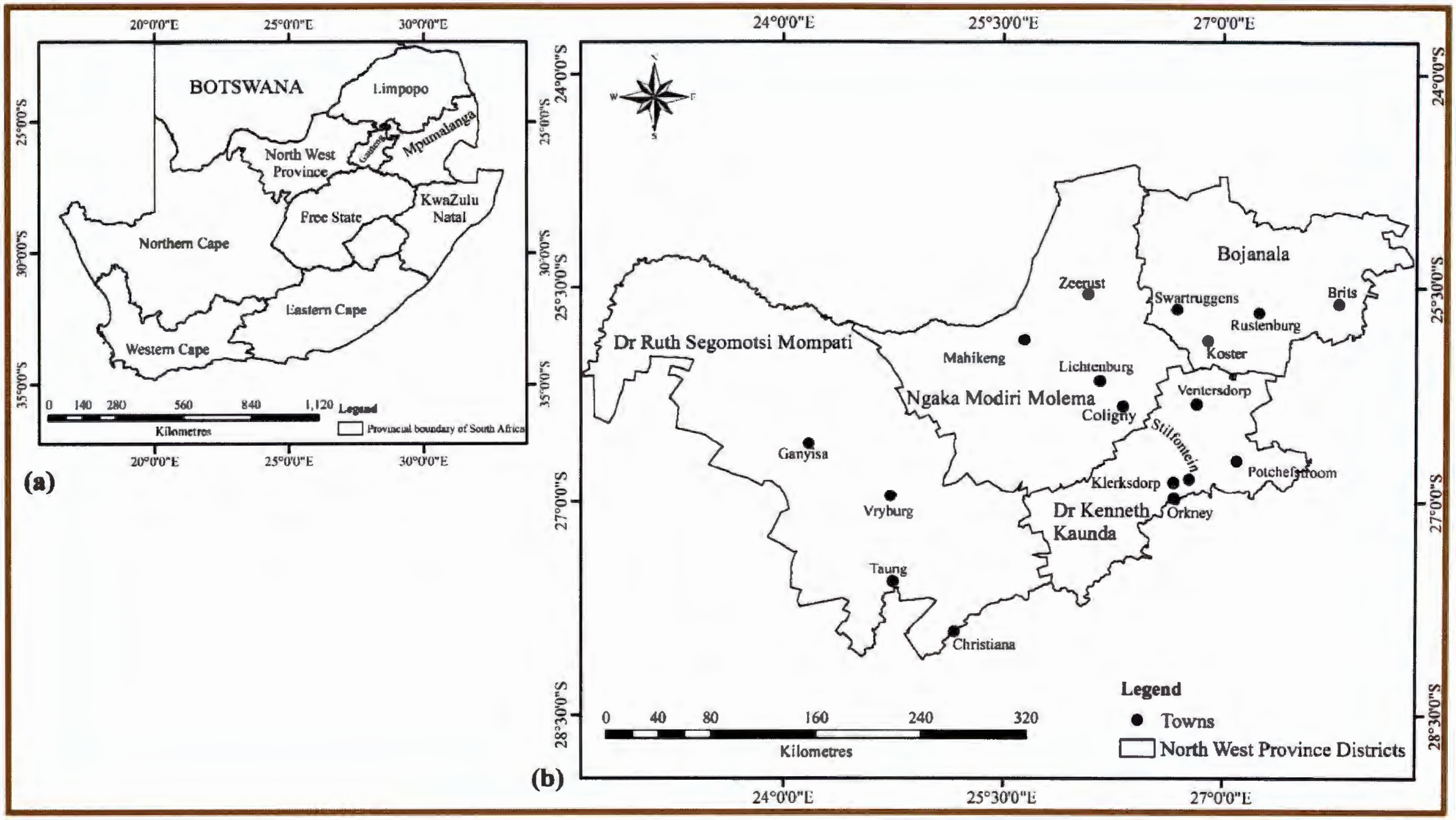


Figure 3: Location context of the four towns selected for the study, in the North West Province.

The province has an above average rainfall of 300 to 700 mm annually in the summer months from August to March, which brings brief but refreshing afternoon thundershowers. Due to the low precipitation levels, the NWP is considered a semi-arid region and, therefore, relies heavily on underground water reserves or karst aquifers.

The main economic activities in the NWP are mining and agriculture, according to (WEST, 2013). The foundation of the province's economy is mining, which generates more than half of the province's revenue and provides jobs for more than 23% of its workforce (WEST, 2013). South Africa's major granite is produced in the province, which is approximately 46%, with most quarries located in the Brits area and 25% of the country's gold from the mines in the Klerksdorp and Potchefstroom areas. The second largest and perhaps oldest economic activity in the province is agriculture. NWP is the country's second-largest producer of sunflowers, accounting for 36% of the market share, and a third of South Africa's maize (Cooper, 2008).

In addition to maize, the province produces other cultivars such as oil, fruit, groundnuts, tobacco, cotton and wheat. General agricultural practices in the semi-arid central and western regions of the province include livestock and game farming. Some of the largest cattle herds in the world are found near Vryburg, located approximately 160 km southwest of the provincial capital, Mahikeng. NWP is known as the Platinum Province, producing approximately 94% of South Africa's platinum. The Bushveld Igneous Complex (BIC) contains the world's largest known deposits of Platinum Group Metals (PGMs) which include: platinum, palladium, rhodium, ruthenium, iridium and osmium. The area surrounding Rustenburg and Brits boasts the single largest platinum production area in the world, while Klerksdorp, Orkney, Stilfontein, Hartbeestfontein (KOSH) are renowned for their gold mines.

2.1.1. Vegetation

The NWP is a province still dominated by vast open areas of natural vegetation, with 67.8% of the total area comprising of grasslands, thickets, woodlands and forests (Cowling *et al.*, 2004). Urban development covers only 2.1% of the province and is concentrated in the eastern parts of the province, with growth nodes in the Rustenburg area, as well as in the Klerksdorp and Potchefstroom areas.

2.1.2. Soil Type

According to De Villiers and Mangold (2002), the low rainfall commonly occurring in the province results in soils in the North West to be only marginally leached over much of the western region. Therefore, the active nature of soils is continually changing and degrading due to human-induced practices and natural conditions. De Villiers and Mangold (2002) further stated that the dominant soil characteristics are red-yellow apedal soil (low clay) particularly in the western parts of the province. However, in the north-western areas exist vast extents of yellow shifting sands; with plinthic catena (ideal crop production soil) of yellowish-brown sandy loams dominating the south and eastern areas and the central area dominated by red or brown non-shifting sands.

2.1.3. Geology

The geology of the NWP is predominantly norite and gabbro of the Bushveld Complex, with Bushveld granophyre in places. Thus due to the intrusion of the Bushveld Complex within the Earth's crust that has been slanted and eroded, the north-eastern and north-central regions of the NWP are characterised by igneous rock formation (De Villiers & Mangold, 2002). Ancient igneous volcanic rocks characterise the western, eastern and southern areas of the province while sedimentary rocks dating back to the Quaternary period (65 million years) occur in the north-western areas (De Villiers & Mangold, 2002).

2.1.4. Topography

Topography (slope, elevation and aspect) has an important influence on environmental factors such as spatial patterns of vegetation and climate. Desmet *et al.* (2009) stated that among the topographic factors, elevation is the most influential in the ecosystem as it creates a microclimate. Desmet *et al.* (2009) further indicated that, with elevation ranging between 920 – 1782 meters above sea level, the province has the most unvarying topography in the country. Hence, the central and western regions are characterised by flat or gently undulating plains while the eastern region is of a more variable topography (Desmet *et al.*, 2009).

2.2. Description of the towns used in the study

2.2.1. Mahikeng

Mahikeng is situated in the Ngaka Modiri Molema District area of jurisdiction in the North West Province. It is dominated by rural (37.43%) and peri-urban settlements (StatsSA, 2012). Mahikeng (formerly known as Mafikeng) was established in 1884 and is currently the capital of the North West Province. In the 1970s until the end of Apartheid in 1994, Mahikeng also briefly served as the capital city of the homeland of Bophuthatswana. This town is located at 25°16′20″E and 25° 40′47″S and it is built on open veld at an elevation of approximately 1500 m, on the banks of the Molopo River. Molopo River ascends east of Mahikeng and flows usually westward for approximately 965 kilometres to join the Orange River near the Southeastern boundary of Namibia. The Madibi Goldfields is approximately 15 km south of the town. The climate of Mahikeng is semi-arid tropical savannah with temperature averaging 18.5°C and mean annual rainfall of 500-650 mm. The town covers an area of approximately 3600 km^2 with a population of about 64,359 (StatsSA, 2012). The geographical distribution of the population is fairly dispersed, exhibiting a population density of 80 persons per square kilometre (StatsSA, 2012).

The topography of Mahikeng is of a lowland. Therefore, the type of soil (Table 1) allows the town to expand outward and not upward, as this would not support multi-storey buildings. The town area is characterised by four types of soils, Haplic Arenosols (ARh), Ferralic Arenosols (ARo), Petric Calcisols (CLp), and Ferric Luvisols (LVf) (Figure 4). According to the South African soil classification system (Group & Macvicar, 1991), the surface (0-20 cm) soil around Mahikeng town is predominantly a dark red sandy loam and is classified as a Hutton form. Roberts (1993) stated that vegetation studies in urban environments are important to ensure ecological effective open space planning in urban areas. According to Mucina and Rutherford (2006), the vegetation of Mahikeng consists of Carletonville Dolomite Grassland, Highveld Salt Pans, Klerksdorp Thornveld, Mafikeng Bushveld, and Western Highveld Sandy Grassland. The vegetation types found in Mahikeng are shown in Figure 5.

2.2.2. Rustenburg

Rustenburg (meaning "town of rest" or "resting place") was established in 1851 and is situated at the foot of the Magaliesberg mountain range, at 27°13′0″E and 25°39′0″S, in Bojanala Platinum District Municipality.

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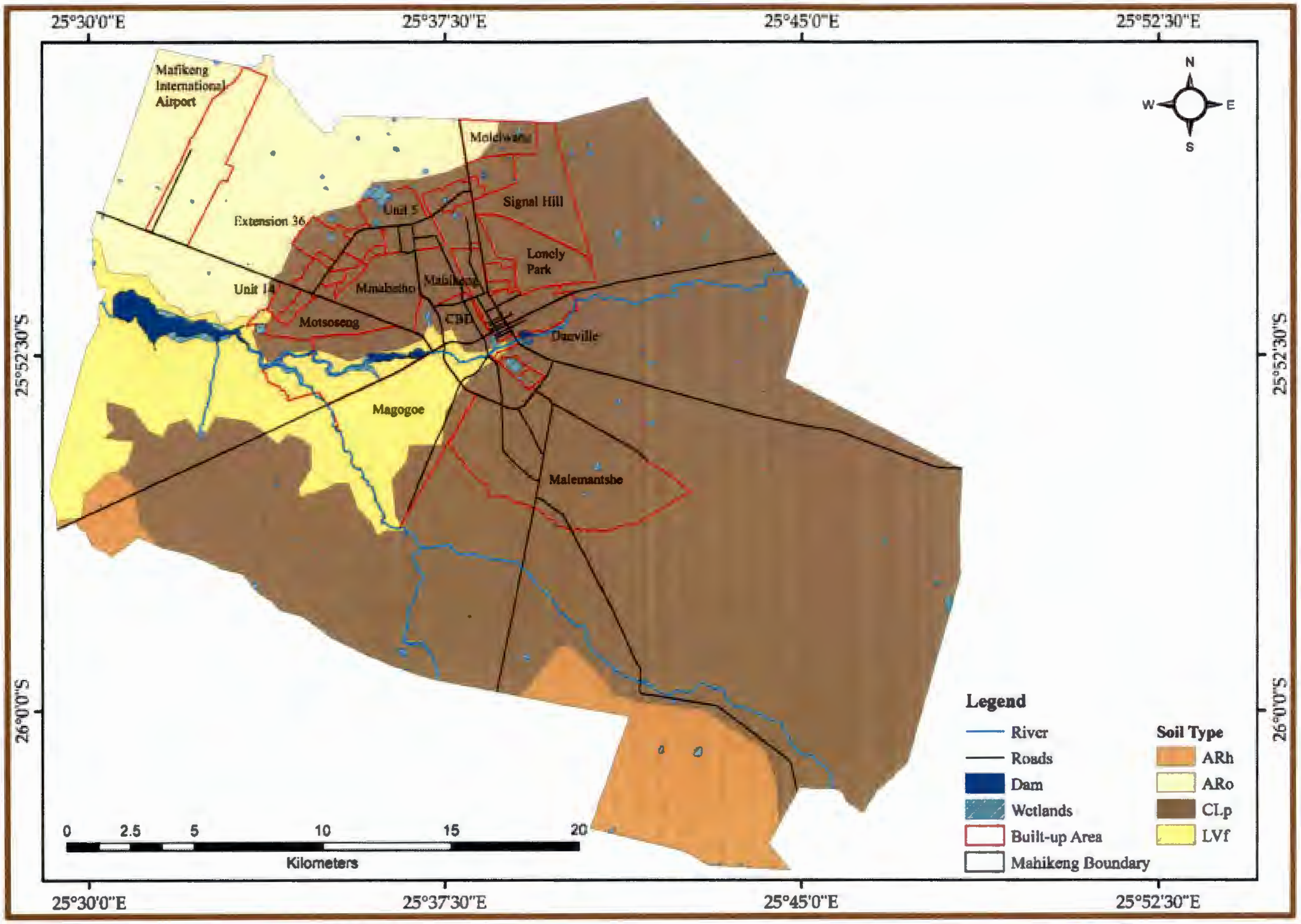

Figure 4: Soil types in Mahikeng.

Table 1: Dominant soil types in Mahikeng.

	Dominant Soil Type			
	ARh	ARo	CLp	LVf
Soil Unit Name	Haplic Arenosols	Ferralic Arenosols	Petric Calcisols	Ferric Luvisols
Topsoil Texture	Coarse	Coarse	Medium	Medium
Drainage Class (0-0.5% slope)	Somewhat Excessive	Somewhat Excessive	Moderately Well	Moderately Well
Gelic Properties	No	No	No	No
Vertic Properties	No	No	No	No
Petric Properties	No	No	Yes	No
TOPSOIL (0-30cm)				
Topsoil USDA Texture Classification	Sand	Sand	Sandy Clay Loam	Sandy Loam
Topsoil pH (H_20)	6.1	5.5	8	6.4
Topsoil Calcium Carbonate (% weight)	0.5	0	13.1	0.5
Topsoil Gypsum (% weight)	0	0	0.1	0
Topsoil Sodicity (ESP) (%)	3	3	3	2
Topsoil Salinity (Ece) (dS/m)	0	0	0.3	0
SUBSOIL (30-100cm)				
Subsoil USDA Texture Classification	Sand	Loamy Sand	Sandy Clay Loam	Sandy Clay Loam
Subsoil pH (H_20)	6.1	5.3	8.1	6.2
Subsoil Calcium Carbonate (% weight)	0.5	0	36.4	0.5
Subsoil Gypsum (% weight)	0	0	0.1	0
Subsoil Sodicity (ESP) (%)	3	4	4	2
Subsoil Salinity (Ece) (dS/m)	0	0	0.4	0

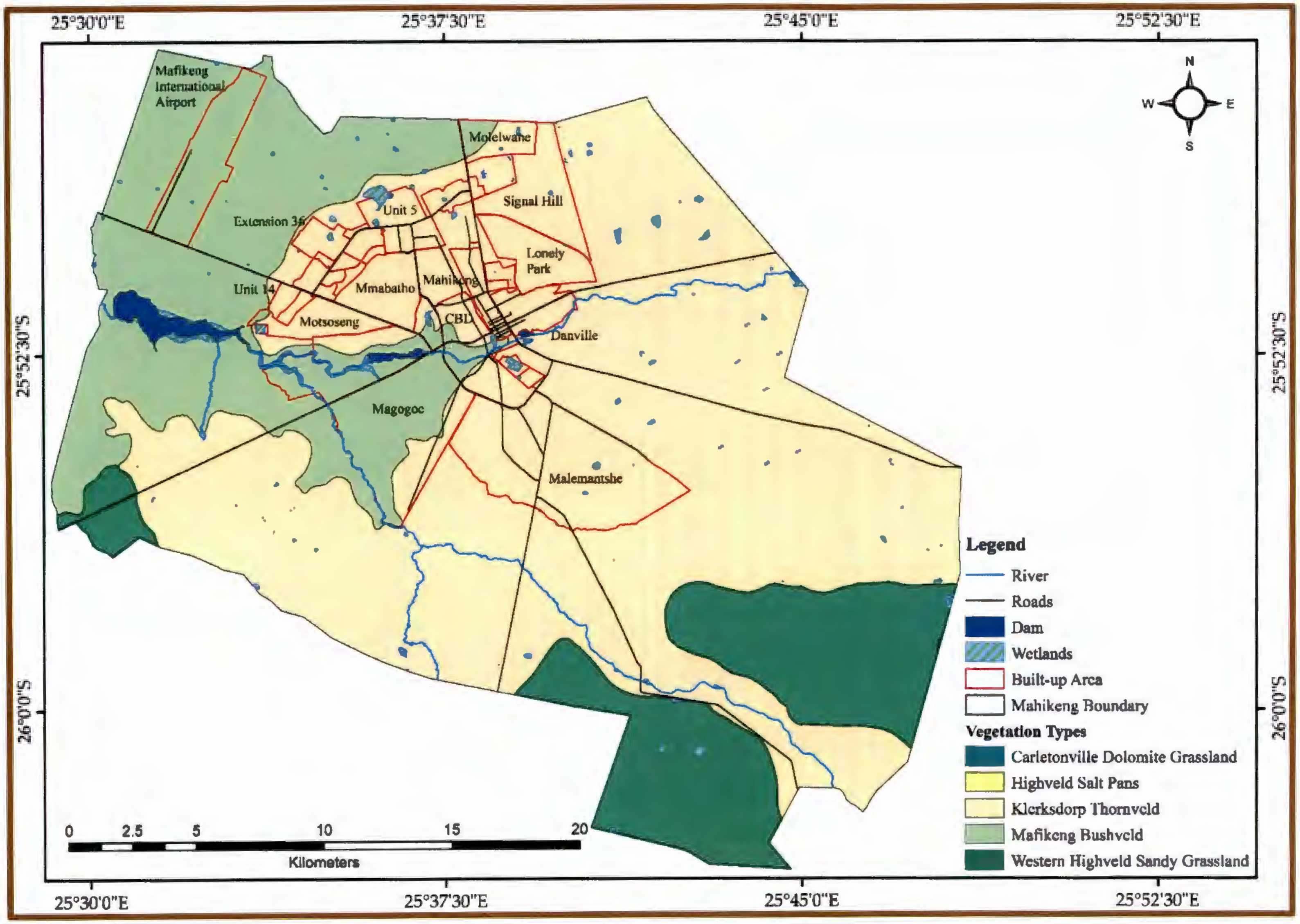

Figure 5: Vegetation types of Mahikeng.

It normally receives about 513 mm of rain per year, with most rainfall occurring during mid-summer (Walmsley & Walmsley, 2002). Rustenburg is the densest and fastest urbanising town in the North West Province, where platinum mining is the driving force, spurring urbanisation (Walmsley & Walmsley, 2002). Rustenburg accounts for the majority of manufacturing production in the North West Province. It is the major contributor to manufacturing production apart from Brits, Potchefstroom, and Mahikeng, contributing more than 50% of total manufacturing products such as non-metallic minerals (24.9%), metal products, machinery and household appliances (18.3%), and food, beverages and tobacco products (19.5%) (Mangold *et al.*, 2002).

Rustenburg, like the other towns in the province, was originally an agricultural centre, which later became a mining centre. The town area is characterised by four types of soil, Lithic Leptosols (LPq), Haplic Lixisols (LXh), Rhodic Nitosols (NTr), and Calcic Vertsols (VRk) (Figure 6). The characteristics of these soil types are as in Table 2. The vegetation types in Rustenburg town area is characterised by six types of natural vegetation; Marikana Thornveld, Moot Plains Bushveld, Gold Reef Mountain Bushveld, Norite Koppies Bushveld, Zeerust Thornveld and Northern Afrotemperate Forest, arranged from the most dominant to the least dominant.

2.2.3. Klerksdorp

Klerksdorp is one of the oldest European settlements in the region across the Vaal River and is situated approximately 40 km to the west of Potchefstroom town (Ndebele, 2013). According to Walmsley and Walmsley (2002), mining in Klerksdorp forms the backbone of the provincial economy, contributing 42% to the Gross Geographical Product (GGP) and 39% of the employment. Mining is the most important economic sector followed by agriculture, with 13% of the GGP and 18% of employment. In 2012 the population of Klerksdorp was 55,351 and it was 178,921 in 2017 covering an area of approximately 522.27 km^2 according to the Community Survey Data (2017). Klerksdorp has a semi-arid climate, with warm to hot summers and cool, dry winters. The average annual precipitation is 482 mm, with most rainfall occurring mainly during summer. The major crops produced in Klerksdorp are maize, groundnuts, sorghum, and sunflower seed. Klerksdorp boasts the largest agricultural cooperative in the southern hemisphere as well as the largest maize silo in the country (Walmsley & Walmsley, 2002).

Klerksdorp town is characterised by three types of soils, Eutric Leptosols (LPe), Lithic Leptosols (LPq), and Haplic Lixisols (LXh) (Figure 8). The characteristics of these soils are as in Table 3. It is dominated by Leptosols (LPq) taking up most of the land at 71%, followed by Haplic Lixisols (LXh) at 20%, then finally Eutric Leptosols (LPe) at 9%. Klerksdorp has only two types of natural vegetation; Vaal-Vet Sandy Grassland taking up 88%, followed by Vaal Reefs Dolomite Sinkhole Woodland to the South Eastern part taking up 12% (Figure 9).

2.2.4. Potchefstroom

Potchefstroom town was founded in 1838 by Voortrekkers and is the second oldest settlement of people of European descent in the former Transvaal. The town is situated on the banks of Mooiriver (Afrikaans for "pretty (or beautiful) river"), 45 km east-northeast of Klerksdorp and roughly 120 Km west-southwest of Johannesburg. Potchefstroom had a population of 43,448, in 2012 and 123,669 in 2017 as per the Community Survey data (2017). It covers an area of approximately 162.44 km^2. It is also an important industrial, service and agricultural growth point of the North West Province. Industries in Potchefstroom include steel, food and chemical processing. The chicken industry is of key importance in Potchefstroom with a number of major players situated around Potchefstroom. The rainfall in Potchefstroom is erratic, according to the Weather Bureau (2000), but the mean annual rainfall exceeds 600 mm. The summer temperatures are high and the mean monthly maximum temperatures exceed 32^{o}C during October to January, whereas during the months of June to August the mean monthly minimum temperatures are below -1^{o}C.

Potchefstroom is characterised by three types of soils, Eutric Leptosols (LPe), Haplic Lixisols (LXh), and Haplic Acrisols (Ach) (Figure 10). The characteristics of these soils are summarised in Table 4. Eutric Leptosols (LPe) and Haplic Lixisols (LXh) are the most dominant soil type of the three at 46%, and 34% respectively, while ACh occupies 20% of the area. Potchefstroom is situated in the Dry Sandy Highveld Grassland of the Grassland Biome (Bredenkamp & Van Rooyen, 1996). It is characterised by five types of vegetation in the Mucina and Rutherford (2006) scheme; Rand Highveld Grassland, Carletonville Dolomite Grassland, Andesite Mountain Bushveld, Gauteng Shale Mountain Bushveld, and lastly, Vaal-Vet Sandy Grassland (Figure 11).

2.3. Synthesis

This chapter has provided an insight into the general characteristics of the North West Province, and the landscape variation within the province. The location and context of the four towns selected for the study, in the North West Province, were explored with highlights on vegetation, soil type, geology, and topography, as they help in understanding the nature of urban growth, the causes and socio-economic effects of urban growth in the South African context. The four towns were ideal for the study because they are the fastest urbanising towns in the province.

The landscape of the NWP varies, thus the different characteristics needed to be looked into such as the soils range in strength. This gave a better understanding of the sprawling city and the least sprawling in terms of land use. Some soils are able to support a skyscraper. If the soil under a building is not stable, the foundation of the building could crack, sink, or worse– the building could collapse. The strength and stability of the soil depend on its physical properties. Soil with good gritty texture is more stable, and so clay or loam textures are often more stable than sand textures because they have better structure and good for building structures. However, a mix of particle sizes (and pore sizes) is best for engineering (just as it is best for growing crops). It is also important that soil is stable through wetting and drying cycles so that expanding soil does not crack roads or foundations. Some clay minerals, from the smectite family, are more likely to shrink and expand during wetting and drying cycles than minerals from other families, such as kaolinite.

The topography of Mahikeng is of a lowland. Therefore, the type of soil (Table 1) allows the town to expand outward and not upward, as this (Sandy Clay Loam) would not support multi-storey buildings. Similarly, Potchefstroom town can develop sideward instead of upwards. Potchefstroom has a more inherent tendency to expand outward due to the fact that it has abundant land to the western side. Rustenburg, like the other towns in the province, was originally an agricultural centre, which later became a mining centre. Rustenburg town has the ability to develop upwards instead of sideward due to the soil type. Additionally, its sideward growth is restricted by mountenous terrain to the south and west, and mines to the north and east of the town. On the other hand, Klerksdorp town also has the ability to expand upward, as a result of the type of soil that is clay loam. Therefore, Rustenburg is expected to sprawl the least, followed by Klerksdorp, Mahikeng, and Potchefstroom which was expected to sprawl the most. Therefore, this chapter gives an understanding of how the towns in question are structured.

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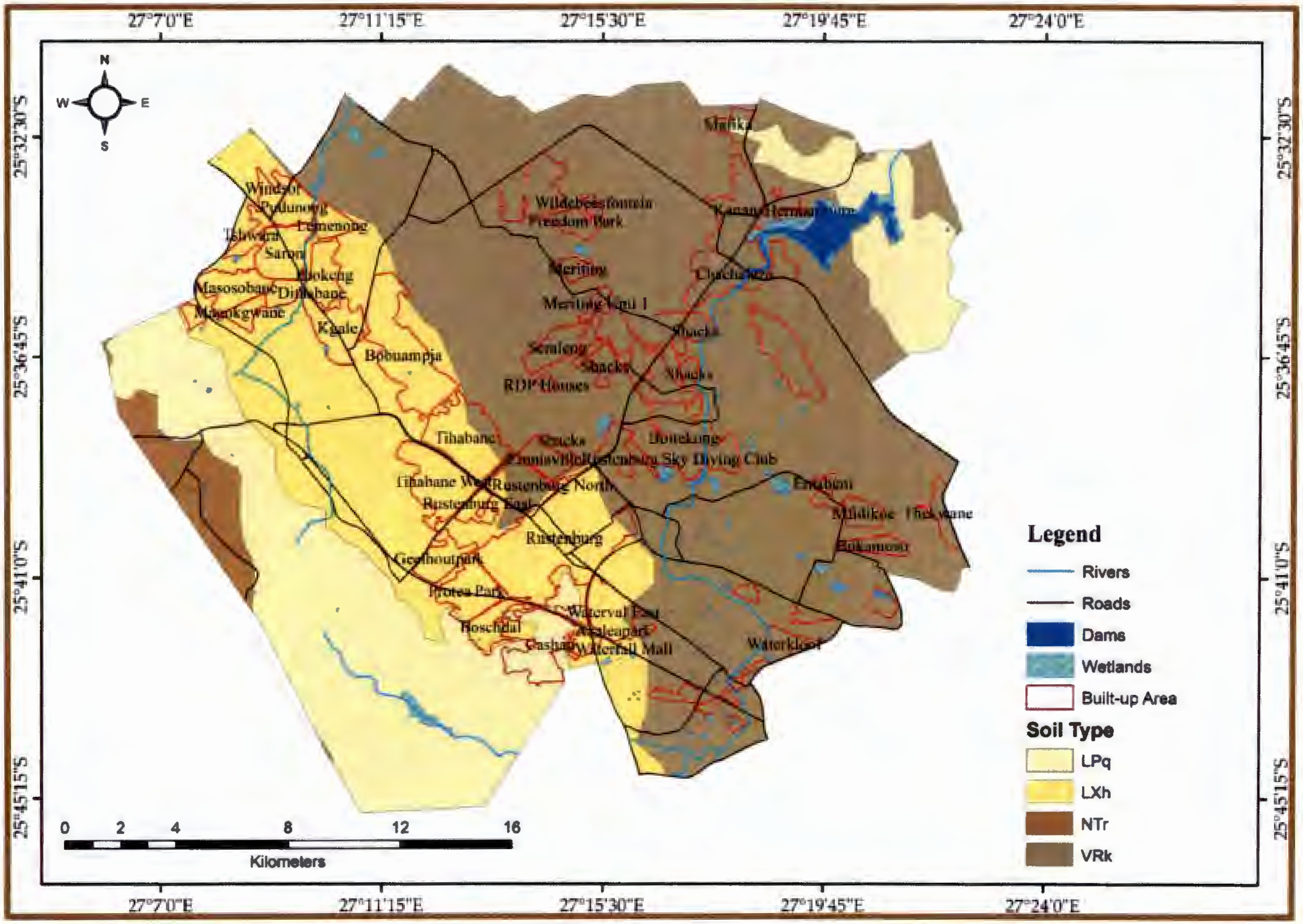

Figure 6: Soil types in Rustenburg.

Table 2: Dominant soil types in Rustenburg.

	Dominant Soil Type			
	LPq	**LXh**	**NTr**	**VRk**
Soil Unit Name	Lithic Leptosols	Haplic Lixisols	Rhodic Nitosols	Calcic Vertsols
Topsoil Texture	Medium	Medium	Fine	Fine
Drainage Class (0-0.5% slope)	Imperfectly	Moderately Well	Moderately Well	Poor
Gelic Properties	No	No	No	No
Vertic Properties	No	No	No	Yes
Petric Properties	No	No	No	No
TOPSOIL (0-30cm)				
Topsoil USDA Texture Classification	Clay Loam	Sandy Clay Loam	Clay (Light)	Clay (Light)
Topsoil pH (H_20)	7.5	6.1	5.7	7.9
Topsoil Calcium Carbonate (% weight)	3.1	0.5	0	4
Topsoil Gypsum (% weight)	0.1	0	0	0.2
Topsoil Sodicity (ESP) (%)	1	2	2	2
Topsoil Salinity (Ece) (dS/m)	0.4	0	0	0.4
SUBSOIL (30-100cm)				
Subsoil USDA Texture Classification	-	Sandy Clay Loam	Clay (Light)	Clay (Light)
Subsoil pH (H_20)	-	5.8	5.6	8.1
Subsoil Calcium Carbonate (% weight)	-	0.1	0	6.6
Subsoil Gypsum (% weight)	-	0	0	0.2
Subsoil Sodicity (ESP) (%)	-	3	2	4
Subsoil Salinity (Ece) (dS/m)	-	0	0	0.5

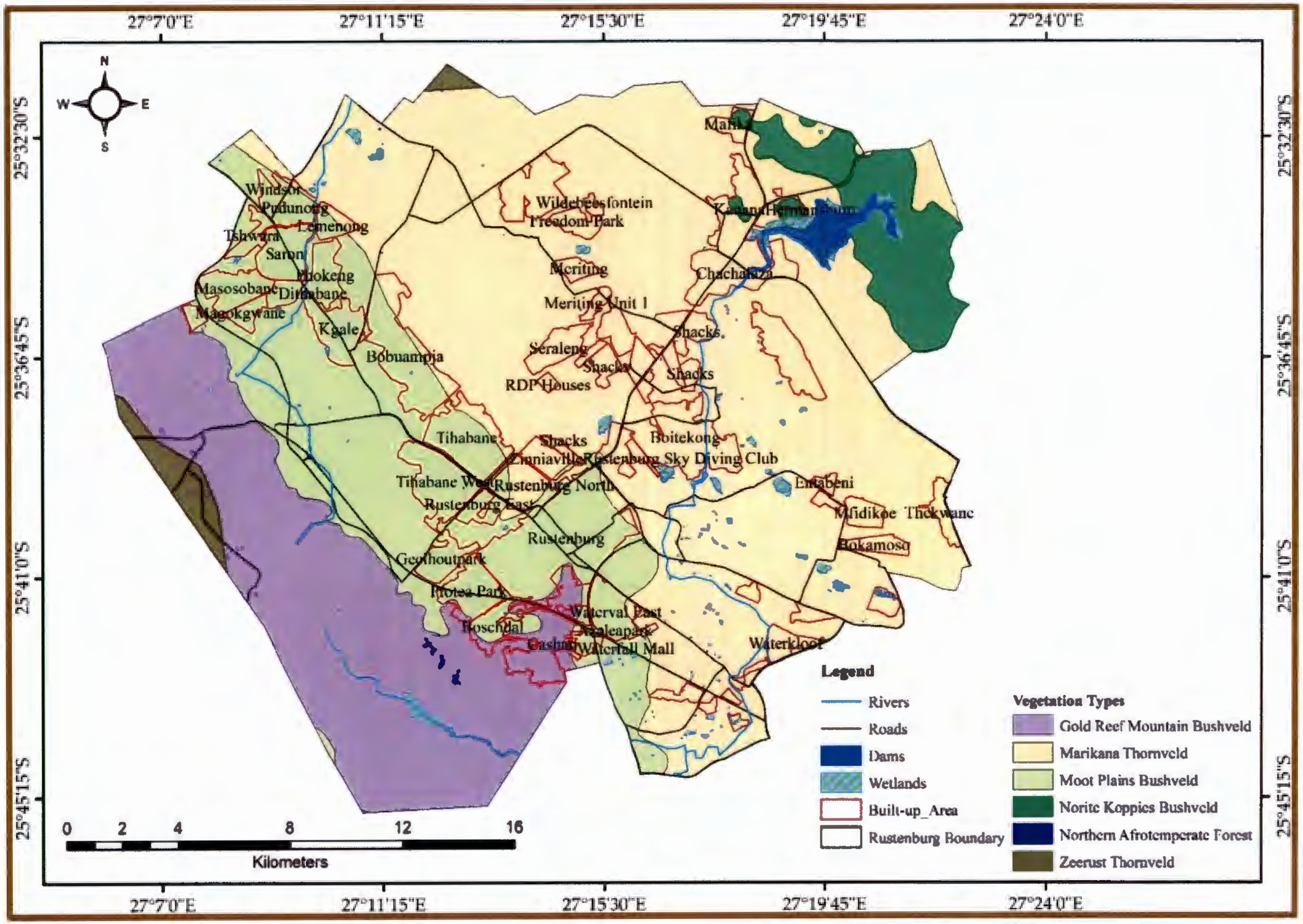

Figure 7: Vegetation types of Rustenburg.

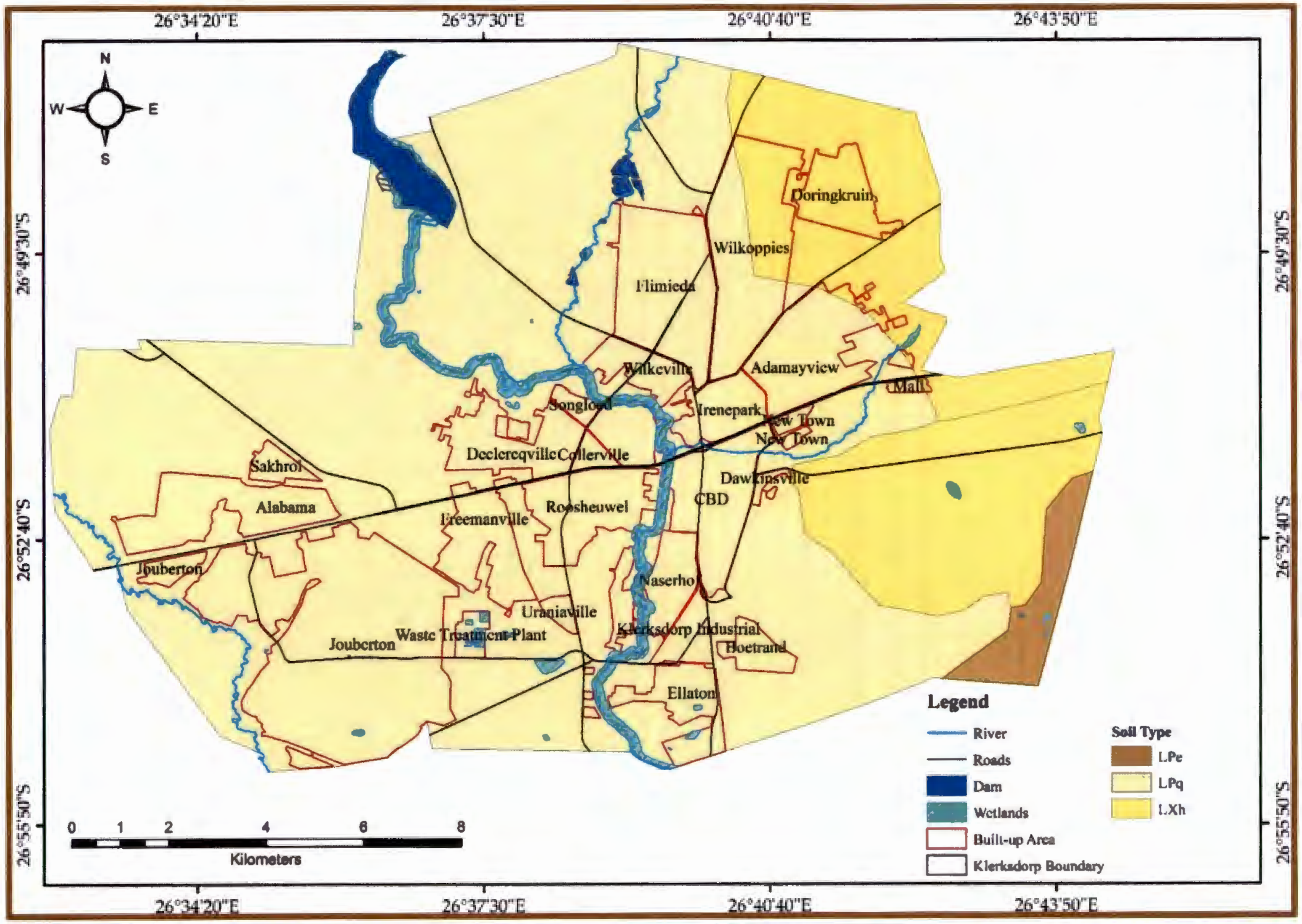

Figure 8: Soil types in Klerksdorp.

Table 3: Dominant soil types in Klerksdorp.

	Dominant Soil Type		
	LPe	**LPq**	**LXh**
Soil Unit Name	Eutric Leptosols	Lithic Leptosols	Haplic Lixisols
Topsoil Texture	Medium	Medium	Medium
Drainage Class (0-0.5% slope)	Imperfectly	Imperfectly	Moderately Well
Gelic Properties	No	No	No
Vertic Properties	No	No	No
Petric Properties	No	No	No
TOPSOIL (0-30cm)			
Topsoil USDA Texture Classification	Loam	Clay Loam	Sandy Clay Loam
Topsoil pH (H_2O)	6.5	7.5	6.1
Topsoil Calcium Carbonate (% weight)	0.8	3.1	0.5
Topsoil Gypsum (% weight)	0.1	0.1	0
Topsoil Sodicity (ESP) (%)	2	1	2
Topsoil Salinity (Ece) (dS/m)	0.1	0.4	0
SUBSOIL (30-100cm)			
Subsoil USDA Texture Classification	-	-	Sandy Clay Loam
Subsoil pH (H_2O)	-	-	6.2
Subsoil Calcium Carbonate (% weight)	-	-	0.4
Subsoil Gypsum (% weight)	-	-	0
Subsoil Sodicity (ESP) (%)	-	-	3
Subsoil Salinity (Ece) (dS/m)	-	-	0

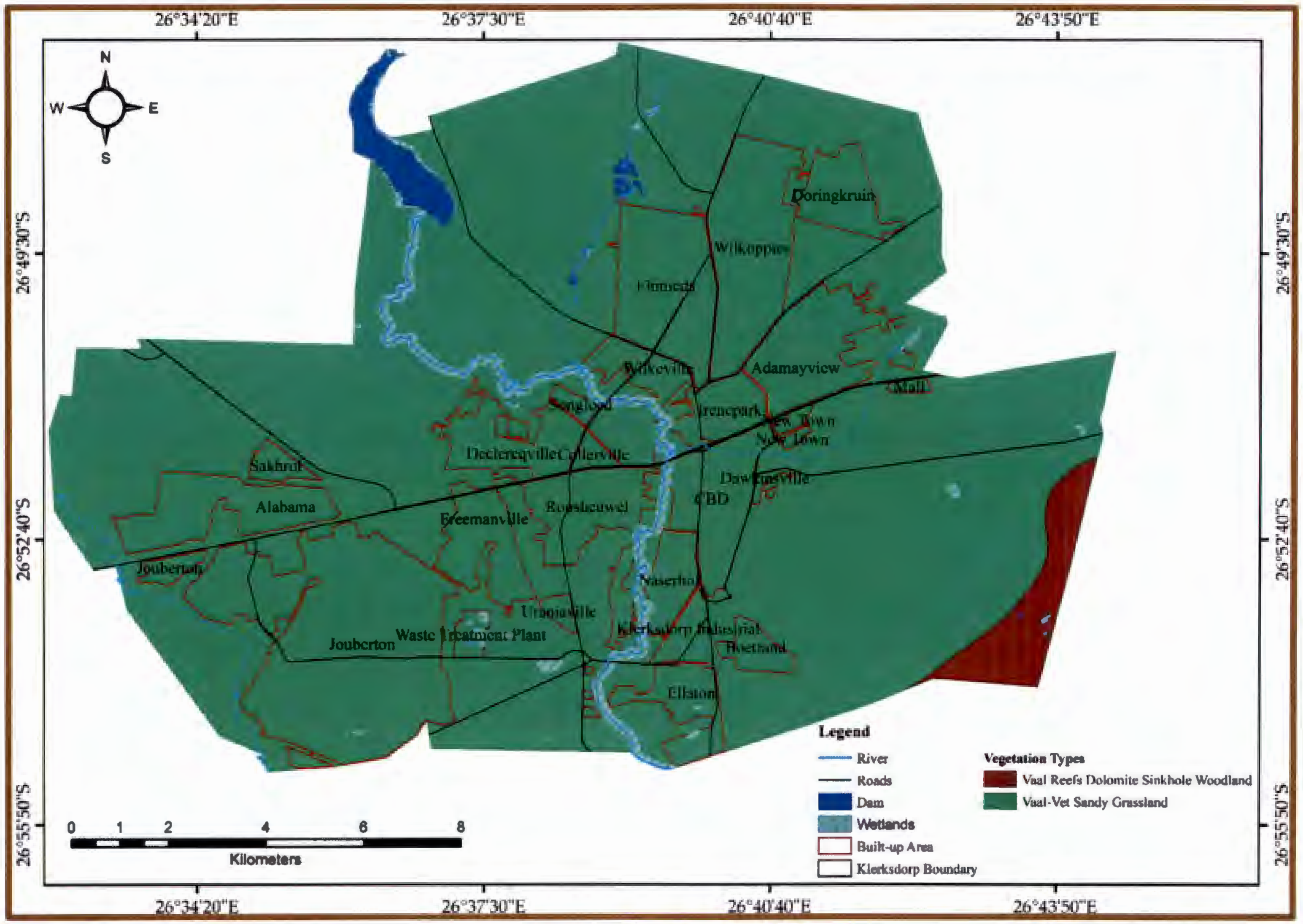

Figure 9: Vegetation types of Klerksdorp.

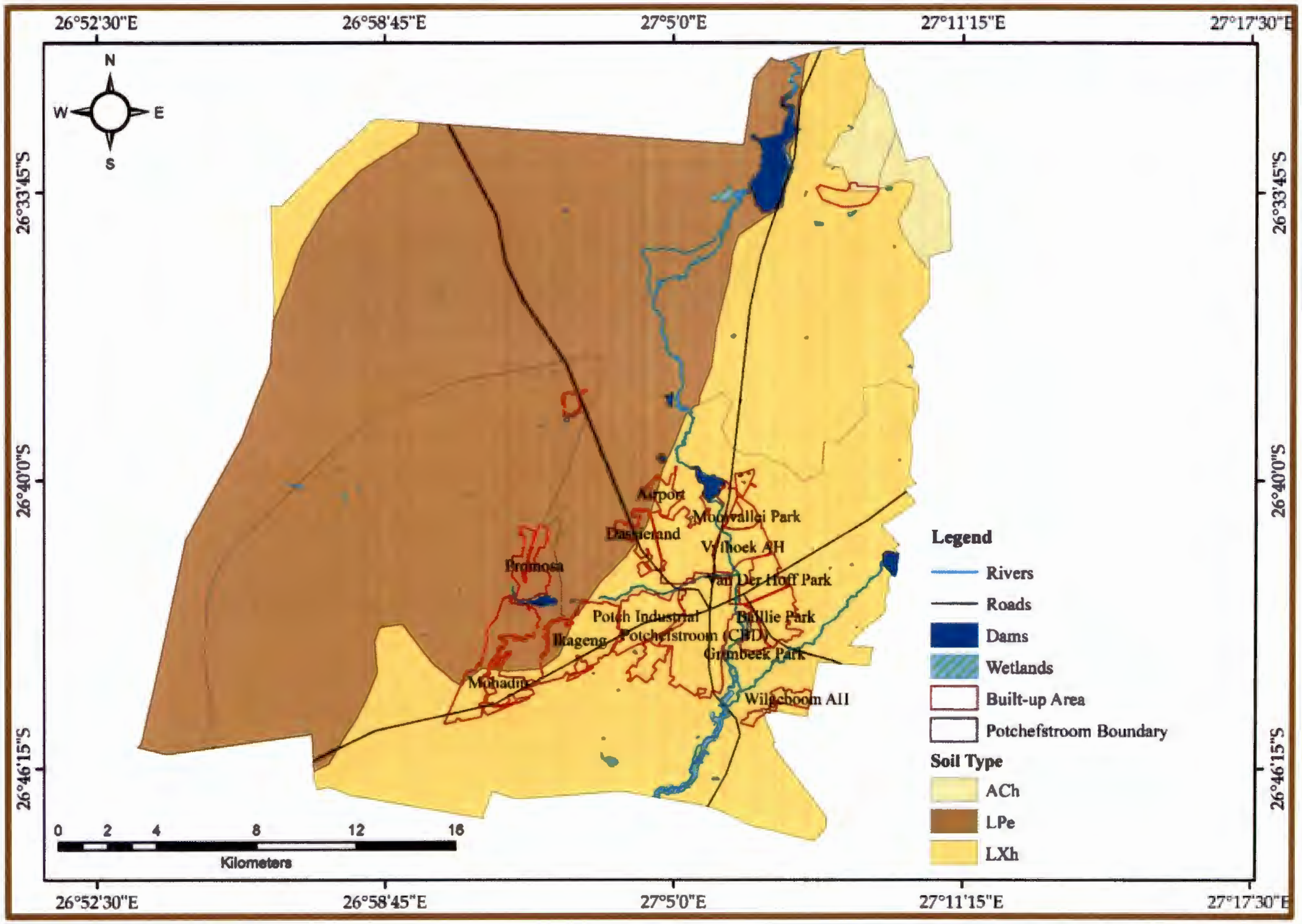

Figure 10: Soil types in Potchefstroom.

Table 4: Dominant soil types in Potchefstroom.

	Dominant Soil Type		
	ACh	LPe	LXh
Soil Unit Name	Haplic Acrisols	Eutric Leptosols	Haplic Lixisols
Topsoil Texture	Medium	Medium	Medium
Drainage Class (0-0.5% slope)	Moderately Well	Imperfectly	Moderately Well
Gelic Properties	No	No	No
Vertic Properties	No	No	No
Petric Properties	No	No	No
TOPSOIL (0-30cm)			
Topsoil USDA Texture Classification	Sandy Clay Loam	Loam	Sandy Clay Loam
Topsoil pH (H_20)	5.1	6.5	6.1
Topsoil Calcium Carbonate (% weight)	0	0.8	0.5
Topsoil Gypsum (% weight)	0	0.1	0
Topsoil Sodicity (ESP) (%)	2	2	2
Topsoil Salinity (Ece) (dS/m)	0	0.1	0
SUBSOIL (30-100cm)			
Subsoil USDA Texture Classification	Sandy Clay	-	Sandy Clay Loam
Subsoil pH (H_20)	5	-	5.8
Subsoil Calcium Carbonate (% weight)	0	-	0.1
Subsoil Gypsum (% weight)	0	-	0
Subsoil Sodicity (ESP) (%)	2	-	3
Subsoil Salinity (Ece) (dS/m)	0	-	0

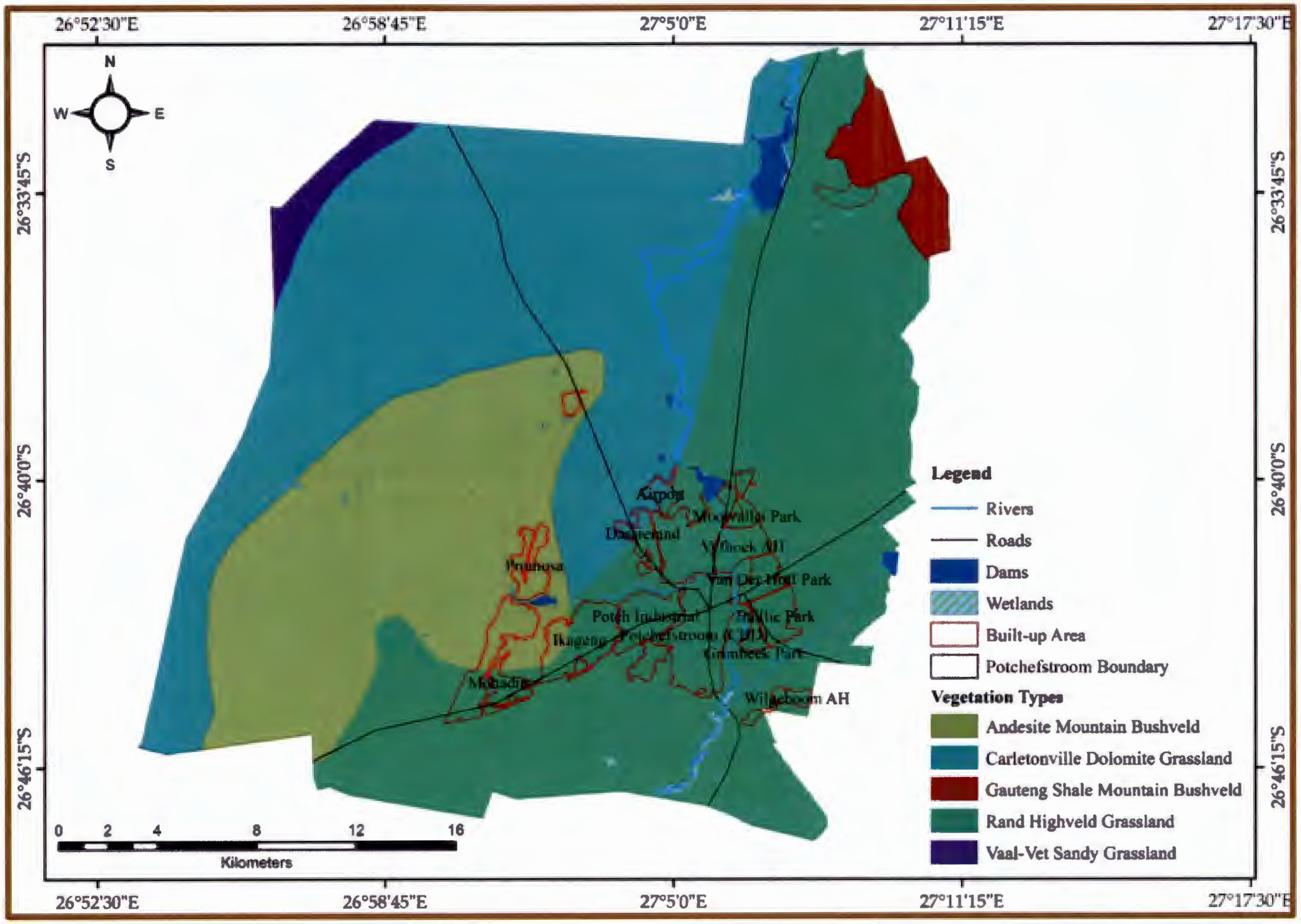

Figure 11: Vegetation types of Potchefstroom.

Chapter 3

OVERVIEW OF URBAN GROWTH AND METHODS OF ASSESSMENT

3.1. Introduction

This chapter identifies gaps in current research about urban growth and situates the study within these loopholes, using literature. Some of the socio-economic effects and environmental effects of urban growth, which are essential for the analysis of urban growth, are discussed. The understanding of the nature, causes and effects of urban growth is necessary in order to evaluate the appropriate methodology for monitoring urban growth concerning South Africa.

Urban growth can be defined as the rise in the population of people living in towns and cities (Adaku, 2014). Where humans dwell, urbanisation is bound to take place as it is a universal phenomenon and all countries are prone to this bewildering phenomenon (Sudhira *et al.*, 2004). For instance, in 2011, the United Nations indicated that 3.6 billion of the world's population (52%) were urban dwellers and it was estimated that the level of urbanisation would increase to 60% in 2030, and that the world would experience a further rise of 67% by 2050 (Saymote, 2014). Considering the less developed regions such as Africa, the urban population is expected to triple from 414 million in 2011 to 1.2 billion in 2050 (United Nations Population Division, 2012). Seto *et al.* (2012) indicated that globally, more than 5.87 million km^2 of land have a positive probability (>0%) of becoming urban areas by 2030, and 20% of this (1.2 million km^2) has high probabilities (>75%) of urban expansion.

3.2. Nature of urban growth in developed and developing countries

According to Cohen (2004), a change in the "urban demographic explosion" in developing countries since the 1970s is due to the explanatory models of urban growth developed by economists around 1980. Economists have concluded that price policies are distorted in favour of cities, as well as national development strategies and economic conditions instead of agricultural productivity, which resulted in rapid urban growth until the year 2000 (Rakodi, 2016). Yeung (2001), stated that at the beginning of the twentieth century, there were only 16 cities in the world with at least one million people, most of whom were in advanced industrial economies. Today it is estimated that there are more than 400 cities in the world with more than one million people, about three-quarters of whom live in low and middle-income countries (Group, 2014). Furthermore, the economies and lifestyles of rural areas are becoming increasingly urban in nature as the percentage of the labour force that works in non-agricultural activities increases. Globalisation and the desire to make cities globally competitive have become the main drivers of urban economic development in much of the world (Yeung, 2001).

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The dramatic increase in capital mobility, a revolution in telecommunications, and political changes have accentuated urban economic growth in and between cities. Countries are rapidly industrialising, especially in the Asian Pacific, while advanced economies are moving away from the manufacturing sector to finance, specialised services and information management (Sassen, 2018). Yeung (2001), indicated that this forces countries, and even individual cities, to redefine their comparative advantage and compete on the global market. The United Nations predicts the world population growth in the near future should occur in urban areas (Seto *et al.*, 2012). In Africa, Asia and Latin America, population growth will become largely an urban phenomenon. By 2030, almost 60% of the population in low and middle-income countries will live in urban areas and thus, in the long run, this is good news. However, the challenge over the next 30 years will be to maximise the potential benefits of inclusive urbanisation while reducing the obvious negative consequences. There is considerable uncertainty about the size and pace of future urban growth (Cohen, 2004). Unquestionably, the fact that the scale of urban growth in developing countries is much lower than the expectations of 20 years ago should warn us to carefully deal with current projections (Cohen, 2004).

It is evident in most cities around the world that the dwellings of workers and old tenements of the nineteenth through to the twenty-first century are generally in the congested heart of cities which are often in slum condition. This has created an excessive problem that would arise from the shortage of land that new homes cannot be erected unless the slums have been cleared. Thus, the question would then be "*while the new houses are being erected where will the people be housed*?" and in more or less the world over the rate of progress is improving and the living conditions remain very slow (Bett *et al.*, 2011). Urban areas continue to expand at the expense of rural areas, intensifying among others, urban sprawl (Grekousis *et al.*, 2013). Between 2000 and 2030, according to Montgomery (2007), urban populations in Africa together with Asia are expected to be doubled. This immense growth of urban populations, coupled with several other factors, may force uncontrolled urban growth. One of the biggest challenges to science, engineering, and technology in the twenty-first century is how to control urban growth to protect natural resources and the ecosystem (Grekousis *et al.*, 2013).

3.2.1. South Africa perspectives

South Africa has the largest and most industrialised economy in Africa and the 28th largest economy in the world (Koma, 2014) bringing in large-scale industrialisation. The process of industrialisation in South Africa has created an urban disparity experienced by much of the black population between different regions of the country (Fine, 2018). The main reason for the relatively high rate of urban growth in South Africa is the higher rate of natural change in population (births exceeding deaths) and not faster urbanisation. For instance, the push factor causing rural-urban migration in South Africa is the same as in most parts of the developing world (e.g. Brazil, Mexico, Nigeria, Kenya, Ethiopia and Mozambique), namely variances in economic opportunity. In terms of growth in industrial employment, cities have consistently outpaced the rest of the country. As a result, cities tend to be more productive, in terms of the values of goods and services they generate and the efficiency with which they are produced. Urban and rural areas are connected through complex patterns of social, economic, environmental and cultural interactions. Therefore, urban areas in practical terms depend on rural areas for food production, water, minerals, recreational areas, energy, along with ecosystem services; at the same time rural areas depend on urban areas for agricultural inputs such as fertilisers, equipment, and machinery (Wu, 2008).

Urbanisation has created a number of environmental problems in South Africa. Two types of urban development occur in South Africa: formal development and informal settlements (shanty towns). Informal settlements occupy contested space in cities. In other words, they are developed on empty land within the city, especially in areas either close to centres of employment or close to public transport. Informal settlements are inhabited mainly by migrant workers who arrive in the city in search of livelihood opportunities and are vulnerable due to their social and ethnic backgrounds, negligible rural landholding and poor occupation (Tomlinson, 2017). The migrants live in poor quality houses located in small informal settlements as newer migrants, built often with temporary plastic roofing material. Other migrants who have been there for some time work as casual labours in different sectors, considered to be the lowest paid and least secure sector in the occupational spectrum, such as the construction industry, as cleaners for the municipality, and as car park security (Revi *et al.*, 2014).

Hope Sr and Lekorwe (1999) assert that in many parts of South Africa, urban areas are rapidly expanding into farmlands and hinterlands, enveloping villages and towns, and transforming culture, lifestyles, and consumption patterns. The location and socio-political context of these settlements expose them to a range of environmental and health risks. Other pressing risks associated with informal settlements are continual cycles of demolition, eviction and displacement associated with lack of security of tenure. The poor migrant urban community is, therefore, doubly exposed to both climate-induced risks and new exposure and risks characterising urban regions. According to Cross *et al.*, (1999) in the Cape Metro Area (CMA), approximately 80% of population growth at that time in the CMA was occurring in townships. 36% of the African population in the CMA lived below the poverty line. This translates into a 32% unemployment rate for blacks compared to a 7% unemployment rate for whites (Mulenga, 2017).

In 2003, nearly 1 in 6 of the South African population lived in shacks. Rising prices of essential commodities such as fuel, electricity, water, and food also affect the poor tremendously. Rouget *et al.* (2003) conducted a study in Cape Town and Port Elizabeth metropolitan areas using Remote Sensing to quantify the extent of habitat transformation at a regional scale. The study showed that agriculture (including commercial forestry plantations), urbanisation and alien plants currently transform 30% of the Cape Floristic Region (CFR). Two Broad Habitat Units (BHUs), Cape Flats Fynbos/Thicket Mosaic and Blackheath Sand Plain Fynbos had lost more than 50% of their original area as a result of urban growth (Rouget *et al.*, 2003). The study also revealed that urbanisation was most likely to occur in 20 years' time. Moreover, future urban development could also affect 9% of the CFR. Rouget *et al.* (2003) further clarified that their spatially explicit model indicated that the coastal primary BHUs, Dune Pioneer, Indian Ocean Forest and Fynbos/Thicket Mosaic, would most be affected by future urban development.

Therefore, a number of factors have led to the growth of informal settlements in South Africa. They include rural-urban migration, natural growth, and poverty. As the country becomes more urbanised, more informal settlements develop (especially in densely populated areas), leading to a high building density and self-constructed shelters, thus leading to a lack of basic services (Hope Sr & Lekorwe, 1999). Rural-urban migration is a significant factor that causes urban growth, due to economic development in the urban areas.

One of the distinguishing characteristics of apartheid in South Africa was the way in which restrictions on settlement and employment divided families across space. The apartheid policy, which was formally adopted in 1948, prohibited mixed settlements between the black majority and the white minority, which affected settlement patterns. The policy, however, restricted the movements of the majority blacks into white settlements, which prevented them from acquiring residences within the urban centres (Pillay, 2008). This policy led to the configuration of the urban landscape in South Africa, which can be perceived even nowadays. The policy adopted had two prongs. The first was the complete segregation of the black population and the pursuit of a policy which envisaged the eventual departure of the black inhabitants from the cities. This was related to the grand scheme of restructuring of population distribution involving several million people as part of a 'White South Africa' policy (Platzky and Walker, 1985). The second entailed the isolation of the remainder of the population into different groups living in separate areas, the 'homelands' (Bantustans).

As a result, the finale product, the Apartheid city, was to have no residence or business mixing and ultimately to result in the formation of detached towns for the diverse groups. In common with nearly all other townships countrywide, the Central Business District and the inner suburbs were zoned White and the other groups were barred to the fringe of the city. With detailed planning, the group area of one group was distinguished from that of another by a buffer strip at least 100 metres broad, but preferably a physical barrier such as a railway, escarpment or river, which would impede contact between the two populations (Kuper *et al.*, 1958). In the White sector, planning followed the free market pattern with individual developers and speculators controlling expansion through the land market in a piecemeal and haphazard process. This typical free enterprise pattern of housing estates, smallholdings and open areas awaiting development is in evidence. In the Indian and Coloured areas a markedly state-controlled expansion took place as the suburbs were laid away, and often built, by the municipal authorities, which possessed the land and set the rate at which it was urbanised.

The outcome was a tightly controlled and rigidly organised urban expansion, reminiscent of state planned urban growth in many European nations. The Black sector exhibited a different pattern as the numbers requiring housing always exceeded the supply of homes and often families lacked the financial ability to compensate for such state housing as was available. This led to the development of slums and informal settlements known as Bantustans for black settlements (Turok, 1994). The allotment of housing was associated to a system of employment permits ('passes' under the pass law), issued selectively to people wanting to live and work in the metropolises. In addition, the state declined to recognise Africans as permanent urban inhabitants. Even though restriction on African urbanisation were lifted by 1986, nationally representative household survey information for the period 1993 to 2002 suggests that these migration patterns may be continuing in post-apartheid South Africa (Posel and Casale, 2003).

3.3. Causes of urban growth

The causes and catalysts of urban growth are to a certain extent, similar to those of urbanisation. In most cases, they cannot be discriminated, since urban growth and urbanisation are highly interwoven (Jedwab *et al.*, 2017). Several researchers have discussed and summarised the causes and catalysts of urban growth and sprawl (Burchfield *et al.*, 2006; Harvey & Clark, 1965; Squires, 2002). Nonetheless, it is important to realise that urban growth may be observed without the occurrence of sprawl, but sprawl must induce growth in an urban area. One of the causes of urban growth and sprawl is population growth, which can result in coordinated compact growth or uncoordinated sprawled growth. Whether it is favourable or unfavourable growth, all depends on the process, pattern and consequences.

The rate of urban population growth is dependent on factors such as the natural increase of urban dwellers, rural-urban migration and the development of rural areas into towns because of economic development and industrialisation, among other factors (Cherniwchan, 2012; Sassen, 2018). The impacts on urban growth, whether hostile or noble, need to be understood and evaluated towards achieving a sustainable urban growth. Thus, a number of factors can be obtained such as positive effects. The positive effects contribute to improvements in the livelihood of farmers in the invaded areas, change their way of living to an urban style, and the indigenous people get the opportunity to be relocated into the urban centres and engaged in urban-based employment. These factors play a significant role in the urban growth of the city and the integration of satellite areas.

Migration is the movement of people between regions or countries for certain reasons (Castles *et al.*, 2013). Due to economic reasons, people can migrate. For instance, people tend to emigrate from places that have few job opportunities and immigrate to places where jobs seem to be available. According to Collinson *et al.* (2006) in South Africa, the primary reason for migration to urban areas or denser rural areas is the search for income and employment. Job prospects often vary from one country to another and within regions of the same country, due to economic restructuring. Secondly, cultural factors can be especially compelling push factors, forcing people to emigrate from a country. Forced international migration has historically occurred for two main cultural reasons; slavery and political instability (Faist, 2000). Thirdly, in the different provinces of South Africa people also migrate for environmental reasons, pulled toward physically attractive regions and pushed from hazardous ones (Collinson *et al.*, 2006).

In this current age of improved communications and transportation systems, people can live in environmentally attractive areas that are relatively remote and still not feel too isolated from employment, shopping, and entertainment opportunities. A good example would be a desire for countryside living where some people prefer to live in the rural countryside, a tendency which always results in sprawl (Bruegmann, 2005). Industrialisation, which is defined in a very general sense as technological development, is not only the change and innovation of production but also a complex structure that changes and transforms the institutional structure of the entire society (Beniger, 2009). The industrial sector, which is a combination of mining, manufacturing and energy subsection, composes the cornerstone of countries' rapid, stable and sustainable growth. With the growing population in any given country, the population growth will cause an increase in demand denotation that more people lead to needed goods, thus an upsurge in growth of industries.

Industrial growth also brings about an improved transportation system in a country (such as South Africa), which increases demand. In South Africa, the construction of single-storeyed buildings to cater to the demand for housing as a result of migration and industrialisation also leads to urban growth. For instance, by adding more storeys to a building instead of more hectares of land, light industrial and commercial land uses can then expand in the upward instead of the outward direction. Likewise, it is claimed that industrial sprawl happens because land at the urban edge is cheaper than that of the urban interior (Lei & Bin, 2008). As indicated by Harvey and Clark (1965) and Barnes *et al.* (2001) this often creates what is known as leap-frog development sprawl and in many instances, these problems cannot be overcome and, therefore, tend to be overlooked.

Cultural exchange between new cultures and those existing in society is beneficial. These exchanges contribute significantly to the urban growth of the city and the integration of satellite areas, uniting all parts of the system on a large scale and facilitating the growth of the city catchment. There is also an evident interdependence between the parts in terms of production, dwelling, consumption; they are intertwined so that none can exist without the other. This implies that with the metropolis, the new urban lifestyle is better for integrating satellite areas (Giddens, 2013). The advantage also opens up the opportunity for areas that are part of new enlarged areas. Eventually, the government will have to integrate new areas in the old cities according to the general plan of the city in the form of urban reclassification. This action, by itself, means that illegal settlers go through a process of legalisation of fact and that, as a result, the government also begins to provide them with infrastructure such as roads, water, schools, electricity, health centres, etc.

3.4. Effects of urban growth

The scale and rate of global environmental change, whether it is heating by greenhouse gases, deforestation, desertification or loss of biodiversity, is largely due to the rapid growth of the Earth's human population (Grimmond, 2007). Given the large and growing fraction of the world's population living in cities and the disproportionate proportion of the resources used by these urban residents, especially in the global north, cities and their inhabitants are the main drivers of global environmental change. Several drawbacks have been attributed to urban growth, in that there will be a shortage of affordable formal housing, increased volumes of traffic; yet most of the city's population will live in an apartment or skyscraper condo (Brueckner & Lall, 2015). Other effects include an increase in population density, coupled with increased land prices inside of urban boundaries and reduced prices outside, along with increasing overall house costs. In addition, the notion of the environmental consequences of urban growth, as well as car reliance, which could bring about the issues of local air pollution, global warming impacts and loss of farmland, are among other factors contributing to the effects of urban growth. Figure 12 portrays a typical example of interacting variables of urban growth and expansion in cities around the world.

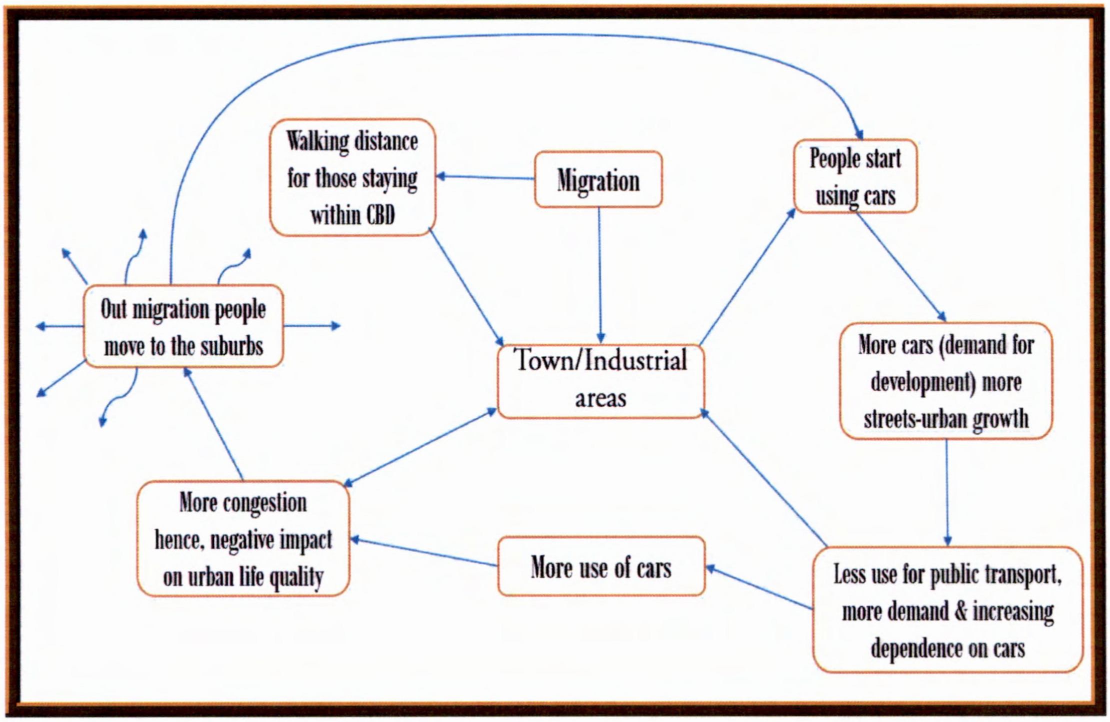

Figure 12: The relationship of interacting variables and effects on urban growth.

The consequences of urban growth may both be positive and negatives. However, negative impacts are generally more highlighted considering that growth is often uncontrolled or uncoordinated. Therefore, the negative impacts override the positive aspects. As a result, the quality of rural life is dwindling especially in the areas around the capital, and in the urban fringe of major towns in South Africa. Occasionally, as a result of people moving from rural areas to urban areas, a high rate of urbanisation also appears hence increasing integration between metropolitan centres and the surrounding area (Antrop, 2004; Champion, 1999; McKinney, 2002). Therefore, the more the amount of urban growth experienced by a city or a county, the greater the potential to increase surface runoff. That is why urban growth has played a key role in changing the relationship between precipitation and surface runoff (Weng, 2001).

3.4.1. Socio-economic effects

Urban areas have a strong influence on places due to various factors, such as the degree of land use or the market maker's infrastructure. The main social effects of this process are; the labour market, urban society, fertility rates, the state of health and pollution, education and training, the lack of opportunities, and problems of psychological adaptation. With families

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and urban society, there has often been a decline in the family concept, through the proliferation of less traditional forms and new types of families. This tendency manifests itself as a consequence of the diversity of the many options for individuals, in which individuals organise themselves to form collective units.

Fertility rate, according to Bradbury *et al.* (2007), is a result of leaving the rural areas to the urban space. This generates changes in the natural growth rate of the population. The phenomenon manifests itself when smaller families are established, with a reduced number of members (Swim *et al.*, 2009). Therefore, the state of health and pollution comes into play. The development of new urban areas without adhering to the measures necessary for the development of sustainable areas has a negative impact both on the environment and on the general condition of reciprocity and health of people. The state of health and pollution is often affected by the increase in levels of contamination in these areas, in particular, air and water pollution (Bucknall *et al.*, 2000; Mink & Mundial, 1993; Solomon *et al.*, 2017).

Furthermore, the location of the rural population in the urban space guarantees their access to education, personal and intellectual development, which provides new characteristics and modes of evolution of the individual (Garbarino, 2017; Pye & Verba, 2015). With poverty, according to Gilbert (2012), the lack of opportunities and problems of psychological adaptation have a socio-economic effect. This problem overlaps with a part of the population displaced from the urban areas, which is not suitable to align with the standards of urban areas, where changes in landscape, social and economic development are the real motors of existence (Gilbert, 2012). It generates a chain of negative effects deviated to violent crimes or behaviour (as determined by the mirage of developed urban areas) and offers multiple possibilities, being true centres of development, progress and social well-being (Gilbert, 2012; Perrons, 2004).

3.4.1.1. The economic impact of urbanisation

The economic impact of urbanisation has both positive and negative aspects, with a direct influence on the urban places, but also in areas outside urban limits. The development and diversification of business activities, as well as the possibility to create new jobs, are positive impacts. Secondly, the gap between businessmen is reduced and thirdly, access to new technologies and different areas of activity is facilitated, which guarantees an increase in people's income (Potts, 2016). The fourth positive effect is the development of infrastructure and an increase in the number of motor vehicles (Figure 12), which generates an increase in the consumption of resources. However, it causes an increase in the level of air pollution and has an impact on the environment and on the health status of people (Mitchell & Popham, 2008). This intensification of transport is determined by the higher density in these areas, but also by the low level of development of the public transport service.

Other socio-economic effects of urban growth can be relate to employment, provision of social services, traffic congestion, and pollution of the environment. For centuries rural-urban migration has been going on, however, it has not always been as large a problem as it is today with the advancement of technology. Populations all over the world have expanded rapidly and are continuing to expand at a geometric rate, so too is urbanisation (Adaku, 2014). Hence, nowadays the problems of urbanisation are more acute, especially in underdeveloped countries. In almost all countries of the world, towns are growing at the expense of surrounding agricultural land (Seto *et al.*, 2011). Thus among the major problems posed by urban growth is the areal expansion of rapidly growing cities.

The wealthier town dwellers in both developed and underdeveloped countries are constantly moving from the crowded cities centres to more pleasant suburbs where they can build larger houses (Moor, 2017). With this kind of shift in many parts of any country, the towns' outskirts are often occupied by squatters who build makeshift dwellings on unused land despite the fact they have no legal rights to the land. For this reason, most towns are surrounded by wide rings of suburbs, which makes it difficult to restrict town growth (Simon *et al.*, 2004). There are unique problems resulting from urban growth in underdeveloped countries. For instance, one main problem is to improve conditions in squatter areas and provide essential services, yet much of the town's population does not contribute towards the rates and taxes which finance such developments (Simon *et al.*, 2004). Altogether, this creates a problem by limiting growth in the suburban developments of the wealthier classes, which also have to be overcome by advanced and advancing countries (Moor, 2017).

3.4.1.2. Consequences of urban growth

Over the years, urban growth has been shown to be a driving force in development. However, many constructors tend to want to build higher-class housing from which they can make high profits rather than construct essential housing for working-class families. Nonetheless, strains on many underdeveloped countries are imposed by the lower standards of health and hygiene and by the need to provide additional educational facilities for rapidly growing populations. Problems of providing social services such as water, sanitation, and sewage disposal are aggravated by the poverty of migrants to the cities such as Lagos, Rio de Janeiro, Vienna, New York, Mumbai, Johannesburg, Nairobi, Harare and Maputo to mention a few (Cities, 2009). For this reason, unless housing can be found for them, squatters removed from one area may settle in another. This adds on to the problem in that the density of population of crowded shantytowns becomes difficult to match. Thus, the slum dwellers inevitably outnumber the new homes provided by city housing authorities (Gilbert, 2008; Pithouse, 2008).

In many parts of the world, urban growth is criticised for increasing public costs such as money being spent on redundant infrastructure outside the urban areas and neglecting the infrastructure within the cities, which are not utilised or underutilised. Studies suggest that urban growth can be threatened by historical and culturally significant sites such as historic downtown areas, historic buildings, historic districts, and prehistoric sites (Bengston *et al.*, 2005). From economic theory, according to Bekele *et al.* (2005), productivity is much more enhanced with opaque development, since ideas move quickly throughout time with people who are in close proximity. This also encourages many developers to construct new houses rapidly. Additionally, expansion of the economic base creates a demand for new housing or more housing space for individuals (Bhatta, 2009).

The rapid development of housing and other urban infrastructure often produces a variety of discontinuous uncorrelated developments (Grimsey & Lewis, 2017). As a result, rapid development is blamed for the problem, owing to the lack of time for proper planning and coordination among developers, governments, and proponents. In addition to this, it has been shown that productivity in the city will decrease, leading to social loss and because of this urban growth leads to regional imbalances (Bekele *et al.*, 2005). The establishment of new and old industry branches in the countryside increases impervious surfaces rapidly. The industry would be required to provide housing facilities to its workers in a large area, which generally becomes larger than the building infrastructure of the industry itself. For this reason, the transition process from agricultural to industrial employment demands more urban housing. This is evident in Rustenburg as the platinum district as well as Klerksdorp as mining and agricultural town.

In many instances, speculation (theorising) is blamed on factors that have been stated in a number of studies (Clawson, 1962; Harvey & Clark, 1965) which show that the future growth, future government policies, and facilities such as transportation (Figure 12), etc., without proper planning, and a monitoring system, may and can cause premature urban growth. On the other hand, lack of planning is blamed for urban growth now and again in that speculation produces withholding of land for development, which is one reason of discontinuous development. During the 20th and into the 21st century governments and different political election manifestos have had an influence on people encouraging them by speculating the direction and magnitude of future urban growth.

3.4.1.3. Positive implication of urban growth

Several planners, proponents and organisations do not always portray urban growth as detrimental. It is depicted as a sign of economic vitality and not as an ecological threat (Cheshire & Hay, 2017). Positive implications of urban growth include higher economic production, opportunities for the underemployed and unemployed, better life because of better services, and better lifestyles. Urban growth can extend better basic services (such as transportation, sewer, and water) towards other specialist services (such as better educational facilities, healthcare facilities to mention a few) to more people (Cobbinah *et al.*, 2015). However, urban growth is uncontrolled and uncoordinated in many instances, hence in the long run it results in sprawl (Deslatte, 2017).

On the other hand, urban growth will result in a higher population density than urban sprawl. With urban sprawl, people are more likely to live in a house in a neighbourhood (Seto *et al.*, 2012). Yet with urban growth, people are more likely to live in an apartment or a condominium skyscraper. Urban design allows more walkable streets; reduced local government cost because of the more efficient provision of services and infrastructure; less urban sprawl, promoting the preservation of open space, farmland, and environmentally sensitive areas (Bhatta, 2010). Cities have always been shaped by public transportation technologies when prior transportation innovations have been more important, and the car has had a more dramatic effect on the city than anything earlier (Cheshire & Hay, 2017). Homes have had to be in close proximity to public transportation locations as well as businesses, for that reason public transportation (Figure 12) made it possible for consumers to live far from their work, though they still needed to live in high densities (Cheshire & Hay, 2017).

Organisations and planners have stressed that urban growth is crucial and its benefit has been in decentralisation, bringing about employment to different parts of a city. It has, however, been argued that the car has had a more dramatic effect on the city, in that car culture has enabled people to commute shorter distances at any time and to own bigger homes (Davis & Schaub, 2005). Moreover, Brueckner (2000) stated that it is not healthy for people to live in areas with highly raised levels of masses and reduced space per individual ratios, as it might create psychological and health problems. For this reason, the Brueckner (2000) recommendation of urban growth is for people to live in larger plots by way of having their own green spaces away from city centres and work areas.

3.4.2. Environmental effects

Studies have pointed out the environmental effects of urban growth. This is in effect a statement of one of the basic laws of ecology, much championed by Alexander von Humboldt (Wulf, 2015), that everything is connected to everything else and that one cannot change just one thing in nature.

Mitchell and Leen (2001) reported that urban growth in America has claimed farmland, forests, and many other valuable ecosystems. As a result of this, the trees and streams have been replaced by asphalt, concrete and corporations ironically name neighbourhood developments after the ecosystems were destroyed, for example, Bear Creek, Oak Tree, River Valley, etc. (Mitchell & Leen, 2001). Despite this, urbanisation of poverty is increasing, especially in townships, informal settlements and a few inner cities of Africa as well as developing countries in other counties. For those who live in informal settlements and in hazardous areas these risks are amplified and for that reason, they either lack essential infrastructure and services or there is the inadequate provision of it (Revi *et al.*, 2014), typically observed in the developing countries of the global South. Urban areas are dynamically linked to rural areas, flows of people, natural and economic resources. Urban and rural areas are becoming increasingly integrated, as a result of better transport, communications and migration.

On the other hand, high concentrations of people, buildings and infrastructure also increase the risk of natural disasters, climate change and variability (Hanson *et al.*, 2011). As a result, the spatial patterns of urban areas, by means of their limits and borders, are changing in a complex way. Likewise, a common experience in Africa, Asia and Latin America, is that squatter settlements or informal settlements are the results of urbanisation, which is a worldwide phenomenon (Turner, 1968). In third world cities, informal settlements have become synonymous with rapid urbanisation and urban growth. Most urban centres in low and middle-income countries have been unable to keep up with both sufficient and equitable economic expansion and provisions for infrastructure and services (Watson, 2015). This has resulted in large developmental deficits; around one in seven people in the world live in poor quality, overcrowded accommodation in urban areas with inadequate provision (or none) for basic infrastructure and services, mostly in informal settlements where they are exposed to a wide range of health risks (UN-Habitat, 2004; Watson, 2015). These problems have amplified manifold due to problems posed by global climate change.

Li *et al.* (2013) highlighted that, globally, urban growth is one of the major causes of ecological and environmental problems in urban areas and the surrounding regions. Other causes are the dispersion out of development, which creates water distribution problems and can lead to excess consumption of water; which is attributed to problems associated with urban growth (Burby *et al.*, 1999). The unsustainable use of water resulting from government subsidies often exceeds the regenerative capacity of water resources and creates water shortages in cities as evident with the predicament in Cape Town, South Africa. Water shortages are further compounded by deterioration in water quality as a result of pollution, thereby threatening the health of urban inhabitants (Vlahov *et al.*, 2007). Crutzen (2004) stated that conversion of vegetated surfaces to urban areas modifies the exchange of heat, water, trace gases, aerosols, and momentum between the land surface and overlying atmosphere leading to the "urban heat island effect".

Seto *et al.* (2010) highlighted that for centuries the physical extent of cities has grown slowly and this has resulted in cities being compact with high population densities. That is why, in the last 30 years, this trend has reversed and so currently, on average around the world urban areas are expanding twice as fast as their population (Angel *et al.*, 2011; Seto *et al.*, 2011). Urban areas drive global environmental change, even though urban land cover represents a relatively small fraction of the total land area (Grimm *et al.*, 2008). Urban growth and associated changes in land cover result in habitat loss (McDonald *et al.*, 2008; McKinney, 2008), threatens biodiversity (McKinney, 2002) and results in loss of land carbon stored in vegetation biomass (Imhoff *et al.*, 2004). According to Pimm and Raven (2000) in some of the most biologically diverse areas in the world, the change in land cover could result in the loss of up to 40% of the species. By the beginning of 2000, 88% of the universal plant cover lands had been destroyed in "biodiversity hotspots" (Myers *et al.*, 2000).

Pauchard *et al.* (2006) indicated that a major driving force of biodiversity loss together with biological homogenization is urbanisation, not only in developed countries but increasingly in less developed countries. As the surrounding landscape gets enveloped and transformed into urban area, it impacts on the environment at multiple spatial and temporal scales, through climate change, loss of wildlife habitat and biodiversity and greater demand for natural resources, in addition to also having adverse impacts on ecology of the area especially hydro-geomorphology (Bett, 2011; Weng, 2001). Furthermore, it has been identified that urban growth is experienced by cities globally and is often associated negatively with the changing of the city landscape resulting in low quality of life for the residents (Bengston *et al.*, 2005). Factors such as loss of agricultural land and open space, congestion, lack of access to services, higher cost of infrastructure, mobility and social interaction and environmental concerns are among the consequential effects. It is important to note that there remains a lack of detailed empirical evidence to determine with certainty the case of growth to be either a positive or destructive despite all the negative assumptions associated with urban growth.

Aguilera *et al.* (2011) stated that urban growth patterns are characteristic of spatial changes occurring in metropolitan areas. Wilson *et al.* (2003) identified three major types of urban growth: expansion, infill, and outlying. The expansion, also known as urban extensions or edge expansion, is a non-infill development extending the urban footprint in an outward direction. Sometimes it is also known as urban fringe growth, considering the fact that infill growth is a new development within remaining open spaces in an already existing built up area. The outlying or leapfrog development, also referred to as urban sprawl, is a change from non-developed to developed land cover occurring beyond existing developed areas in such a way that demands the extension of public facilities.

3.5. Remote Sensing methods in the assessment of urban growth

Several methods, as well as techniques, have been developed and applied to quantify and characterise urban growth processes and patterns. Traditionally, visual interpretations of high-resolution aerial photographs were utilised to acquire comprehensive information on mapping of urban areas (Herold *et al.*, 2005).

A number of researchers (Haque & Basak, 2017; Yang & Lo, 2002; Yu *et al.*, 2011), have stated that Remote Sensing imagery is a powerful tool for land use changes including urban growth processes at different spatial scales. Moreover, Remote Sensing could provide fundamental observations of urban growth, especially in developing countries, and environmental conditions that are not available from other sources. Notwithstanding, it lacks the ability to describe the underlying urban processes as indicated by Herold *et al.* (2005). According to Pham *et al.* (2011), spatial metrics are useful tools to objectively quantify and describe the underlying structures and patterns of the urban landscape from geospatial data. Researchers generally considered the built up area as the parameter for quantifying urban sprawl (Epstein *et al.*, 2002). It is quantified by considering the impervious area in preference to the built up as the key feature of urban sprawl, which is delineated using topographic sheets or through the data acquired remotely.

Different approaches have emerged to evaluate a variety of spatial, demographic or social characteristics associated with different urban patterns. The most popular of these measures are routinely based on population information (often the most readily available data). Therefore, census data such as sprawl index are used either alone as population density per county, census block (Lopez & Hynes, 2003; Schneider & Woodcock, 2008) or in conjunction with land cover information, such as the ratio of population to urban area or the amount of land developed per person (Hasse & Lathrop, 2003; Schneider & Woodcock, 2008; Wolman *et al.*, 2005). Nonetheless, a few studies have included measures of accessibility and proximity (Galster *et al.*, 2001) such as auto dependence, road network accessibility or even distance to jobs or commercial areas. Despite the fact that these studies are useful for understanding the human/social ramifications of dispersed land, the primary shortcoming is that all rely on demographic data (such as population, households) rather than explicit land use information.

In the analysis by Pham *et al.* (2011), the results showed that growth can be better-characterised using land cover patterns that are derived from remotely sensed imagery in conjunction with census information. According to Tsai (2005) and Kasanko *et al.* (2006), the simpler land-based measures of sprawl include documenting the extent of built up areas, growth rates and percentage change in the area. Hasse and Lathrop (2003) further indicated that detailed analysis of the amounts of new residential, industrial and commercial land has also been attempted, including estimations of the land cover types these areas replaced. For that reason, more sophisticated spatial measures offer a means to quantify complex dimensions of sprawl such as patchiness, clustering, scatter, dispersion, interspersion, etc., to be estimated using landscape pattern metrics (Dietzel *et al.*, 2005; Luck & Wu, 2002), or spatial statistics such as Moran's I (Tsai, 2005). Pattern metrics is a useful technique to measure urban land configuration, especially considering that conversion of urban land often occurs at the scale of plots or patches either within the city or outside it and neither at the level of individual pixels.

3.5.1. Manual methods

Urban sprawl pattern identification and computation of landscape metrics such as drainage networks (rivers, streams and water bodies), roads and railway networks and administrative boundaries can be digitised from the topographic maps (Bett *et al.*, 2013) as individual layers prior to field data collection. The urban growth analysis tool (Bett *et al.*, 2013) was utilised to generate GIS layers and calculate metrics to qualitatively and quantitatively describe the attributes associated with urban growth. Formal and informal settlements (shacks) were analysed in terms of the length and width of buildings in conjunction with other urban features, which determined the type and resolution of the satellite images to be used in establishing optimal image classification (Bhaskaran *et al.*, 2010).

A study undertaken by Bhaskaran *et al.* (2010), on mapping urban features using IKONOS satellite data showed that whilst spectral analysis of images had yielded satisfactory results, it could have not been enough to extract urban features from very high resolution (VHR) satellite data such as IKONOS. Using both per-pixel and object-based classification methods, the study describes an approach for mapping urban features from VHR satellite data. In combination with object-based classification methods, parametric per-pixel supervised (maximum likelihood) classification methods were used to map urban features over New York City. The criteria established by Anderson (1976) was used as the basis for the classification scheme. Thus after a detailed visual examination and the analysis of the separability of classes between different class pairs seven classes were determined. In the study, classification was initially performed using the supervised method (maximum likelihood classification) or the MLC algorithm.

3.5.2. Automated methods

Most of the classification methods were developed initially in the seventies and eighties; however, many advances in classifiers and specific algorithms have occurred in the last decade (Phiri & Morgenroth, 2017). Visual analyses in the early 1970s were the first land cover classification methods to be applied to Landsat imagery followed by classification methods based on supervised and unsupervised pixels-based that use maximum likelihood classifiers, K-Means and the Iterative Self-Organising Data Analysis (ISODATA) techniques. Other methods such as object-based image analysis (OBIA), knowledge-based analysis, sub-pixel, and hybrid approaches, became common in land cover classification after 1980.

In a study by Bhaskaran *et al.* (2010) an object-oriented classification approach was utilised to improve class accuracy for both the vegetation classes and the white roof. The primary analysis step was carried out to segment the image into different homogeneous objects. This was necessary to improve thematic accuracy for the estimation of the optimal segments for both classes (Bhaskaran *et al.*, 2010). From field surveys and other reliable secondary data sources, accuracy assessment was performed using ground truth data obtained. Specific classes such as the white roof and vegetation recorded low user accuracies of 79.82% and 70.07%, respectively, while the per-pixel approach produced reasonable overall accuracy. Consequently, using an object-oriented classification method, the study was able to improve the accuracy of these two classes further to 89% and 97%, respectively. It was noted that with the limited spectral resolution of IKONOS data, given the high spatial accuracy, a combined classification approach for extracting sub-pixel urban features was recommended (Bhaskaran *et al.*, 2010).

Another case study (Myint *et al.*, 2011) compared per-pixel with object-based classification of urban land cover extraction using high spatial resolution imagery. Myint *et al.* (2011) stated that a researcher typically encounters serious problems when identifying urban land cover classes employing high-resolution data using traditional digital classification algorithms. For a group of pixels that need to be considered together as an object, according to Myint *et al.* (2011), the normal approach is to use spectral information alone and ignore spatial information. To examine if an object-based classifier can accurately identify urban classes Myint *et al.* (2011) used QuickBird image data over a central region in the city of Phoenix, Arizona. To demonstrate whether spectral information alone is practical in urban classification, the spectra of selected classes of randomly selected points was used, in order to determine whether they could be effectively discriminated. Based solely on spectral information, the overall accuracy was only 63.33%. Furthermore, five different classification procedures with the object-based paradigm that separates spatially and spectrally similar pixels at different scales were used. A high overall accuracy of 90.40% was achieved using an object-based classifier, even though the most commonly used decision rule, such as the maximum likelihood classifier, produced a lower overall accuracy of 67.60%. This study showed that the object-based classifier is a significantly better approach than the classic per-pixel classifiers.

An extremely challenging task for a study conducted by Salehi *et al.* (2012), was a land cover classification of very high resolution (VHR) imagery over urban areas. A number of impervious land covers such as buildings, roads, and parking lots were spectrally too similar to be separated using only the spectral information of VHR imagery. Therefore, additional information was required for separating such land covers by the classifier. For that reason, the vector data is one source of additional information, which is available in archives for many urban areas. Salehi *et al.* (2012), indicated that a more effective way to incorporate vector data into the classification process is through the object-based approach since the misregistration between different layers is less problematic in object-based as compared to pixel-based image analysis. Therefore, based on a small subset of QuickBird imagery coupled with a layer of terrain spot heights a hierarchical rule-based object-based classification framework was developed to classify the complex urban environment. To assess the general applicability of the rule-set, different thematic layer features (spectral, contextual, class-related, and morphological) were employed for the same classification framework and a similar one using slightly different thresholds applied to larger subsets of QuickBird and IKONOS imagery, respectively. Results showed Kappa coefficients of 0.88 and 0.80 for the QuickBird and IKONOS test images, respectively, and overall accuracy of 92% and 86%. For impervious land cover types the average producer's accuracies were 82% and 74.5%, respectively, for the QuickBird and IKONOS images.

Mudau *et al.* (2014) conducted a study on monitoring urban growth around Rustenburg city using SPOT 5 images. Images were geo-rectified using 25 cm aerial photography and a 20 m Digital Elevation Model (DEM). A panchromatic band with 2.5 m spatial resolution and four multispectral bands with 10 m spatial resolution were fused through an Intensity, Hue, and Saturation (IHS) transformation with a 4-3-2 band combination for Red-Green-Blue colour composite. A fused pan-sharpened image was then used for classification. This approach allowed maximum spectral and textural distinction between urban areas and non-urban areas (Mudau *et al.*, 2014). Object-based classification was utilised and the post-classification change detection method was used to quantify urban growth. The study showed that there was a significant urban expansion of 11.1 km^2 in Rustenburg, 25.5% growth between 2007 and 2012. This showed that the city had a higher growth rate than other South African cities in the past decade. The study conducted demonstrated the value of satellite imagery in examining urbanisation trends in growing cities (Mudau *et al.*, 2014).

According to Fallatah *et al.* (2018), the management and planning of public resources and services are crucial for mapping of informal settlements. Hence, in 2003, a process was developed to monitor urban inequality by UN-Habitat, to support the reporting of Sustainable Development Goals (SDGs). Informal settlement indicators were used as a framework for image analysis and they included the extension of vegetation, the lacunarity of housing/free land, the type of road and material segment, the measurements of the structure of the urbanised areas, roofing extent of built up areas and housing dimensions. For this reason, for identifying informal settlements object-based image analysis methods (OBIA) were recommended. Therefore, to map informal settlements based on the ontology of Kohli *et al.* (2012) and the indicators of Owen and Wong (2013) for a city in the Middle East this study documented the application of OBIA. Three informal settlements with different histories of land use to represent informal old and new settlements were selected in the city of Jeddah, in Saudi Arabia.

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The degree of vegetation was the most successful indicator detected with 100% accuracy and user accuracy 84%, followed by roads network, with 84% producer and user accuracies in older informal settlements and producer accuracy of 73% and 96% user accuracy in all case studies. The lacunarity of housing structures or free land in informal settlements was well identified while using $GLCM_{Ent}$ (R), the texture indicator, was detected with low producer accuracy in all case studies. Roofing extent of the built up area was detected with improved producer and user accuracy compared to the texture measures. The housing size indicator generally did not distinguish formal and informal settlements. Informal and formal were distinguished with a total accuracy of 83%. This research concludes that OBIA is a useful method for mapping the indicators of informal settlements in the cities of the Middle East. However, a set of generic rules for mapping informal settlements remains elusive, and each indicator requires significant localised tuning (Fallatah *et al.*, 2018).

Many techniques have been applied to characterise and quantify impervious surfaces by means of measurements on the ground or remotely sensed data. A field study using GPS, although expensive and slow, can provide reliable information on impervious surfaces. Manual digitizing from hard-copy maps or remote sensing imagery (especially aerial photographs) have been used for mapping imperviousness. Subsequently, this technique became more involved with automation methods such as scanning and the use of feature extraction algorithms. Weng (2012) identified four different approaches for the assessment of urban growth, i.e., using a planimeter to measure impervious surface on aerial photography, counting the number of intersections on the overlain grid on an aerial photography, conducting image classification, and estimating impervious surface coverage through the percentage of urbanization in a region. According to Weng (2012) and Slonecker *et al.* (2001), these studies concluded that in the 1970s and 1980s, aerial photography was the main source of remote sensing data for estimating and mapping impervious surfaces.

Wide ranges of models and methods for building extraction from imagery have been developed. Thus most extraction algorithms use edge-based techniques that comprise of linear feature detection for a perpendicular boundary and flat roof, grouping for parallelogram structure hypothesis extraction, and structure polygons verification using knowledge such as geometric structure, shadows and walls, illuminating angles, substructures like doors or windows, etc. (Jin & Davis, 2005). These edge-based techniques primarily use the geometric properties of buildings, while other techniques are combined with consideration of image attributes at multiple scales. In addition to geometry, the information contained in the image can be better exploited through detailed image models with rich radiometric attributes (Gavankar & Ghosh, 2018; Lang & Förstner, 1996; Zhang, 2010). With data fusion algorithms, it is possible to utilise both panchromatic and multi-spectral images from different sensors (Nunez *et al.*, 1999; Zhang, 2010).

Although the extraction of large features from coarse imagery is not a difficult task, the extraction of small objects or linear features is challenging (Quackenbush, 2004). In moderately high spatial resolution imagery, the pixel size is wider than the dimensions of the linear features, which complicates automated extraction of these features. However, high spatial resolution imagery has very rich and clear information on the target object (Kamal *et al.*, 2015) and typically has pixels that are smaller than the dimensions of the specific linear features. Therefore, high spatial resolution imagery has become very useful for linear feature extraction and is now used by several researchers for road mapping and other purposes. Satellite imagery of very high spatial resolution is necessary for automated linear feature detection (Casado *et al.*, 2015; Quackenbush, 2004), and has become a determinant factor for the effectiveness of the algorithms and techniques for the extraction of linear feature available (Mekuriaw *et al.*, 2017). Hu *et al.* (2015) have indicated that the success of linear feature extraction depends on the spatial resolution of the image.

Researchers developed and used a wide range of techniques to detect and extract linear features from high spatial resolution images. Many of these have been developed to detect and map roads (Quackenbush, 2004). Some of the techniques are automated (Behling *et al.*, 2015), while others are semi-automated (Yun & Uchimura, 2007). The most popular automated techniques used for linear and non-linear feature detection from high-resolution images are multi-spectral classification (Matikainen *et al.*, 2017), edge detection (Mekuriaw *et al.*, 2017), mathematical morphology (Frigato & Silva, 2008; Mangala & Bhirud, 2011), segmentation/classification (Lin, 2009; Soilán *et al.*, 2017), and the Hough transform (Fitton & Cox, 1998).

3.5.2.1. Traditional pixel-based image classification methods

Researchers have generally established that when pixel-based methods are applied to high-resolution images a "salt and pepper" effect is produced that contributes to the inaccuracy of the classification (Campagnolo and Cerdeira, 2007; De Jong *et al.*, 2001; Gao and Mas, 2008; Van de Voorde *et al.*, 2004). The overall objective of classical pixel-based image classification procedures is to automatically categorise all pixels in an image into land cover classes or themes in a pixel-by-pixel manner. Usually, multispectral data are used to perform the classification, and only the spectral information for each pixel is utilised as the basis of categorisation. The classical pixel-based algorithms are minimum-distance/nearest neighbour, parallelepiped and Maximum Likelihood Classifiers (MLC), ISODATA and K-means classifiers (Lillesand *et al.*, 2014).

Most traditional pixel-based classification approaches are based solely on the digital number of the pixel itself. In this way, only spectral information is used for classification. The situation gets worse when only certain features of interest are extracted. As a result, the classification produces the salt-and-pepper effect pseudocolour layer. An object-oriented classification is suggested to overcome these limitations (Aplin & Smith, 2008). In the pixel-based image analysis, the multispectral data is used to perform the classification and the spectral pattern present within the data in question for each pixel is used as the numerical basis for the categorisation. The pixel-based classification approach is based on conventional statistical techniques (binary method) such as supervised and unsupervised classification as the two most common approaches in image classification (Hussain *et al.*, 2013).

In supervised classification, the image is analysed through the process of pixel categorisation, specifying the algorithm of the computer, the numerical description of the different types of land cover present in a scene (Hussain *et al.*, 2013). On the other hand, in unsupervised classification pixels are grouped according to the reflectance properties of the pixels (characteristics). These groupings are called "clusters" (Aplin & Smith, 2008). The user identifies the number of clusters that will be generated and the bands that will be used. With this information, the image classification software generates clusters. According to a number of researches such as Manoj *et al.* (2013); Yang *et al.* (2017), there are several image clustering algorithms such as K-means and ISODATA.

Clustering is a technique which is used to analyse the data in an efficient manner and generate the required information (Manoj *et al.*, 2013). To cluster the dataset, the K-means technique is applied. The K-mean technique is based on central point selection and calculation of Euclidian Distance. Here in K-mean, the dataset will be loaded and from the dataset, central points are selected using the Euclidian distance formulae and based on Euclidian distance, points are assigned to the clusters. The main disadvantage of K-mean is of accuracy, as in K-mean clustering the user needs to define a number of clusters. Because of the user-defined number of clusters, some points of the dataset have remained un-clustered. On the other hand, according to Li *et al.* (2010), ISODATA is one of the most popular and widely used clustering methods in geoscience applications, but it can run slowly, particularly with large data sets. Yet it is very effective to generate a preliminary overview of images. The ISODATA clustering algorithm has good adaptability and flexibility. However, with the development of remote sensing technology, the spatial resolutions are increasing rapidly and the sizes of the data are becoming larger. Thus, clustering large amounts of images is considerably time-consuming in personal computers because of the limitation of both hardware and software resources (Li *et al.*, 2010).

Traditional pixel-based processing generates square classified pixels. Object-based image classification, on the other hand, is very different since it generates objects of different shapes and scales. There are many image segmentation algorithms, one of which is multi-resolution segmentation (Benz *et al.*, 2004). Image segmentation produces homogeneous image objects (Benz *et al.*, 2004; Blaschke *et al.*, 2000) by grouping pixels. The objects are generated at different scales in an image at the same time. These objects can be classified according to texture, context and geometry (Chen *et al.*, 2012).

3.5.2.1.1. Drawbacks of pixel-based image classification approach

One of the drawbacks of pixel-based classification is that the spatial extent of pixels may not correspond to the degree of interest in the land cover feature. The problems of mixed classification are well known, whereby a pixel represents more than one type of land cover that often leads to incorrect classifications (Newman *et al.*, 2011). Another problem is when the object of interest is considerably larger than the pixel size, which leads to an inappropriate classification.

3.5.2.2. Newer classification methods

Many advanced classification approaches have been widely applied for image classification in recent years, such as artificial neural networks, fuzzy-sets, and expert systems. In general, image classification approaches can be grouped as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and per-field (Li *et al.*, 2014). With non-parametric classifiers, it is not required to assume a normal distribution of the data set. No statistical parameters are required to separate image classes (Phiri & Morgenroth, 2017). Therefore, nonparametric classifiers are particularly suitable for incorporating non-spectral data into a classification procedure. A lot of previous research has indicated that non-parametric classifiers can provide better classification results than parametric classifiers in complex landscapes (Foody, 2002; Paola & Schowengerdt, 1995). The most commonly used non-parametric classification approaches include neural networks, decision trees, support vector machines, and expert systems. In particular, the neural network approach has been widely adopted in recent years.

Spatial resolution is an important factor affecting the selection of a suitable classification method. For example, high spectral variation within the same land-cover class in high spatial and radiometric resolution images such as QuickBird and IKONOS often results in poor classification accuracy when the traditional per-pixel classifier is used. In this circumstance, per-field or object-oriented classification algorithms outperform per-pixel classifiers (Benz *et al.*, 2004; Jensen, 2005; Mallinis *et al.*, 2008; Stow *et al.*, 2007; Thomas *et al.*, 2003; Zhou *et al.*, 2008). Since mixed pixels create a problem in medium and coarse resolution imagery, per-pixel classifiers have difficulties in dealing with them. Sub-pixel-based classification methods can provide better area estimation than per-pixel-based methods (Lu & Weng, 2006). In the earlier and best-known work of Landgrebe (1980), a contextual classifier called Supervised Extraction and Classification of Homogeneous Objects (SECHO) was used which can be regarded as a "per field" classifier (Sharma & Sarkar, 1998).

3.5.2.2.1. Object-based image analysis (OBIA)

Phiri and Morgenroth (2017) indicated that most studies have reported superior performance of OBIA in different landscapes such as forests, agricultural areas, wetlands and urban settlements. However, OBIA presents challenges such as the selection of the optimal segmentation scale, which may result in excessive or insufficient segmentation and the low spatial resolution of Landsat images. Phiri and Morgenroth (2017) also noted that when appropriate procedures are followed, other classification methods have the potential to produce accurate classification results. Overall, Phiri and Morgenroth (2017) indicated that research is required for the application of hybrid classification as they are considered a complex method of land cover classification.

The main strength of object-based classification is elimination of the possibility of incorrectly classifying individual pixels. The result is that the classification may be more accurate than the pixel-based method. By focusing on real-world objects, maps produced through object-based classification could be more recognisable and directly usable by analysts (Benz *et al.*, 2004). Object-based information can be integrated with other spatial data in a vector-based geographic information system (GIS) environment.

3.5.2.2.2. Artificial neural networks

Artificial Neural Networks (ANNs) provide a mechanism for learning from data and mapping of data. They can resolve complex problems and can "learn" from prior applications. ANNs can be made to provide an alternative approach for problems that are difficult to solve such as decision-making problems in GIS. Nevertheless, models built using neural networks are hard to understand; they are essentially a "black box" model (Yen and Langari, 1999). Additionally, neural networks do not depend on fixed functional relationships and do not require any a priori cognition of the variable relationships (Cheng, 2003). This independence is a major advantage of neural networks because they can be utilised as powerful predictive tools when modelling complex nonlinear problems (Olden & Jackson, 2001). Neural networks are robust to noise and exhibit a high level of automation (Openshaw, 1997). Furthermore, they do not make any assumptions regarding the nature of the distribution of the data (Grekousis & Hatzichristos, 2012).

3.5.2.2.3. Decision trees

The decision tree model is a logical model (deductive reasoning) represented as a binary (two-way split) tree that shows how the value of a variable (named target variable) can be predicted by using the values of a set of predictor variables. It has a number of advantages when compared to numerically oriented techniques such as linear and nonlinear regression (function fitting), logistic regression, Artificial Neural Networks (ANNs), and genetic algorithms (McKenzie and Ryan, 1999, Breiman, 2001). Decisiontrees are easy to build and interpret, and can automatically handle interactions between both continuous (ordinal, interval) and categorical (nominal) variables. Linear regression, for instance, is appropriate only if the data can be modelled by a straight line function, which is often not the case. In addition, linear regression cannot easily handle categorical variables, nor is it easy to look for interactions between variables. As with linear regression, nonlinear and logistic regressions are not well suited for categorical variables (Breiman, 2001).

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Decision trees can identify the most decisive variables, which are those that are used for creating the splits near the top of the tree. In addition, they do not require the specification of the form of a function to be fitted to the data as is necessary for other competing procedures (e.g., nonlinear regression). Breiman, (2001) further stated that ANNs are often compared to decision tree models because both methods can model data that have nonlinear relationships between variables, and both can handle interactions between variables. In contrast, once a decision tree model has been built, it can be converted to statements that are implemented easily in most computer languages without requiring a separate interpreter. Moreover, decision trees can identify a target (dependent) variable. This is not possible with unsupervised machine learning methods like cluster analysis, factor analysis (principal component analysis) and statistical measures (Lin *et al.*, 2002; Manzoor *et al.*, 2006; Tariq *et al.*, 2006), which treat all variables equally without predicting the value of a variable.

These methods (ANNs, Fuzzy classification and OBIA) rather look for patterns, groupings or other ways to characterise the data that may lead to the understanding of the way the data interrelate. In addition, decision trees can indicate the relative weight of each predictor variable in explaining the training data, while bivariate analysis demonstrates only the implication of a couple of predictor variables against the target variable. Therefore, if the goal of an analysis is to predict the value of some variable, then decision tree modelling is a recommended approach. However, predicting the future remains a hard task, even with decision trees (Breiman, 2001).

3.5.2.2.4. Support vector machines

The Support Vector Machines (SVM) approach consists in finding the optimal hyperplane that maximises the distance between the closest training sample and the separating hyperplane. Vapnik (1998) highlighted that SVMs are based on the Structural Risk Minimization principle from computational learning theory. Unlike traditional learning techniques, SVMs do not depend explicitly on the dimensionality of input spaces. They solve classical statistical problems such as pattern recognition, regression, and density estimation in high-dimensional spaces. Thus, SVMs are very universal learners. In their basic form, SVMs learn linear threshold function. Nevertheless, by a simple "plug-in" of an appropriate kernel function, they can be used to learn polynomial classifiers, Radial Basic Function (RBF) networks, and three-layer sigmoid neural nets (Vapnik, 1998). One remarkable property of SVMs is that their ability to learn can be independent of the dimensionality of the feature space. SVMs measure the complexity of hypotheses based on the margin with which they separate the data, not the number of features. This means that we can generalize even in tile presence of very many features, if our data is separable with a wide margin using functions from the hypothesis space (Vapnik, 1998).

3.5.2.2.5. Fuzzy classification

Fuzzy clustering has been proven particularly useful in spatial analysis (Openshaw, 1989). In fuzzy clustering, each cluster has a cluster centre that represents a typical object in the cluster. An important advantage of using fuzzy models is that they are capable of integrating knowledge from human experts naturally and conveniently, while traditional models fail to do so (Yen and Langari, 1999). Other significant properties of fuzzy models are their ability to handle nonlinearity and interpretability feature of the models (Yen and Langari, 1999). The advantage of fuzzy clustering is that objects can be linked with multiple clusters to different degrees, whereas in common clustering, each object corresponds to one cluster only. This degree is known as the membership value and reveals how close each object is in the centre of a cluster. If the membership value of an object in a cluster is high, for example, 95%, this entails that it almost coincides with the cluster's centre and is, therefore, classified in this cluster. Conversely, if the membership value is low (e.g. 5%), the object has little similarity to the cluster.

3.5.2.2.6. Sub-pixel classifiers

Sub-pixel Classifier is an advanced image exploitation tool designed to detect materials that are smaller than an image pixel, using multispectral imagery (Arif *et al.,* 2015). It is also useful for detecting materials that cover larger areas, but are mixed with other materials that complicate accurate classification. The advantage to sub-pixel classification is that addresses the "mixed pixel problem" by successfully identifying a specific material when materials other than the one being considering for are combined in a pixel. On the other hand, sub-pixel classification can also discriminate between spectrally similar materials, such as individual plant species, specific water types, or distinctive man-made materials. As a result, this allows one to develop spectral signatures that are scene-to-scene transferable. Therefore, it is capable of detecting and identifying materials covering an area as small as 20% of a pixel. This greatly improves the ability to discriminate Material of Interest (MOIs) from other materials, and enables one to perform wide area searches quickly to detect small or large features mixed with other materials (Arif *et al.,* 2015).

Lee and Lathrop (2005) conducted a study that tested the usefulness of linear mixture modelling (LMM) in the sub-pixel analysis of Landsat Enhanced Thematic Mapper (ETM) imagery to estimate the three key land cover components in an urban/suburban setting: impervious surface, managed/unmanaged lawn and tree top. Thus, fuzzy c-means clustering (FCM) method was applied to classify the impervious surface training pixels. The accuracy of the Landsat LMM outputs was evaluated using two separate approaches based on digital orthophoto quarterquads (DOQQ) and IKONOS. The results further substantiate the utility of a linear mixture modelling approach to the sub-pixel estimation of the built or impervious surfaces. An accuracy assessment was conducted comparing LMM estimates with visually interpreted digital orthophotography (for a selected subset of homogeneous 363 pixel plots), as well as with maximum-likelihood classification of high spatial resolution IKONOS imagery for two study sub-areas. LMM impervious surface estimates showed a high degree of similarity with the reference data as displayed by RMSE on the order of ±8 to 15% (for the 363 pixel DOQQ and IKONOS comparisons). In conclusion the authors put forward that these sub-pixel based techniques can then be easily scaled to provide improved knowledge of the area and spatial distribution of impervious surface, grass and tree cover at the scale of individual towns or watersheds (Lee and Lathrop, 2005).

3.6. Performance of image classification techniques

3.6.1. Object-based image analysis

Traditional image segmentation methods have been commonly divided into three approaches: pixel, edge and region-based segmentation methods. Object-based image analysis comprises two parts: (1) image segmentation and (2) classification based on objects' features in spectral and spatial domains. Image segmentation is a kind of regionalisation, which delineates objects according to certain homogeneity criteria and at the same time requiring spatial contingency (Liu and Xia, 2010). Through segmentation, the image is divided into homogeneous, continuous and contiguous objects. Several parameters are used to guide the segmentation result. In multiresolution segmentation the scale parameter determines the maximum allowed heterogeneity for the resulting image objects. The colour criterion defines the weight with which the spectral values of the image layers contribute to image segmentation, as opposed to the weight of the shape criterion. Smoothness is used to optimise image objects with regard to smooth borders, and compactness allows optimising image objects with regard to compactness (Baatz *et al.*, 2004).

According to Hay and Castilla (2006), OBIA has various advantages. Firstly, the change of classification units from pixels to image objects reduces within-class spectral variation and generally removes the so-called salt-and-pepper effects that are typical in pixel-based classification. Secondly, the way it classifies an image by partitioning it into objects, similar to the way humans comprehend the landscape, free of speckled appearance and with comparatively higher accuracies; image-objects exhibit useful features (shape, texture, context relations with other objects) that single pixels lack and can be readily integrated in vector GIS (Liu & Xia, 2010).

A study by Weih and Riggan (2010) compared object-based classification and pixel-based classification of multi-resolution images. The study showed that when merging colour infrared high-spatial resolution aerial imagery with medium spatial resolution satellite imagery, an object-based classification would outperform both supervised and unsupervised pixel-based methods. The results also showed that pixel-based methods (both supervised and unsupervised) produced a very fragmented urban feature class that was less homogeneous. The results are, therefore, very important to consider when the classification is used to develop landscape metrics that are sensitive to fragmentation.

Blaschke (2010) stated that image segmentation is the division of an image into different regions, each having certain properties, and it provides the building blocks of Object-based Image Analysis (OBIA). According to Martha *et al.* (2011), in developing a robust OBIA approach segmentation is a momentous challenge and methods have been developed for automating the optimisation of scale parameters by means of Estimation of Scale Parameter tools (ESP1 and ESP2) for the multi-resolution image segmentation of remotely sensed data (Drăguţ *et al.*, 2014). Cleve *et al.* (2008) indicated that the OBIA classification process is generally preceded by segmentation. Therefore, segmentation serves an initial step of OBIA and generally involves the creation of image-objects that represent meaningful entities by assembling neighbouring pixels with similar characteristics. This study made use of Multi-resolution segmentation (MRS) and Spectral Differencing Segmentation (SDS), image segmentation algorithms (Trimble, 2014).

3.7. Change detection using Remote Sensing approaches

Lunetta and Elvidge (1999) categorised change detection analysis approaches into either post-classification change methods or pre-classification spectral change detection. Change detection analysis is useful in many applications such as land use change, the rate of deforestation, wetlands, habitat fragmentation, coastal change, urban sprawl and other cumulative changes. The use of GIS and remote sensing for land use/ land cover changes has become one of the best ways to analyse and monitor changes globally over the past decades, with the availability of a suite of sensors operating at various imaging scales and scope (Al-doski *et al.*, 2013).

Urban growth usually leads to changes in land cover. Urban growth/sprawl has been a serious problem for many rapidly developing countries (Noor & Rosni, 2013). Over the past decades, as indicated by Lu *et al.* (2005), different change detection methods have been developed and documented, they all have their own advantages and disadvantages. The main techniques are summarised in the sections that follow.

3.7.1. Image differencing

Image differencing has been one of the most widely used techniques to determine changes between images (Ridd and Liu, 1998). It has been used in a variety of geographical environments. In contrast, change vector analysis is a change detection procedure that is a conceptual extension of image differencing. This simple method is widely used and consists of subtracting registered images acquired at different times, pixel-by-pixel and band by band and generating an image based on the result. The image differencing method is usually applied to single bands but can be also applied to processed data such as multi-date vegetation indices or principal components (Ridd and Liu, 1998).

Weng (2001) developed a methodology to relate urban growth studies to distribute hydrological modelling using an integrated approach of remote sensing and GIS. Landsat Thematic Mapper data were utilised to detect urban land-cover changes. To examine the changing spatial patterns of urban growth GIS analysis was then conducted. This methodology was applied to the Zhujiang Delta of southern China, where dramatic urban growth had occurred over the past two decades, and the rampant urban growth had created severe problems in water resources management. The urban expansion map was overlaid with the runoff change map to analyse the impact of land-use and land-cover change on the environment. Image differencing was then performed between the 1989 and the 1997 runoff layers. The resulting differencing image was reclassified into runoff change zones. The areal extent and spatial occurrence of these zones were studied in reference to the spatial patterns of urban growth in order to understand the effects of land-use and land-cover changes. Results revealed a notably uneven spatial pattern of urban growth and an increase of 8.10 mm in annual runoff depth during the 1989–1997 period. An area that experienced more urban growth had a greater potential for increasing annual surface runoff. Highly urbanized areas were more prone to flooding. Urbanisation lowered potential maximum storage, and thus increased runoff coefficient values (Weng, 2001).

3.7.2. Principal component analysis (PCA)

Principal component analysis is one of the statistical techniques used extensively in remote sensing image analysis in applications well beyond that of change detection. The PCA method provides a powerful tool for data analysis and pattern recognition. It is frequently used in signal and image processing as a technique for data compression, dimension reduction or their decorrelation as well. Furthermore, it has been used for determining the intrinsic dimensionality of multispectral imagery, data enhancement for geological application, and land cover change detection. According to Petrou and Petrou (2010), there are various algorithms based on neural networks or multivariate analysis, which can perform PCA in any given data set. However, there have been limitations in the estimation of PCA projection from data. With high dimensional data like satellite images, its computational complexity makes it difficult to deal directly.

Deng *et al.* (2008) applied PCA in urban change detection through a new method using multitemporal and multisensor data (SPOT-5 and Landsat data) to detect land-use changes in an urban environment based on PCA and hybrid classification methods. After geometric correction and radiometric normalisation, PCA was used to enhance the change information from stacked multisensor data. Then, a hybrid classifier combining unsupervised and supervised classification was performed to identify and quantify land-use changes. Finally, stratified random and user-defined plots sampling methods were synthetically used to obtain a total of 966 reference points for accuracy assessment. Although errors and confusion existed, this method showed satisfying results, with an overall accuracy of 89.54% and 0.88 for the kappa coefficient. When compared with the post-classification method, PCA-based change detection also showed better accuracy in terms of overall, producer's, and user's accuracy and the Kappa index. The results suggested that significant land-use changes had occurred in Hangzhou City from 2000 to 2003, which may be related to rapid economic development and urban expansion. Deng *et al.* (2008), further indicated that most changes occurred in cropland areas due to urban encroachment.

3.7.3. Post classification comparison (PCC)

One of the most intuitive methods of change detection is the post-classification comparison, which is the comparative analysis of independently produced classifications (overlay of two independently produced classified images) for different dates (Raja *et al.*, 2013). It can be used to identify not only the amount and location of the change but also the nature of change, and that is why this method can produce 'from-to' change information. This makes it helpful in differentiating which land cover or land use class has changed to another class. On the other hand, the accuracy of the change detection result will be highly depended upon by the accuracy of the classifications (Jensen, 2005). The post classification change detection method reduces the need to perform geometric and atmospheric correction (Jensen, 2005). Post classification comparison is made on classified images and used as the standard for evaluating the results of other methods, and it is often considered *a-priori* to be a superior change detection method (Jensen, 2005).

However, in the final change detection map, every inaccuracy in the individual data classification map will also be propagated. As a result, it is imperative that the post-classification change detection methods used in the individual classification maps be as accurate as possible. Thus, it has been identified (Lu *et al*, 2004) that the image classification stage in this method takes a long time because the accuracy of the classification needs to be high to get good change detection results. Recently, numerous studies have indicated the use of post-classification comparison change detection technique for land cover change analysis in urban studies. Yin *et al.* (2011) used the post-classification comparison to detect changes in Shanghai metropolitan area, China based on Landsat MSS, TM and ETM+ images from 1979, 1990, 2000 and 2009. By overlaying the classified images over each other they were able to compare the changes in pixels of the layers pixel-by-pixel.

Liu and Zhou (2004) undertook a study in Chaoyang District located in the eastern part of Beijing, China. Two classifiers were employed in this study, namely, the maximum likelihood (MLC) and artificial neural network (ANN) classifiers. Multi-temporal Landsat TM images were classified for land use, and the post-classification comparison of these classified images showed change trajectories through the time series. These change trajectories were then analysed by assessing their rationality against a set of logical rules to separate cases of 'real land use change' and possible classification errors. The analysis results showed that the overall accuracy for land use change in the urban fringe area was 86%, with a fuzziness of 7%. Although it is argued that the uncertainty still exists on classification accuracy assessed by this method, it nevertheless provides an alternative approach for more reasonable assessment when ideal simultaneous 'ground-truthing' is not available (Liu and Zhou, 2004).

3.7.4. Change vector analysis (CVA)

Change vector analysis technique uses two spectral channels to map both the magnitude of change and the direction of change between the two (spectral) input images for each date (Li *et al.*, 2018). Moreover, it is an empirical method of detecting radiometric change between multitudes of satellite images in any number of spectral bands. This method yields information about the type of spectral changes and the degree of change by calculating a vector magnitude and direction in multispectral change space for each pixel. According to Lambin and Strahler (1994) a threshold indicating change and no change area, like in image differencing, also needs to be determined in this method. One advantage of CVA is the potential capability to process any number of spectral bands desired. This then makes CVA very important because not all change is easily identified in any single band or spectral features. However, according to Kontoes (2008), no effective method has been developed to handle more than two spectral bands.

Li *et al.* (2018) conducted a study in two cities of Des Moines and Ames in central Iowa, US. They developed a framework to map urban expansion at an annual interval from 1985 to 2015 by using the time series of Landsat data. First, the time series of Landsat data (1985–2015) were grouped into three periods, i.e., 1985–2001, 2001–2011, and 2011–2015, according to the available National Land Cover Database (NLCD). Then, a temporal segmentation approach was implemented for each period using three indicators representing changes from vegetation, water, and bare land to urban. Three temporal segments representing phases of prior change, change, and post change, were generated accordingly. Thereafter, urban extents before 2001 and after 2011 were classified using a change vector analysis (CVA) based approach aided by the NLCD and identified temporal segments. Finally, urbanised pixels in each period were determined according to the identified turning years. From their study, Li *et al.* (2018) indicated that the approach of temporal segmentation was reliable for detecting changes caused by urban growth, with an overall accuracy of 90% in identifying turning years (±1 year). Using an independent validation sample set, the CVA based approach reached an overall accuracy of 87%. The derived product of urban dynamics showed a relatively stable increment of urban growth in Des Moines and Ames, Iowa, US, and most urbanised areas were converted from vegetated lands within 2–3 years (Li *et al.*, 2018).

3.7.5. Image rationing (IR)

In image rationing (IR) two images from two dates are divided band by band and pixel by pixel. If the ratio of two images is equal to 1, then no change has occurred, but if the ratio is greater than or less than one that means change has occurred (Singh, 1989). A threshold needs to be decided. IR produces images with a non-Gaussian distribution of pixel values and if a threshold is decided based on standard deviations from the mean, the change will not be equal on both sides. This feature of IR has been criticised (Lu *et al.*, 2004; Singh, 1989). One of the most common ratios is the Normalized Difference Vegetation Index (NDVI). The NDVI is calculated as: (NIR-RED)/(NIR+RED). However, a simple image ratio as illustrated by Singh (1989), is calculated as: $Rx_{ij}^k = \frac{x_{ij}^k(t_1)}{x_{ij}^k(t_2)}$. The data are compared on a pixel-by-pixel basis.

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where, $x_{ij}^k(t_2)$ is the pixel value of band k for pixel x at row i and column j at time t_2. If the intensity of reflected energy is nearly the same in each image then $Rx_{ij}^k = 1$, this indicates no change (Singh, 1989). The advantage of IR is that the effect of different Sun angles, shadows and topography is reduced, the disadvantage is the non-Gaussian distribution of the ratio image making threshold selection difficult (Lu *et al.*, 2004).

Nelson (1982) stated that intensively investigation for rationing has not been like in image differencing. A study conducted by Todd (1977) used the ratio of band 5 data from two dates to determine urban change in Atlanta, Georgia. Only ratios to the low side of the mean were considered changed. Thus, the overall evaluation indicated that 91.4% of all land cover change was correctly identified.

3.8. Synthesis

This chapter has provided insights into urban growth, which is often considered a local problem. In addition, relevant key points on the nature of urban growth, its causes and socio-economic effects were discussed in terms of the global and the South African contexts. One of the distinguishing characteristics of apartheid in South Africa was the way in which restrictions on settlement and employment divided families across space. The apartheid policy, which was formally adopted in 1948, prohibited inter-racial marriages between the black majority and the white minority. This policy let to the configuration of the urban landscape in South Africa, which can even be perceived nowadays. With detailed planning, the group area of one group was distinguished from that of another by a buffer strip at least 100 metres broad, but preferably a physical barrier such as a railway, escarpment or river, which would impede contact between the two populations. The outcome was a tightly controlled and rigidly organised urban expansion, reminiscent of state planned urban growth in many European nations.

Under apartheid the Black sector exhibited a different pattern as the numbers requiring housing always exceeded the supply of homes and often families lacked the financial ability to compensate for such state housing as was available. This led to the development of slums and informal settlements known as Bantustans for black settlement. Thus, Africans were treated as temporary residents whose sole purpose was to satisfy industry's labour demands. As a result, migration labour system has been a key feature of the economic development of South Africa. Although populations are increasingly living in urban areas as identified in major areas of South Africa, the literature review shows that there is a large spatial variation in the size and position of urban expansion between and within countries. The literature review revealed that urbanisation has created a number of environmental problems. Literature shows that the full environmental impact of urban growth will not be limited to urban boundaries. The urbanisation process (urban growth), according to different studies, has significant hydrological effects, such as influencing the amount of runoff, which in turn pollutes rivers and causes erosion.

As urbanisation remains one of the main global environmental changes in the near future, it is essential to characterise and understand its changing patterns of urban growth. Different methods of image classification have been used to understand and to study urban growth and sprawl. The maximum likelihood classification (MLC) technique determines parameter values for which the given observation would have the highest probability. The MLC is one of the most widely used statistical estimation techniques. For that reason, methods based on digital pixels are designed to provide objective and repeatable procedures to identify the types of land cover. Thus, this approach refers to pixel-based methods, since each pixel is compared from one date to another independently of its neighbours. As a result, the MLC was selected as the parametric classification method in this study.

According to studies, OBIA has several advantages. Firstly, the change of classification units from pixels to image objects reduces within-class spectral variation and generally removes the so-called salt-and-pepper effects that are typical in pixel-based classification. The second advantage is the way it classifies an image by partitioning it into objects, similar to the way humans comprehend the landscape, free of speckled appearance and with comparatively higher accuracies; image-objects exhibit useful features (shape, texture, context relations with other objects) that single pixels lack and can be readily integrated in vector GIS. Studies have also compared object-based classification and pixel-based classification of multi-resolution images. The studies showed that when merging colour infrared high-spatial resolution aerial imagery with medium spatial resolution satellite imagery, an object-based classification would outperform both supervised and unsupervised pixel-based methods. Hence the results also showed that pixel-based methods (both supervised and unsupervised) produced a very fragmented urban feature class that was less homogeneous.

Classification algorithms that rely on object-based image analysis (OBIA) are relatively new in comparison with the MLC. Therefore, OBIA has generally had better success with narrow band and high spatial resolution data. An OBIA approach has been proposed as an alternative analysis framework that can mitigate the deficiency associated with the pixel-based classification approach. Thus, since the 1970s OBIA approaches for analysing remotely sensed data have been established and investigated. A number of studies as indicated in this chapter, have shown that image segmentation is the division of an image into different regions, each having certain properties, and it provides the building blocks of Object-based Image Analysis (OBIA). Therefore, segmentation serves an initial step of OBIA and generally involves the creation of image-objects that represent meaningful entities by assembling neighbouring pixels with similar characteristics. Due to its advantages OBIA was selected for analysing the urban areas in this study, in comparison with the MLC approach.

Chapter 4

METHODOLOGICAL APPROACH TO THE STUDY

4.1. Introduction

This chapter provides the research design, data analysis, image processing and GIS analysis methods employed. The basic methodology of this work was developed to exploit the integrated use of Remote Sensing and GIS, as well as urban planning knowledge and models to develop appropriate techniques for monitoring urban sprawl. The chapter also reports the fieldwork methods that were used to determine urban sprawl metrics in the towns selected for the study.

The important end goal of this research was to determine guidelines for choosing an appropriate methodological approach to the study of urban sprawl. The most important factor in deciding which classification method to use is the amount of a *priori* knowledge an analyst has about a study area. If the analyst were not intimately familiar with the land-use/land cover patterns of an area, unsupervised classification would most likely be more effective. Regardless of a *priori* knowledge, an analyst may want to use unsupervised classification as a means to identify land-use/land cover classes, which can then be applied to a supervised classification in what is termed hybrid classification. In some situations, unsupervised classification may be the only method capable of producing viable land-use/land cover classes.

4.2. Data sources

To ensure that the first objective of the study was met, primary and secondary data sources were collected. Fieldwork was carried out from 1st of September 2015 to the 30th of November 2015, in all the four towns under study (Mahikeng, Rustenburg, Klerksdorp and Potchefstroom). During data collection, the primary goal was to collect data on the field metrics of urban sprawl, as well as its extent. A handheld GPS (Garmin E-Trex 12 channel) was used for recording the coordinates of the field data collection points. A digital camera was also used to photograph the land cover material at the visited sites. Secondary data were collected from a topographic map of 1:50,000 scale. Multispectral satellite imagery of the study areas was obtained, from the South African National Space Agency (SANSA).

Other secondary data included demographic details of the original census abstracts of all the towns in the study area for 1996, 2001, 2007 and 2016, from the Directorate of Census Operations, Statistics South Africa. The town maps of these regions were obtained from the Chief Directorate National Geo-Spatial Information of Survey Settlements and Land Records.

4.2.1. Field data

The main land cover types that were identified in the field in all four towns were impervious surface (i.e. concrete, tar, and roof surfaces), vegetation (thickets, bushes, shrubs, grasses, and trees), bare land and water in places. Therefore, during fieldwork GPS coordinates representing each of these cover types were recorded so that they could be used as training areas for thematic information extraction using image classification procedures. Photographs were also taken for future reference (e.g. Figure 1). The location of the field data coordinates was made to be widespread in each of the towns. A total of 23 sites were recorded in Mahikeng, 34 in Rustenburg, 21 in Klerksdorp and 18 in Potchefstroom.

4.2.2. Selection of images

Suitable images of the study area were acquired from the South African National Space Agency (SANSA) archive. Along archive of imagery was needed because the research needed to conduct a change analysis in urban sprawl in the four towns under study. Between Landsat and SPOT (*Systéme Pour l'Observation de la Terre*) programs which have the longest image archive, SPOT images were preferred due to high spatial resolution. In South Africa, both the Landsat and SPOT imagery are readily and freely availability. However, high spatial resolution was a cardinal requirement because some of the urban metrics that would indicate urban sprawl are small in size, for example, shack (Figure 1b). Therefore, SPOT imagery was ideal for this study.

Dates of imagery were selected between May and July to help ensure consistency in cover classes and phenology. For the historical analysis of change in urban sprawl, imagery dating back as far as possible where needed. The SPOT programme commenced in 1986 with the launch of SPOT 1. However, although listed on the SANSA catalogue, imagery from the sensors on SPOT 1, SPOT 2 and SPOT 3 were not available due to technical problems. Therefore, only images from the SPOT 4 High-Resolution Visible Near Infrared (HRVIR) were obtained. Cloud-free scenes were needed, which imposed further restrictions on the images that could be obtained for use. It was also important to use dates on which all four towns had SPOT images in the SANSA catalogue. In terms of season, the dry season (April to October of each year) was preferred due to the generally cloud-free weather. Based on these considerations, images from April and May 1999, 2013 and 2017 were obtained from SANSA. The characteristics of the images are summarised in Table 5. Both multispectral and panchromatic bands of the respective images on the respective dates were obtained from SANSA. The differences in imagery dates (2013 and 2017) and date of field data collection (2015) did not influence the results, given that the features that constitute urban land remain the same in nature over time although the actual extent of the urban area can change.

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4.3. Image processing and analysis

The main software used for this analysis were ERDAS Imagine 2016 and eCognition Developer 9. These software packages performed different processing and analysis tasks. The images were imported into ERDAS Imagine 2016. Then much of the preprocessing was accomplished using ERDAS Imagine 2016. Figure 13 summarises the ensuing image processing and analysis procedures.

4.3.1. Image pre-processing

Preprocessing involved radiometric correction by conversion of the digital number (DN) data to radiance values, geometric correction, pansharpening and image subsetting.

4.3.1.1. Radiometric corrections

Due to the differences in radiometric resolution (Table 5), the image data were converted from digital numbers (DN) to at-sensor radiance (L_{SAT}) units (W m^{-2} sr^{-1} μm^{-1}). This was because some of the image data were in 8-bit resolution while some were in 16 bits. The conversion was implemented using the band-specific calibration gain coefficients (G) and bias (B) values supplied in the SPOT image metadata, using Equation 1.

Table 5: List of satellite images collected for the study area.

Acquisition Date	Satellite	Sensor	Cloud Cover	Path (K)	Row (J)	Spatial resolution*		Pre-processing level	Radiometric resolution
						M	P		
1999/04/20	SPOT 4	HRVIR	0 %	128	402	20m	10m	1A	8 bits
1999/04/18	SPOT 4	HRVIR	0 %	100	403	20m	10m	1A	8 bits
1999/04/03	SPOT 4	HRVIR	0 %	130	404	20m	10m	1A	8 bits
1999/04/19	SPOT 4	HRVIR	0 %	130	403	20m	10m	1A	8 bits
2013/05/01	SPOT 5	HRG	0 %	128	402	10m	5m	1A	8 bits
2013/05/01	SPOT 5	HRG	0 %	100	403	10m	5m	1A	8 bits
2013/04/05	SPOT 5	HRG	0 %	130	404	10m	5m	1A	8 bits
2013/05/01	SPOT 5	HRG	0 %	130	403	10m	5m	1A	8 bits
2017/05/27	SPOT 6	NAOMI	0%	128	404	6m	2.5m	1A	16 bits
2017/05/04	SPOT 6	NAOMI	0%	100	403	6m	2.5m	1A	16 bits
2017/04/02	SPOT 6	NAOMI	0%	130	404	6m	2.5m	1A	16 bits
2017/05/04	SPOT 6	NAOMI	0%	130	403	6m	2.5m	1A	16 bits

*Multispectral (M), Panchromatic (P)

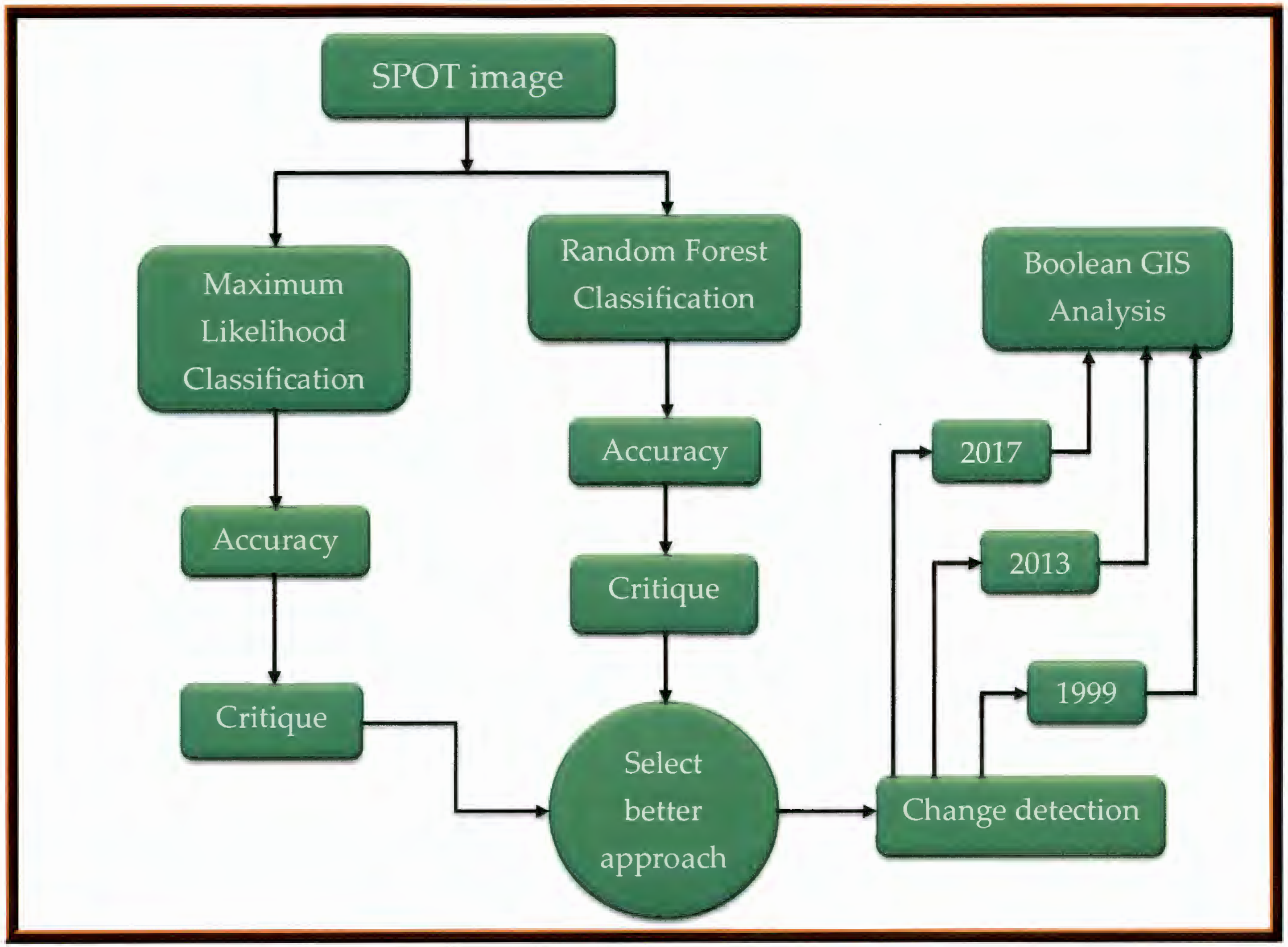


Figure 13: Flow diagram of image processing and urban sprawl monitoring methods.

$$L_{SAT} = \frac{DN}{G} + B \text{ .... (Equation 1)}$$

where; L_{SAT} is the at-sensor radiance (W m^{-2} sr^{-1} μm^{-1}), for wavelength l,

G is the band absolute calibration gain (W^{-1} m^2 sr μm),

B is the band offset value.

Many studies (Prakash *et al.*, 1999; Su, 2000; Turner & Congalton, 1998) have indicated that it has been observed that for multi-temporal SPOT images of flat areas the relative variation in solar elevation angle is not significant, and when the images belong to the same season (e.g. dry season), the atmospheric, phenological and seasonal factors can be assumed to be comparable. The removal of atmospheric and phase angle effects requires information about the gaseous and aerosol composition of the atmosphere and the bi-directional reflectance characteristics of elements within the scene (Eckhardt *et al.*, 1990). Based on the on these reasons, no radiometric normalisation was done for the images of the four towns as the images belonged to the same phenological season (dry season). The images were acquired before the fire season, thereby reducing atmospheric effects associated with smoke and radiation scattering.

4.3.1.2. Geometric corrections

The main purpose of geometric corrections is to improve the reliability of relative spatial or absolute locational aspects of image brightness values (Hussain *et al.*, 2013). Several methods and algorithms have been developed to maximise extraction of information from digital satellite imagery. Examples in literature document the role of multi-temporal data sets as a means to detect, identify, map and monitor ecosystem changes, irrespective of their causal agents (Coppin & Bauer, 1996). The development of more sophisticated classifiers like, neural networks (Paola & Schowengerdt, 1995), guided clustering (Bezdek *et al.*, 1994), fuzzy sets (Bastin, 1997), sub-pixel classification approaches (Foody & Cox, 1994), the integration of textural information (Ryherd & Woodcock, 1996),and the incorporation of contextual techniques, for example, segmentation (Lobo, 1997). In addition, ancillary data has been made use of in stratification (Fuller *et al.*, 1994), and in post-classification correction or filtering routines (Harris & Ventura, 1995). Hence, image pre-processing is essential prior to the extraction of information from the imagery as it ensures that the image is of similar spatial characteristics and radiant energy as when the image was captured.

The SPOT images used for the study were acquired using different sensors (HRVIR, HRG, and NAOMI) on board the SPOT 4, 5 and 6 satellites (as shown in Table 5). There are differences in sensor calibration between SPOT sensors that can be minimized using sensor calibration algorithms (Meygret, 2005). Furthermore, on board the SPOT 4 the HRVIR sensor does not have a true panchromatic band, but a "Red" band in black and white, with a spectral sensitivity of 0.61-0.68 µm compared to 0.48-0.71 µm in the SPOT 5 panchromatic bands (HRG). Maintaining high spatial resolution when mapping the built up area was important because some built up areas have a diameter of less than 3.5 m and are scattered as was the case of informal settlements (Figure 1). Therefore, it was judged that the error introduced by sensor differences had little effect on the accuracy of the mapping of the built up area coverage.

The images obtained from SANSA were at the level 1A of pre-processing. Level 1A involves only corrections to normalise detectors to compensate for radiometric variations due to detector sensitivity, but without geometric corrections (Pradines, 1986). Therefore, geometric corrections were necessary for the images. Geometric correction involved registration of the images to a common coordinate system. The first step was to establish a reference image. Since the images had differences in spatial resolution (Table 5), there was need to bring the pixels' sizes to a common value. Since high spatial detail was required in order to extract the spatial detail of the urban sprawl metrics (e.g. shacks, Figure 1), the spatial resolution of the 1999 SPOT 4 HRVIR image was enhanced to 10m by pan-sharpening the 20 m-resolution multispectral images with the 10m panchromatic band. After experimenting with the various pan-sharpening algorithms built-in inside the software ERDAS Imagine 2016, the Resolution Merge pan-sharpening technique was selected for use because it preserved the spatial detail of the urban features.

Thereafter pixel aggregation and resampling was employed to degrade the 6 m resolution of the SPOT 6 NAOMI image to 10 m, to match the resolution of the SPOT 5 HRG and the pan-sharpened SPOT 4 HRVIR images. Therefore, since the 2013 HRG image was the one originally at 10 m resolution, it was made the reference image for purposes of geometric registration of the images. This image was projected to the UTM projection. Thereafter the 1999 and 2017 images were made to conform to the projection of the reference image using image-to-image registration. In the process, a number of ground control points were used. The

GCPs consisted mainly of road crossings and unique landmarks. The GCPs were collected to serve as reference points for the geometric correction of image scenes. The image bands were then resampled to using the Nearest Neighbour resampling algorithm to ensure that the original pixel values were preserved. The error of registration (root mean square error) was kept to sub-pixel values.

Table 6 summarises the geometric pre-processing attributes. The total Root Mean Square (RMS) of resampling was kept to less than 0.5-pixel value. To achieve this, GCPs with the highest RMS error was removed from the transformation process for better accuracy. Table 7 list the total RMS values that resulted and the images were then resampled to a pixel size of the following.

Table 6: Ortho-rectification parameters for the SPOT images.

Projection type	Universal Transverse Mercator
Spheroid	WGS 1984
Datum	WGS 1984
Scale factor at central meridian	0.9996
Longitude of central meridian	3° E &W
Latitude of origin projection	0°
False easting	500000m
False northing	10000000m

Table 7: The final total Root Mean Square (RMS) values of the study towns images.

Towns	Image Years			Total RMS Error		
Mahikeng	1999	2013	2017	0.4201	0.2714	0.2153
Rustenburg	1999	2013	2017	0.4425	0.2513	0.2401
Klerksdorp	1999	2013	2017	0.4241	0.5104	0.4183
Potchefstroom	1999	2013	2017	0.4130	0.2602	0.2013

4.3.1.3. Image subsetting to extract study areas

Vector shapefiles of the study towns were obtained from Google Maps®. These shapefiles were projected to the UTM projection of the images and then displayed on the respective images of the study towns in ERDAS Imagine 2016. Then Area of Interest (AOI) files was created for the respective towns. Using the town municipal boundary AOI files that was created for each town, an image subset of each town was generated using the Create Subset function in ERDAS Imagine 2016. The resulting image subsets for Mahikeng, Rustenburg, Klerksdorp, and Potchefstroom spanned an area of 56 105.67 ha, 46 392.16 ha, 44 054.89 ha, and 57 182.08 ha, respectively. The subsets contained heterogeneous mixtures of features and not only built up land, i.e. including vegetation, water, and bare land. Figures 14, 15, 16 and 17 show the SPOT image subsets of Mahikeng, Rustenburg, Klerksdorp, and Potchefstroom, respectively.

4.3.2. Images processing for extracting urban sprawl thematic data

The literature review (Chapter 3) showed that one of the most widely use classifiers is the Maximum Likelihood Classifier (MLC). The Maximum Likelihood Classifier (MLC) was selected for use because it is one of the most popular and commonly used for extracting major classes in the world (Huang *et al.*, 2002). Therefore, the MLC was selected for use in extracting the urban sprawl thematic data. However, the MLC, like many pixel-based classifiers, suffers from the disadvantage of a salt-and-pepper appearance. This is because neighbouring pixels can be classified differently even though they belong to the same cover class (e.g. vegetation). For the urban areas of the North West Province of South Africa, fieldwork revealed that urban features are not contiguous, for example, the shack dwellings in Figure 1 are separated by bare land even though the whole landscape on which they occur is actually an urban settlement interspersed with bare land and vegetation. The same was observed for the suburb landscape: it had built up land (houses, car parks, tar roads) interspersed with trees and grass (Figure 1a). Object-based classifiers would overcome this salt-and-paper classification of urban land by grouping the entire landscape of buildings, trees, grass, and road surfaces as urban land. Therefore, in this research, the MLC was compared to the object-based classification. Random Forest (RF) was shown in the literature to be one of the most accurate object-based classifiers. The RF classifiers were, therefore, compared with the MLC.

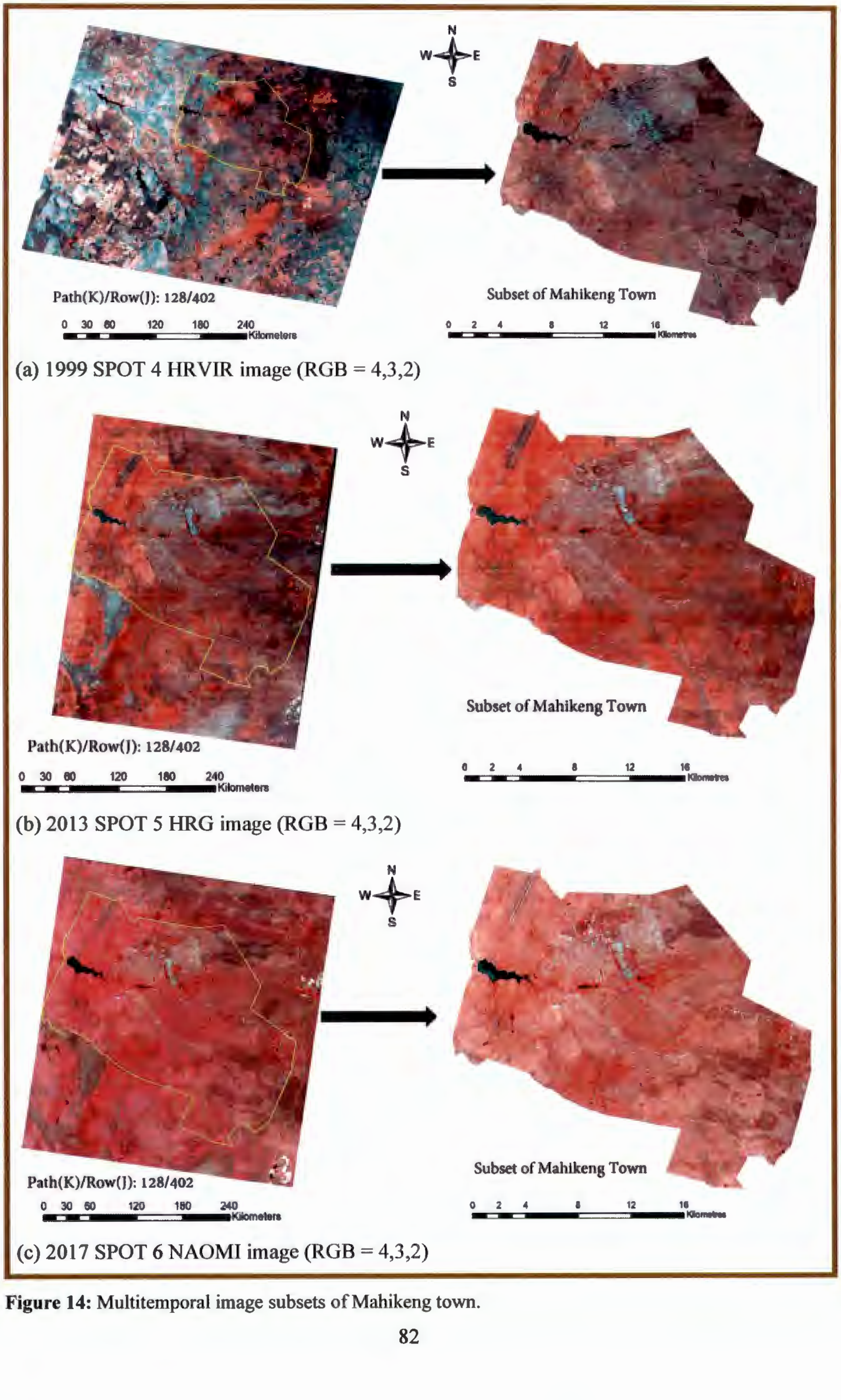
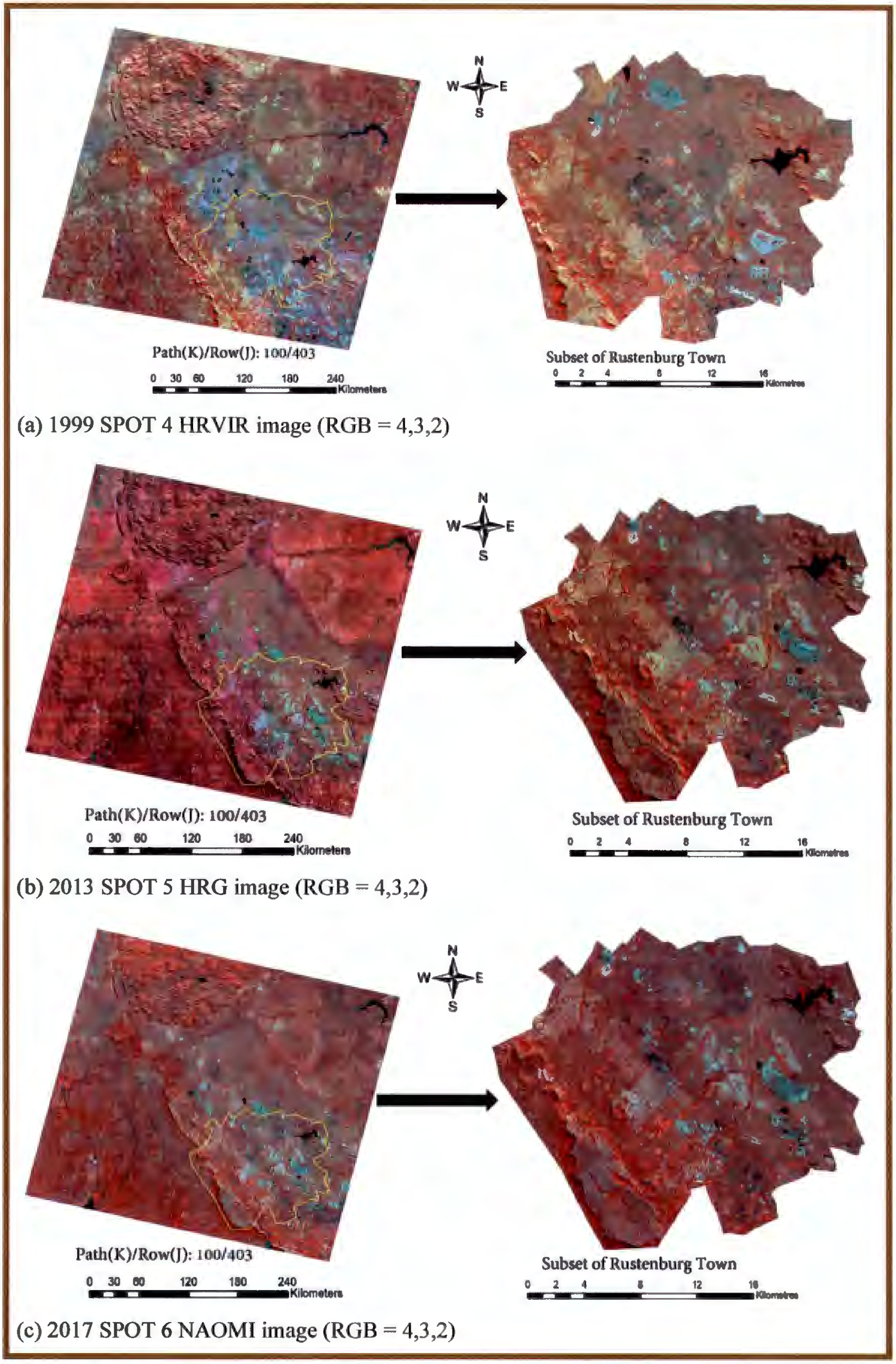


Figure 14: Multitemporal image subsets of Mahikeng town.



(a) 1999 SPOT 4 HRVIR image (RGB = 4,3,2)

(b) 2013 SPOT 5 HRG image (RGB = 4,3,2)

(c) 2017 SPOT 6 NAOMI image (RGB = 4,3,2)

Figure 15: Multitemporal image subsets of Rustenburg town.

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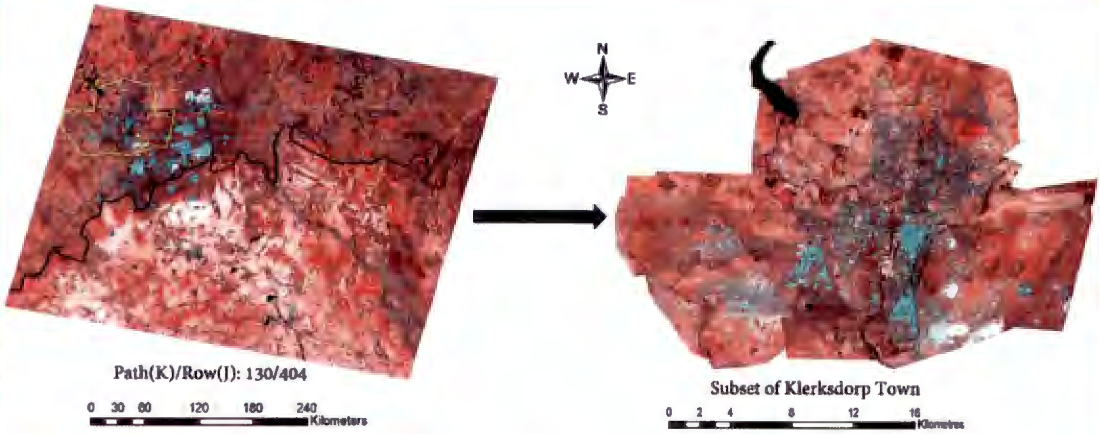
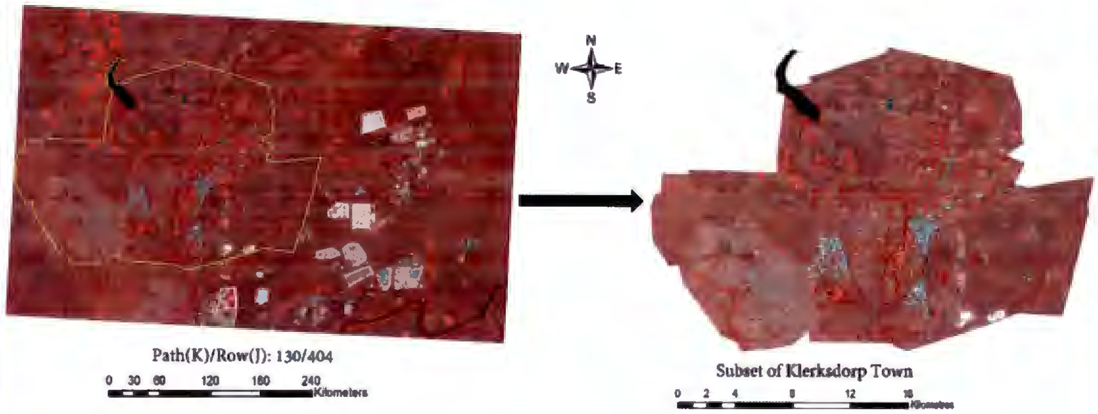
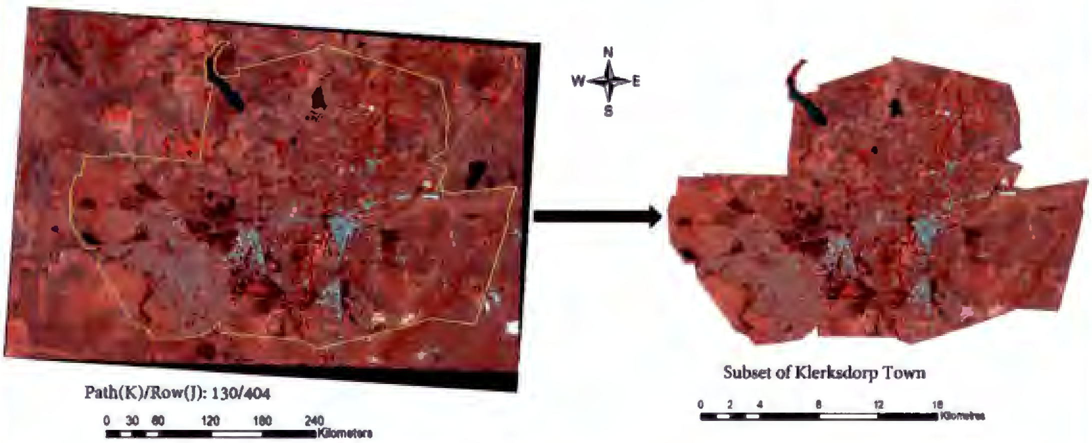


(a) 1999 SPOT 4 HRVIR image (RGB = 4,3,2)



(b) 2013 SPOT 5 HRG image (RGB = 4,3,2)



(c) 2017 SPOT 6 NAOMI image (RGB = 4,3,2)

Figure 16: Multitemporal image subsets of Klerksdorp town.

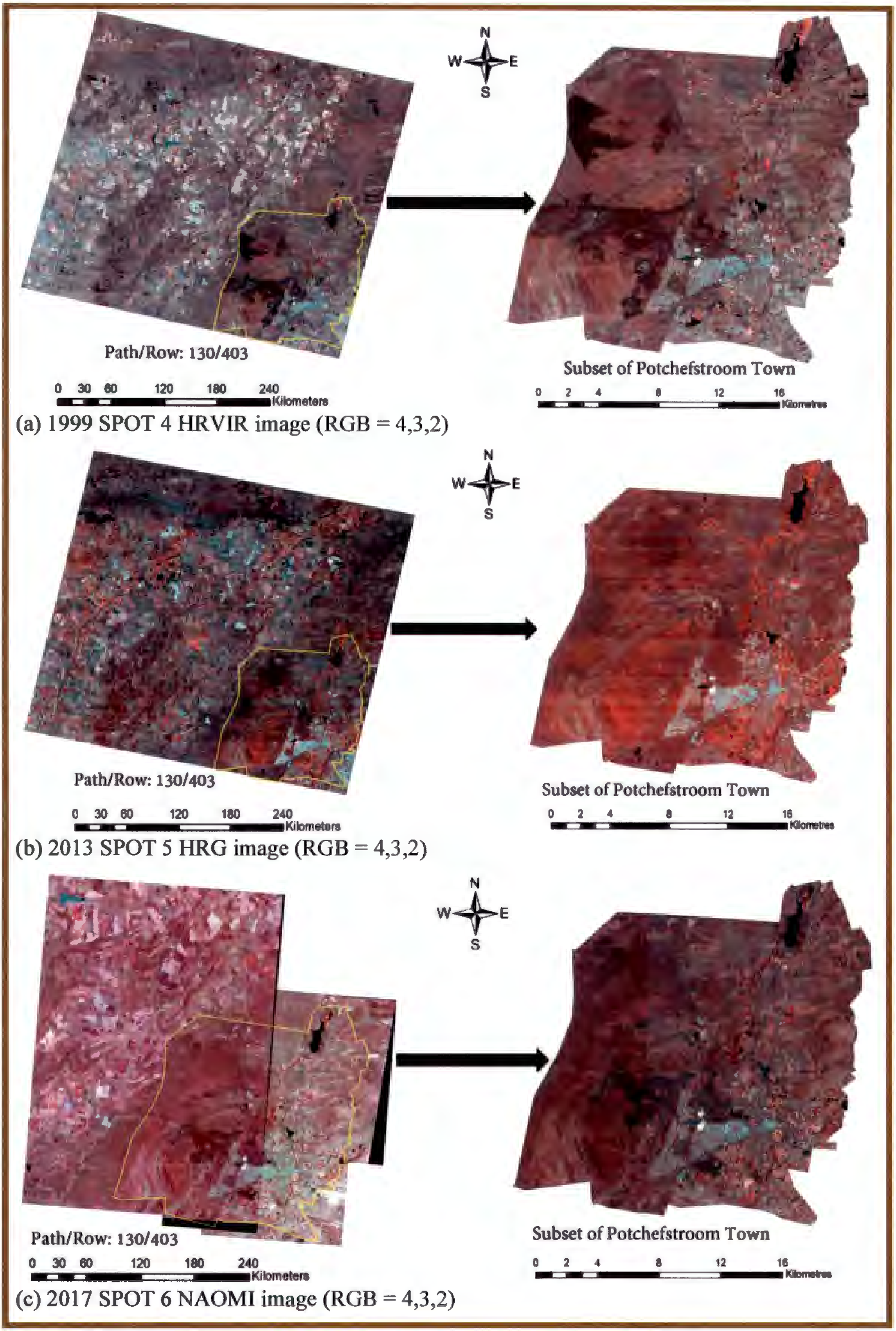


Figure 17: Multitemporal image subsets of Potchefstroom town.

As a classifier, Random Forest is effective in prediction, and the law of large numbers does not over-fit. Therefore, Random Forests are a combination of predictors for trees, so each tree depends on the values of a randomly sampled vector, and all trees in the forest will have the same distribution. In addition to this, the Random Forest classification process votes for the most popular class, after a large number of trees are generated. A number of literature articles (Breiman, 2001; Cutler *et al.*, 2007; Gislason *et al.*, 2006) have indicated the benefits of utilising Random Forest for extracting desired features.

4.3.2.1. Selecting training areas

The location of a training sample is normally done by fieldwork or by the use of aerial photographs and map interpretation (Mather & Koch, 2011). For image data, spectral signatures of urban land were chosen through fieldwork and combining spectral and contextual information. It was then necessary to determine appropriate band sets for use. The bands that were selected for use were the green, red and near-infrared bands for each image. Four classes were used for classification using the MLC and the RF classifiers: (1) Built up, (2) Barren land, (3) Thicket, Bushland and Scrub forestland (TBS), and (4) Water bodies. Each of the four land cover classes comprised of different features. Table 8 summarises the characteristics of the four classes.

Twenty-five training samples per class were gathered from each SPOT image. Then the maximum likelihood classification algorithm and object-based image analysis (OBIA) classifier Random Forest was used to classifying the respective images into the four classes. ERDAS Imagine 2016 was used for the maximum likelihood classification and eCognition Developer 9 for the OBIA classification using Random Forest.

4.3.2.2. Maximum likelihood classification (MLC)

For each class representative sites from the field, based on the field work in 2015 were selected. Polygons around each selected training site were generated manually through on-screen digitising using ERDAS Imagine 2016. To validate the suitability of these training classes a transformed divergence was used (Jensen, 1996).

The MLC is a parametric classifier that assumes the training area data for each class to have a normal distribution that involves an assumption of the selected signature classes in the normal distribution. Many studies have established the MLC to be a very accurate pixel-based classifier in comparison with others like minimum distance to means and the parallelepiped classifier (if the input samples/clusters have a normal distribution) because it takes the most variables into consideration. Since it uses a statistical decision criterion to assist in the classification of overlapping signatures, pixels are assigned to the class of highest probability. Therefore, MLC can be applied to two class and multiclass problems direct and thus the predicted results can be intuitively generated from MLC for a posterior class probabilistic output, which is a valuable indicator for classification to indicate how likely a sample belongs to a given class.

Table 8: Descriptions of the classes used for image classification to extract urban sprawl thematic data?

Land covers	Description
Water Bodies	Open bodies of water. This included streams, rivers, dams, brackish and natural ponds as well as artificial ponds.
Barren Land	Non-vegetative land and quarries (i.e. areas with human-induced effects that result in exposing soil surface layers and changes in topsoil that comprises areas with active excavation and quarries and opencast mines).
Thicket, Bushland and Scrub forest (TBS)	All kinds of vegetation such as cropland, pasture, shrubs, forests, grasslands, and dry grass.
Built up area	All kinds of residential areas such as apartment buildings, single houses, shacks, shopping centres, industrial and commercial facilities as well as highways and major streets (tarred, gravel).

A priori probabilities have been used successfully as a way to incorporate relief effects and other terrain characteristics in improving classification accuracy. Mahalanobis classification has been known to be slower to compute than Parallelepiped or Minimum distance while the Maximum likelihood or Bayesian decision rule has an extensive equation that takes a long time to compute thus the computation time increases with the number of input bands and hence they do not always produce superior results. Nevertheless, maximum likelihood classification requires many more computations per pixel than either the parallelepiped or minimum distance classification algorithm. On the other hand, even though it is much slower due to extra computations, it is still considered to give more accurate results than either of the mentioned algorithms (Geosystems, 2002).

4.3.2.3. Image segmentation and random forest classification

The Random Forest classifier was available in the eCognition Developer 9 software under the Random Trees function. The preliminary step for its application in eCognition Developer 9 is to generate objects with which training areas for the classification can be generated. Therefore, two steps were required for the Random Forest classification: image segmentation to generate objects, and Random Tree classification.

4.3.2.3.1. Image Segmentation

Image segmentation was conducted using the multiresolution segmentation algorithm in eCognition Developer 9. Multiresolution segmentation is an accurate segmentation algorithm (Witharana & Civco, 2014). Therefore, among the algorithms in eCognition Developer 9, multiresolution segmentation was selected for use. A rule set was applied and the objects were generated using the multiresolution segmentation algorithm. The algorithm requires the specification of the weights of the band, the shape (and its mutual colour), the scale parameter and the compactness (and its mutual smoothness), which are expounded by Benz *et al.* (2004). Compactness, colour, shape and smoothness constitute the criteria of the "homogeneity composition". The scale parameter is defined as the maximum standard deviation of the homogeneity criteria compared to the weighted image layers for the resulting image objects (eCognition Developer, 2014). Compactness optimises the resulting image objects in regard to the overall compactness within the shape criterion (i.e. targets objects with well-defined edges). Smoothness optimises the resulting image objects in regard to smooth borders within the shape criterion (i.e. defines objects that have softer edges).

In the generation of objects, the weights of the bands were set to 1 to allow an equal contribution of the three bands (green, red, near infrared). The shape parameter was specified as 0.9 (i.e. "colour" = 0.1) to emphasize the texture (shape) of the built up area in the generation of segmentation objects at the expense of colour (i.e. the at-sensor radiance values). This is because urban land has high texture variance due to the mixture of built up surfaces, vegetation and soil (even water in the case of residential areas with swimming pools). This is evident in Figure 1. The compactness was established at 0.9 (i.e., smoothness = 0.1) to emphasize the sharpness of the edges of urban land. With this setting segmentation then proceeded, in stages (levels).

The multi-resolution segmentation is a growing segmentation strategy that assembles objects to create larger objects. The most important determinant of multiple resolution segmentation is the scale parameter (Benz *et al.*, 2004). By varying the scale parameter only, four levels of segmentation were implemented before accepting the resulting objects for further use in Random Forest classification. The criterion for acceptance was how representative the objects generate were in outlining the boundaries of urban area features. This was judged visually on-screen. Three scale parameters were tested: 110, 140, and 160, all with the same shape and compactness values as specified (Table 9). Within each segmentation level, an image object is not only related to its neighbours, but also to its sub-object and its super-object, which provides context information useful for classification analysis. In this study, the results from segmentation level 3 at the scale parameter 160 were accepted for further use, since this segmentation level gave the best results in the visualization of the urban features. Thus for optimal separation with respect to the other levels the segmentation parameter, 160 produced homogeneous segments for the study.

Table 9: Segmentation parameters and criteria.

Segmentation Level	Scale Parameter	Shape Factor	Compactness	Number of objects
Level 1	110	0.1	0.9	1689
Level 2	140	0.1	0.9	2305
Level 3	160	0.1	0.9	2713

4.3.2.3.2. Random forest classification

The Random Forest classifier is based on recursive partitioning at nodes as employed in a decision tree, in which the partitioning is complete when the data can no longer be assigned to separate classes by the partitioning or when the partitioning does not improve the classification (Pal & Mather, 2003). However, instead of using a single decision tree, Random Forest combines multiple trees or a "forest", rather than using a single regression tree, which can improve the results (Breiman, 2001). Unlike the MLC classifier, Random Forest is a non-parametric classifier which does not assume any statistical distribution in the training area data. Instead, based on the largest number of "votes" in the tree set the terminal node is the final class label, using the simple regression tree, nodes and divisions. So, therefore, not all variables are used to find the best division, in each node but a subset randomly selected thru them (eCognition Developer, 2014).

The same training sites used for the MLC classifier were used for the Random Forest classification, except that in the Random Forest classification these training areas were encompassed inside the respective objects that were generated by multiresolution segmentation. This was as opposed to using only a few pixels to define the training area in the case of the MLC classification. Two user-defined parameters must be specified when using the Random Forest classifier (Belgiu & Drăguţ, 2016): the number of decision trees that will be generated (*Ntree*) and the number of variables that will be selected and tested to determine the best division when growing trees (*Mtry*). Therefore, because research has shown that errors stabilize before 500 classification trees are reached (Belgiu & Drăguţ, 2016) *Ntree* was set at 500. The accuracy value of the forest has been set to 0.01 and the forest learning completion criteria, both for the accuracy of the forest and for the maximum number of trees. As is common practice (Belgiu & Drăguţ, 2016), *Mtry* has been established in the square root of the number of input variables (which were four classes in this study; i.e. *Mtry* = 2).

4.3.2.4. Classification accuracy assessment

Accuracy assessment used an error (confusion) matrix, in which overall accuracy (OA, %), user's accuracy (UA, %), producer's accuracy (PA, %) and the Kappa coefficient ($\hat{K}$) were computed (Congalton, 1991). For the assessment, 100 random points were generated on the respective MLC and Random Forest classifications of the four towns per image date. The reference data against which to judge correctness of classification were obtained from 10m resolution images on Google Earth® of dates close to the SPOT images in Table 5.

To generate a set of random points the "create precision points" function in ERDAS Imagine 2016 was used on the MLC classified images. The total number of random points for each classified image was, therefore, 100. The same coordinates of the 100 points on a given image date were used to assess the accuracy of the Random forest classification corresponding to that image date for the respective towns. The equalised random point option was used to generate 25 points for each of the four classes in Table 8. The options for generating the random coordinates in ERDAS Imagine 2016 were completely random, equalised random, and stratified random. The stratified random method generates a set of accuracy assessment points proportional to the size of the class area for each class. Equalized random generated a series of accuracy assessment points where each class has the same number of points, whereas the completely random strategy generates random coordinates irrespective of the class they belong to.

4.4. Change detection to map urban sprawl using GIS analysis

After accuracy assessment, the classified images produced by the classification method that produced higher accuracy (between the MLC and Random Forest classifier) were then used for change detection to map urban sprawl in the four towns under study. Boolean analysis was used to map the change in urban sprawl between 1999, 2013 and 2017 for the respective towns. This was implemented by recoding in ERDAS Imagine 2016. Therefore, the classified images that were generated using eCognition Developer 9 were exported to the ERDAS Imagine format and then processed using ERDAS Imagine 2016. Thereafter, overlay analysis based on Boolean algebra was employed to map growth in urban land. For this, the built up area class on each classified image was coded using unique values whose addition would enable identification of growth in urban land (i.e. urban sprawl).

The codes assigned need to be carefully designed such that their addition results in a unique value whose meaning is unique and can, therefore, be interpreted (Munyati & Sinthumule, 2016). Munyati and Sinthumule (2016) on the change in woody cover at the representative site in the Kruger National Park, South Africa, based on historical imagery, which highlighted the use of Boolean analysis for change detection and proved to be effective. The codes that were assigned to the built up class from the respective years for a given town were as shown in Table 10. The other classes in Table 8 were recorded to a value of zero, in order to isolate built up land only and, therefore, to map urban sprawl. The Boolean addition overlay operator in ERDAS Imagine 2016 was then applied to the resulting re-coded images. The meanings of the codes after the Boolean addition operation were as shown in Table 10.

Table 10: Boolean overlay analysis for change detection.

Built up area Code	Study Year	Built up area in Year 1 & 2 (1999 & 2013)	Built up area in Year 2 & 3 (2013 & 2017)	Built up area in Year 1 & 3 (1999 & 2017)	Built up area on all three dates
3	**1999**				
5	**2013**	**8**	**12**	**10**	**15**
7	**2017**				

4.5. Synthesis

This chapter detailed the methodological approach to the study, through the research design, data analysis, image processing and GIS analysis methods employed. The basic methodology of this work was to develop the appropriate methods procedures that are appropriate for monitoring urban sprawl in the South African context, by integrating the use of Remote Sensing and GIS. Fieldwork methods used to determine urban sprawl metrics in the towns selected for the study were reported. The literature review (Chapter 3) showed that one of the most widely used classifier is the Maximum Likelihood Classifier (MLC). The Maximum Likelihood Classifier (MLC) was selected for use because it is one of the most accurate pixel-based classifiers which is commonly used for extracting thematic data from imagery. Therefore, in this research, the MLC was compared to the object-based classification. Random Forest (RF) was shown in the literature to be one of the most accurate object-based classifiers. The RF classifier based on multiresolution segmentation was, therefore, compared with the MLC.

By varying the scale parameter value of the multiresolution segmentation algorithm only, four levels of segmentation were implemented before accepting the resulting objects for further use in Random Forest classification. Three scale parameters were tested: 110, 140, and 160, all with the same shape and compactness values as specified (Table 9). The results from segmentation level 3 at the scale parameter 160 were accepted for further use, since this segmentation level gave the best results in the visualization of the urban features. Accuracy assessment used an error (confusion) matrix, in which overall accuracy (OA, %), user's accuracy (UA, %), producer's accuracy (PA, %) and the Kappa coefficient ($\hat{K}$) were computed. After accuracy assessment, the classified images produced by the classification method that produced higher accuracy (between the MLC and Random Forest classifier) were then used for change detection to map urban sprawl in the four towns under study. The highest overall mapping accuracy of the maximum likelihood classification was 77% (with $\hat{K}$ = 0.7644) while for Random Forest it was 91% ($\hat{K}$ = 0.9069). Then Boolean analysis was used to map the change in urban sprawl between 1999, 2013 and 2017 for the respective towns.

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Chapter 5

ESTABLISHING AN OPTIMAL REMOTE SENSING AND GIS METHODOLOGY FOR MONITORING URBAN GROWTH

5.1. Introduction

This chapter addresses Objective 2 of the study by presenting and analysing results from the image processing and GIS analysis procedures outlined in Chapter 4. A comparison of classification of the urban land using the Random Forest classifier based on Object-Based Image Analysis (OBIA) with the Maximum Likelihood Classifier (MLC) is made. The chapter then analyses the spectral characteristics of the urban growth features (in terms of histograms and maps) and discusses them as a basis of subsequent implementation of the methodology in change detection to monitor urban growth. The results of the Boolean overlay analysis to monitor urban growth in the four towns under study are presented in terms of maps. To establish an optimal method for monitoring urban sprawl is a complex process that possibly will be affected by a number of factors. Figure 13 summarises the process for developing the optimal Remote Sensing and GIS methodology for monitoring urban sprawl in the town of the North West Province. The methodology that is subsequently developed in this chapter follows from a comparison of the results presented: between OBIA and MLC classification.

5.2. Mapping urban growth: MLC versus OBIA random forest classification

Classification algorithms that rely on object-based image analysis (OBIA) are relatively new in comparison with the MLC. According to Huth *et al.* (2012); Kim *et al.* (2011) application of OBIA has been extended in several fields, in particular for forest mapping and land use land cover classification. OBIA has generally had better success with narrow band and high spatial resolution data. An OBIA approach has been proposed as an alternative analysis framework that can mitigate the deficiency associated with the pixel-based classification approach. Blaschke (2010) stated that since the 1970s OBIA approaches for analysing remotely sensed data have been established and investigated. Therefore, the classification process begins with a segmentation of neighbouring pixels into homogenous units or objects.

Comparison of MLC and OBIA approaches in this study used both a visual analysis of the products of the respective thematic maps outputs and evaluation of the corresponding accuracy assessment measures (producer's accuracy, user's accuracy, overall accuracy, and kappa coefficient), on the basis of the classes in Table 8. Figures 18 – 20 give a visual comparison of the urban classification output between the MLC and the OBIA Random Forest classifiers, using only Mafikeng town for illustration purposes. It has been stated in a number of articles (Allard *et al.*, 2012; Martha *et al.*, 2012) that OBIA allows analysts to use textural and contextual information in classifying single-band images. As shown in Figures 18 – 20, in this study OBIA classification was able to distinguish between built up area and other classes such as water, better than the MLC classification.

While both the OBIA Random Forest and the MLC approaches produced aggregations of LULC types in the study area, the most vital difference between the Pixel-Based Image Analysis (PBIA) and Objet-Based Image Analysis (OBIA) classified thematic maps from visual assessments is that the characteristics of OBIA have more pronounced boundaries and have significantly less salt-and-pepper effects compared to those achieved from PBIA classifications. This variance can be attributed to the fact that the characteristics of OBIA are comprised on multi-pixel units and were classified as such, whereas those of PBIA were classified as per-pixel level. Classifications at per-pixel level are more susceptible to confusions and misclassifications than OBIA since they only base their grouping on spectral characteristics. In this study, the OBIA Random Forest classifier was made to emphasise image texture over the spectral characteristics during the segmentation stage (see Table 9). The salt-and-pepper problem of PBIA is very evident in Figures 18 – 20 in the case of heterogeneous regions on the imagery scene (e.g. the wooded areas around Modimola Dam). This observation is consistent with the findings of (Bhaskaran *et al.*, 2010; Drăguţ & Blaschke, 2006; Matinfar *et al.*, 2007).

The OBIA classification approach has an advantage over PBIA by offering the opportunity to integrate spatial and spectral information into the classification, improving the accuracy of the thematic maps. The OBIA classification approach proved to be a very effective tool for producing LULC thematic maps of heterogeneous mountains around Rustenburg from high resolution multispectral imageries that can be visually interpreted relatively easily compared to those achieved from the PBIA approach.

5.3. Accuracy assessment of MLC and OBIA random forest classified images

For the set of images, the error matrix was conducted between the MLC and OBIA classified images. Tables 11 – 34 show the resulting error (confusion) matrices, on the basis of the commonly used (Congalton & Plourde, 2002; Foody, 2002) statistics of overall accuracy, user's accuracy, producer's accuracy and the Kappa coefficient of agreement ($\hat{K}$).

For all classifications, Random Forest had higher overall classification accuracy than the MLC. The highest overall mapping accuracy of the maximum likelihood classification was 77% (with $\hat{K}$ = 0.7644) while for Random Forest it was 91% ($\hat{K}$ = 0.9069). On the basis of producer's accuracy, the built up class which indicated urban land in the subsequent urban sprawl change detection was more accurately delineated using the OBIA Random Forest classifier on all images. Urban land classification using the OBIA Random Forest classifier was best classified on images of Potchefstroom town. This is perhaps due to the uniformity of the vegetation around Potchefstroom, which stands out from the texture of the built up land in comparison with the vegetation around the other towns (Figures 14 – 17). In terms of user's accuracy on the more accurate OBIA Random Forest classification, the largest source of classification confusion between the built up land and the other classes was the bare land class in all towns (Tables 11 – 34). This is explainable by the fact that urban land in the towns in the semi-arid North West Province of South Africa also consists of bare surfaces, as shown in Figure 1.

5.3.1. Accuracy assessments for Mahikeng town land-use/land cover maps

The results of the accuracy assessment for the town of Mahikeng are presented in Table 12, 20 and 28. The results from the thematic map in the study area for the overall classification accuracy in 1999 was 79% with an overall kappa statistic of 0.7846. Barren land was correctly classified resulting into user accuracy of 73%, built up land according to the actual representation as on the ground was classified yielding user accuracy of 78% and thicket, bush-land and scrub forest land (TBS) yielded 75%. Water bodies were correctly classified at 95% thus making it the highest user's accuracy. Classification of the 2013 had an overall accuracy of 80% ($\hat{K}$ = 0.7947), slightly better than the 1999 image. Barren had a user's accuracy of 76%, built up area had user's accuracy of 78% and thicket, bush-land and scrub forest land (TBS) had user's accuracy of 71%. Water bodies had the highest user's accuracy, at 96%.

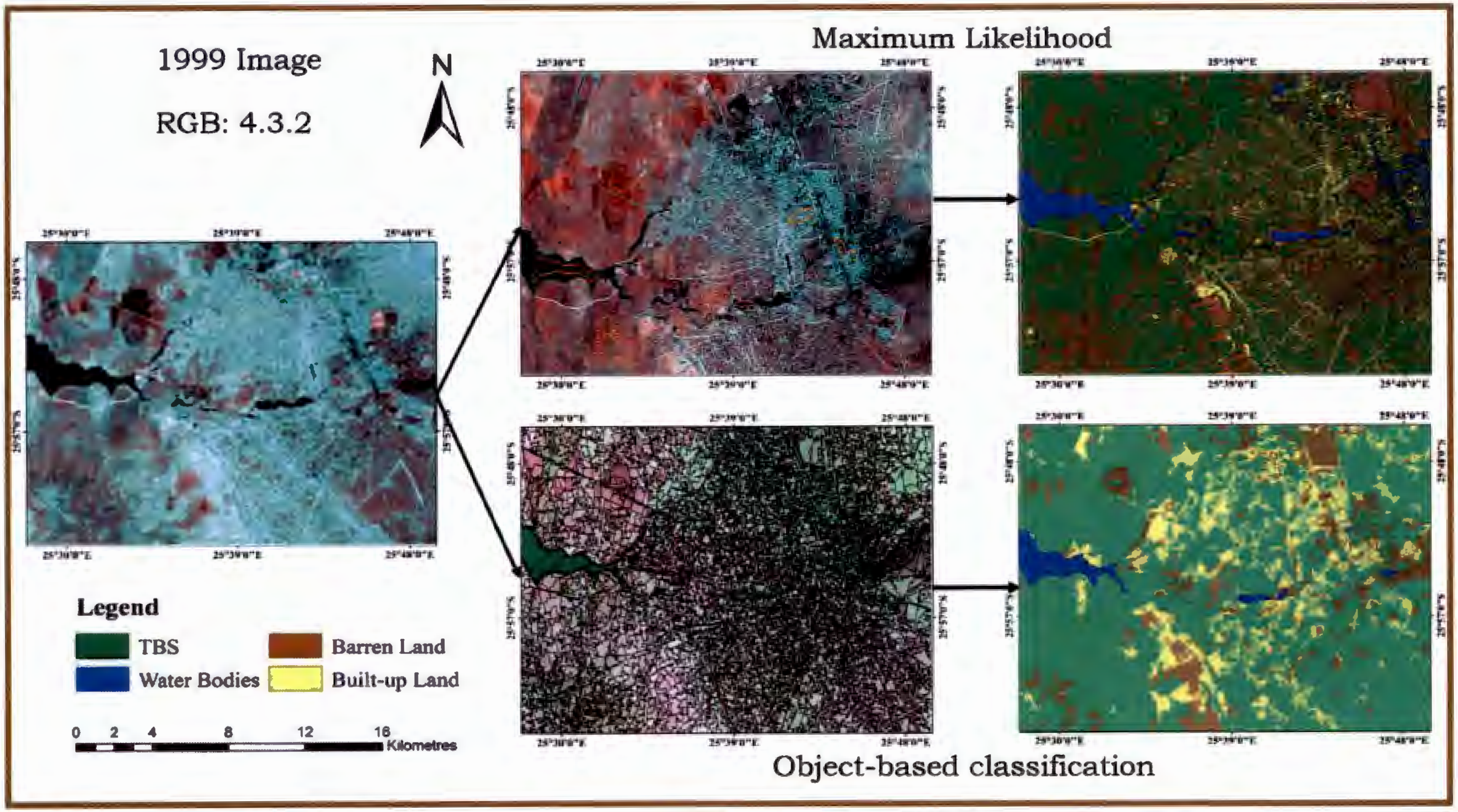

Figure 18: Illustration of the accuracy of Object-based versus Maximum Likelihood classification of urban land.

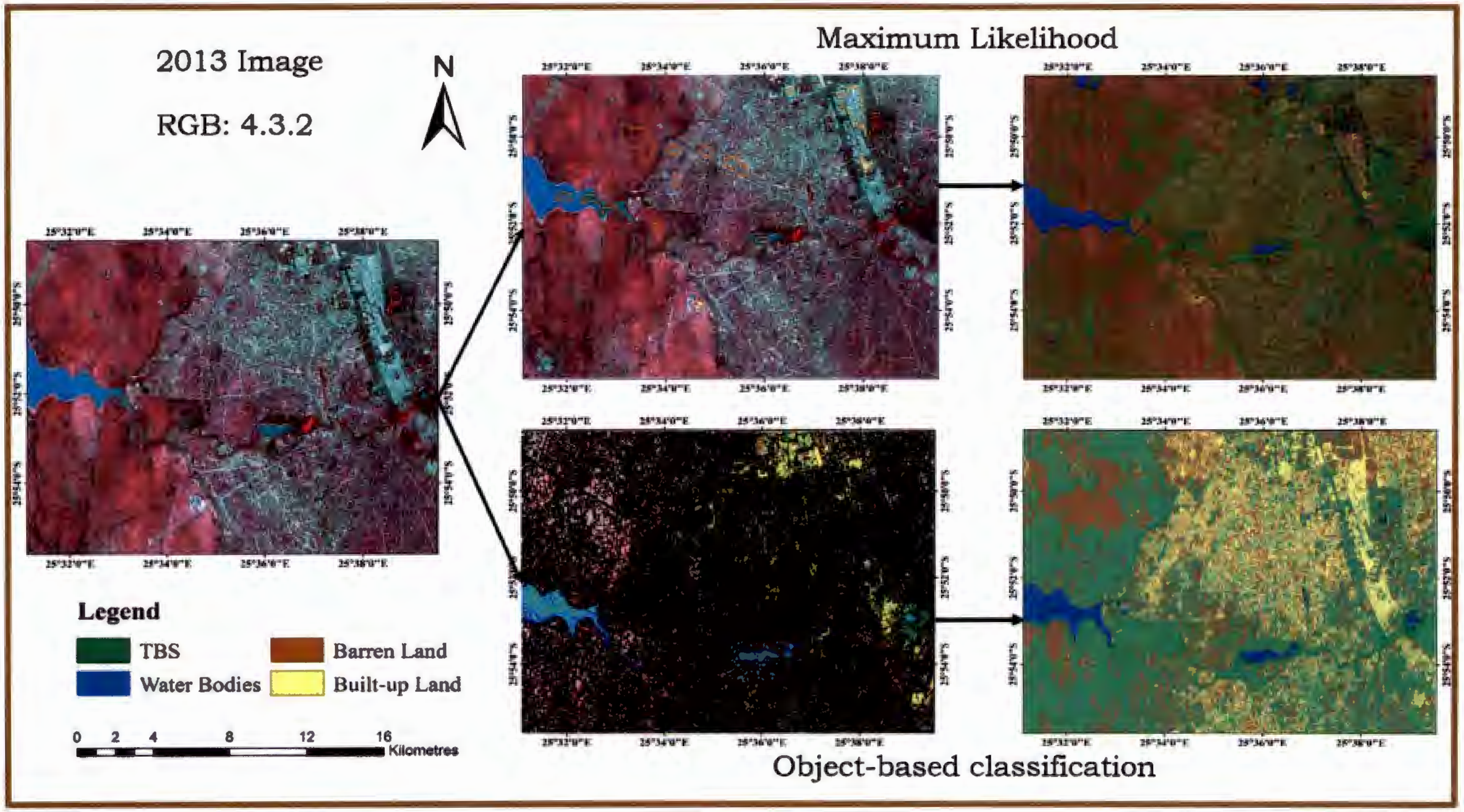

Figure 19: Illustration of the accuracy of Object-based versus Maximum Likelihood classification of urban land.

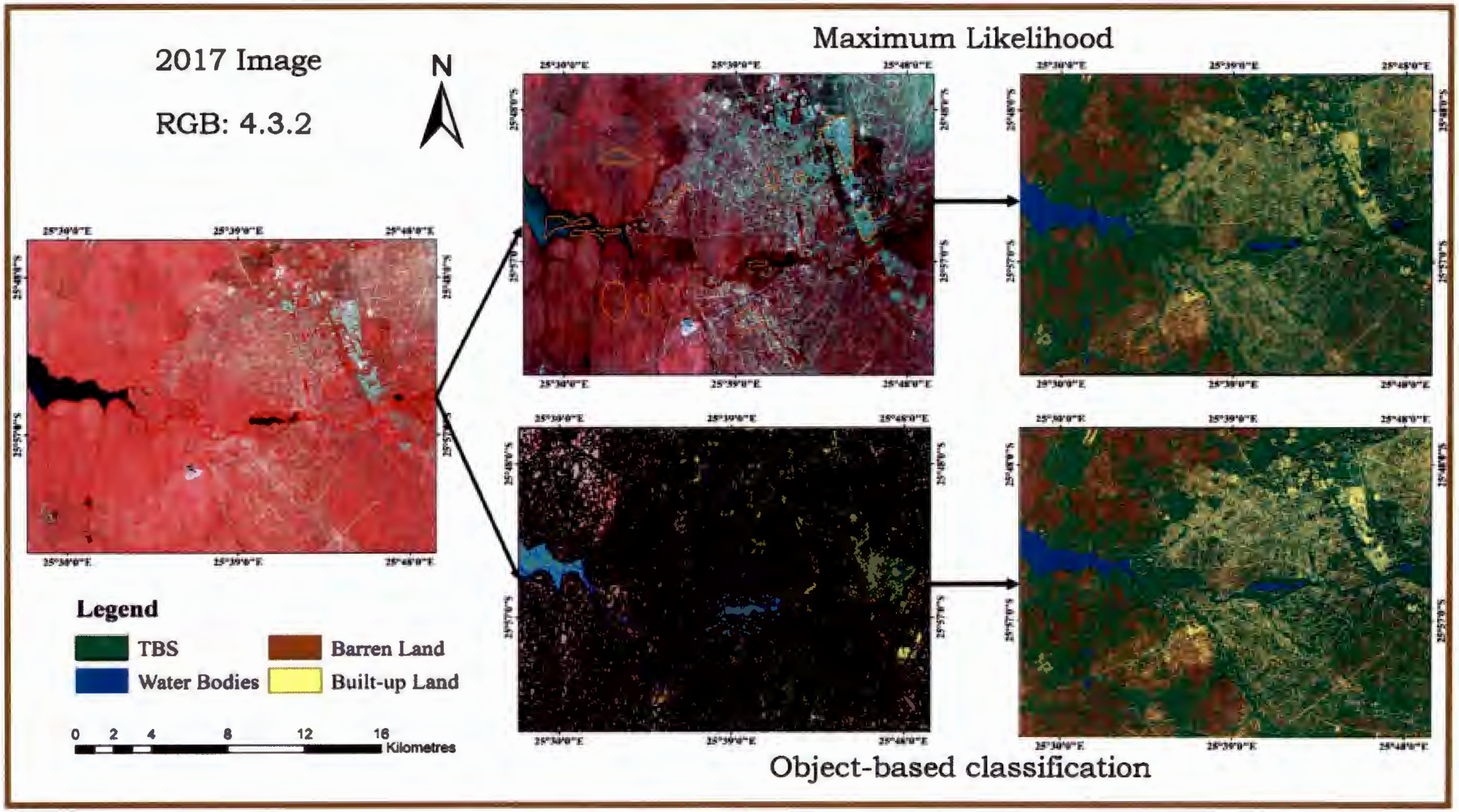

Figure 20: Illustration of the accuracy of Object-based versus Maximum Likelihood classification of urban land.

From the classification of the 2017 image the overall mapping accuracy for the study area was 86% ($\bar{K}$ = 0.8557) with individual classes being mapped at accuracies above 75% (user's), and above 80% (producer's). The built up area had a user's accuracy of 75%, barren land resulted had a user's accuracy of 83%, and TBS land had 87%. For this image, the water bodies had a user's accuracy of 100%, meaning that water had no classification confusion with any of the other classes. Water bodies' user and producer accuracy had the highest values.

5.3.2. Accuracy assessments for Rustenburg town land-use/land cover maps

Tables 14, 22 and 30 show the error matrices of classification of the multitemporal images of Rustenburg. The overall classification accuracy of the 1999 image of Rustenburg was 70% ($\bar{K}$ = 0.6940). The built up area had a user's accuracy of 69%. The concentration of built up structures within the central part of the study area contributed to this accuracy value. Barren land had a user's accuracy of 63%, which could be attributed to the expansion of the town as a result of mining industries. TBS land yielded a user accuracy of 71%, and 77% for the water bodies.

Barren land had a user's accuracy of 81%. This class included areas with human-induced effects that result in exposing soil surface layers and changes in topsoil. It, therefore, comprised areas with active excavation and opencast mines and quarries. However, 4% of the accuracy assessment points for this class were classified as built up area while 5.4% was classified as TBS. These errors were mainly due to the similarity between barren land, rooftops of some built up area as well as built up areas near the mines and quarries. Dry areas of TBS pixels were classified as barren land because the vegetation had less chlorophyll on the date of this image (18 April 1999). In addition, natural fires in Southern African ecosystems are often ignited by lightning although human activity is responsible for the majority of the fires particularly in grasslands and savannah biomes (Silva *et al.*, 2003). The burning season lasts from May to October, with its peak in July. Hence, barren areas (burned areas) could have been confused with TBS areas.

For the 2013 image of Rustenburg the overall classification was 88% ($\bar{K}$ = 0.8761). The user's accuracies for barren land was 81%, 88% for built up area, and 85% for the TBS class, while water had 100%. These results generally mean that the overall classification accuracy is good and that there is an acceptable agreement that exists between the classification and the actual land cover categories.

Table 11: Accuracy assessment for Mahikeng 1999 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	3	1	5	26	65%
Barren Land	2	16	4	2	24	67%
Built up Area	4	4	18	1	27	67%
Water Bodies	2	2	2	17	23	74%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	64%	72%	68%	---	68%

Overall Kappa ($\hat{K}$) = 0.6740

Table 12: Accuracy assessment for Mahikeng 1999 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	21	2	0	5	28	75%
Barren Land	1	19	4	2	26	73%
Built up Area	2	4	21	0	27	78%
Water Bodies	1	0	0	18	19	95%
Column total	25	25	25	25	100	---
Producer's accuracy	84%	76%	84%	72%	---	79%

Overall Kappa ($\hat{K}$) = 0.7846

Table 13: Accuracy assessment for Rustenburg 1999 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	5	4	3	29	59%
Barren Land	2	14	3	2	22	64%
Built up Area	3	4	15	1	23	65%
Water Bodies	2	2	3	19	26	73%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	56%	60%	76%	---	65%

Overall Kappa ($\hat{K}$) = 0.6439

Table 14: Accuracy assessment for Rustenburg 1999 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	2	2	3	24	71%
Barren Land	4	15	4	1	24	63%
Built up Area	2	5	18	1	26	69%
Water Bodies	2	3	1	20	26	77%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	60%	72%	80%	---	70%

Overall Kappa ($\hat{K}$) = 0.6940

Table 15: Accuracy assessment for Klerksdorp 1999 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	4	4	1	26	65%
Barren Land	3	16	3	1	23	70%
Built up Area	3	4	15	3	25	60%
Water Bodies	2	1	3	20	26	77%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	64%	60%	80%	---	68%

Overall Kappa ($\widehat{K}$) = 0.6739

Table 16: Accuracy assessment for Klerksdorp 1999 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	19	3	1	2	25	76%
Barren Land	4	19	5	3	31	61%
Built up Area	2	1	18	1	22	82%
Water Bodies	0	2	1	19	22	86%
Column total	25	25	25	25	100	---
Producer's accuracy	76%	76%	72%	76%	---	75%

Overall Kappa ($\widehat{K}$) = 0.7441

Table 17: Accuracy assessment for Potchefstroom 1999 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	15	3	1	2	21	71%
Barren Land	4	17	2	1	24	71%
Built up Area	3	3	19	1	26	73%
Water Bodies	3	2	3	21	29	72%
Column total	25	25	25	25	100	---
Producer's accuracy	60%	68%	76%	84%	---	72%

Overall Kappa ($\widehat{K}$) = 0.7141

Table 18: Accuracy assessment for Potchefstroom 1999 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	2	0	5	24	71%
Barren Land	5	19	3	0	27	70%
Built up Area	1	4	21	0	26	81%
Water Bodies	2	0	1	20	23	87%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	76%	84%	80%	---	77%

Overall Kappa ($\widehat{K}$) = 0.7644

Table 19: Accuracy assessment for Mahikeng 2013 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	18	4	3	3	28	64%
Barren Land	3	17	4	1	25	68%
Built up Area	2	3	16	1	22	73%
Water Bodies	2	1	2	20	25	80%
Column total	25	25	25	25	100	---
Producer's accuracy	72%	68%	64%	80%	---	71%

Overall Kappa ($\hat{K}$) = 0.7040

Table 20: Accuracy assessment for Mahikeng 2013 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	20	6	1	1	28	71%
Barren Land	2	16	3	0	21	76%
Built up Area	2	3	21	1	27	78%
Water Bodies	1	0	0	23	24	96%
Column total	25	25	25	25	100	---
Producer's accuracy	80%	64%	84%	92%	---	80%

Overall Kappa ($\hat{K}$) = 0.7947

Table 21: Accuracy assessment for Rustenburg 2013 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	19	3	4	2	28	68%
Barren Land	1	16	3	1	21	76%
Built up Area	2	3	17	1	23	74%
Water Bodies	3	3	1	21	28	75%
Column total	25	25	25	25	100	---
Producer's accuracy	76%	64%	68%	84%	---	73%

Overall Kappa ($\hat{K}$) = 0.7241

Table 22: Accuracy assessment for Rustenburg 2013 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	23	3	1	0	27	85%
Barren Land	1	21	3	1	26	81%
Built up Area	1	1	21	1	24	88%
Water Bodies	0	0	0	23	23	100%
Column total	25	25	25	25	100	---
Producer's accuracy	92%	84%	84%	92%	---	88%

Overall Kappa ($\hat{K}$) = 0.8761

Table 23: Accuracy assessment for Klerksdorp 2013 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	16	2	2	5	25	64%
Barren Land	3	18	3	3	27	67%
Built up Area	2	3	17	2	24	71%
Water Bodies	4	2	3	15	24	63%
Column total	25	25	25	25	100	---
Producer's accuracy	64%	72%	68%	60%	---	66%

Overall Kappa ($\hat{K}$) = 0.6540

Table 24: Accuracy assessment for Klerksdorp 2013 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	22	0	0	0	22	100%
Barren Land	0	20	3	5	28	71%
Built up Area	0	5	22	2	29	76%
Water Bodies	3	0	0	18	21	86%
Column total	25	25	25	25	100	---
Producer's accuracy	88%	80%	88%	72%	---	82%

Overall Kappa ($\hat{K}$) = 0.8149

Table 25: Accuracy assessment for Potchefstroom 2013 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	16	3	3	3	25	64%
Barren Land	4	19	2	2	27	70%
Built up Area	3	2	18	1	24	75%
Water Bodies	2	1	2	19	24	79%
Column total	25	25	25	25	100	---
Producer's accuracy	64%	76%	72%	76%	---	72%

Overall Kappa ($\hat{K}$) = 0.7140

Table 26: Accuracy assessment for Potchefstroom 2013 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	19	1	0	0	20	95%
Barren Land	4	21	2	0	27	78%
Built up Area	1	3	23	2	29	79%
Water Bodies	1	0	0	23	24	96%
Column total	25	25	25	25	100	---
Producer's accuracy	76%	84%	92%	92%	---	86%

Overall Kappa ($\hat{K}$) = 0.8557

Table 27: Accuracy assessment for Mahikeng 2017 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	19	4	1	1	25	76%
Barren Land	3	17	3	1	24	71%
Built up Area	2	3	20	2	27	74%
Water Bodies	1	1	1	21	24	88%
Column total	25	25	25	25	100	---
Producer's accuracy	76%	68%	80%	84%	---	77%

Overall Kappa ($\hat{K}$) = 0.7644

Table 28: Accuracy assessment for Mahikeng 2017 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	20	1	2	0	23	87%
Barren Land	2	20	2	0	24	83%
Built up Area	3	4	21	0	28	75%
Water Bodies	0	0	0	25	25	100%
Column total	25	25	25	25	100	---
Producer's accuracy	80%	80%	84%	100%	---	86%

Overall Kappa ($\hat{K}$) = 0.8557

Table 29: Accuracy assessment for Rustenburg 2017 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	18	4	2	1	25	72%
Barren Land	3	17	3	1	24	71%
Built up Area	2	3	19	1	25	76%
Water Bodies	2	1	1	22	26	85%
Column total	25	25	25	25	100	---
Producer's accuracy	72%	68%	76%	88%	---	76%

Overall Kappa ($\hat{K}$) = 0.7543

Table 30: Accuracy assessment for Rustenburg 2017 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	23	0	1	0	24	96%
Barren Land	1	23	4	0	28	82%
Built up Area	1	2	20	0	23	87%
Water Bodies	0	0	0	25	25	100%
Column total	25	25	25	25	100	---
Producer's accuracy	92%	92%	80%	100%	---	91%

Overall Kappa ($\hat{K}$) = 0.9069

Table 31: Accuracy assessment for Klerksdorp 2017 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	17	4	2	1	24	71%
Barren Land	5	18	3	1	27	67%
Built up Area	2	2	19	2	25	76%
Water Bodies	1	1	1	21	24	88%
Column total	25	25	25	25	100	---
Producer's accuracy	68%	72%	76%	84%	---	75%

Overall Kappa ($\hat{K}$) = 0.7442

Table 32: Accuracy assessment for Klerksdorp 2017 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	18	2	1	0	21	86%
Barren Land	4	20	1	0	25	80%
Built up Area	3	3	23	3	32	72%
Water Bodies	0	0	0	22	22	100%
Column total	25	25	25	25	100	---
Producer's accuracy	72%	80%	92%	88%	---	83%

Overall Kappa ($\hat{K}$) = 0.8251

Table 33: Accuracy assessment for Potchefstroom 2017 MLC classified.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	19	4	2	1	26	73%
Barren Land	3	16	4	1	24	67%
Built up Area	2	3	17	3	25	68%
Water Bodies	1	3	2	20	25	80%
Column total	25	25	25	25	100	---
Producer's accuracy	76%	64%	68%	80%	---	72%

Overall Kappa ($\hat{K}$) = 0.7140

Table 34: Accuracy assessment for Potchefstroom 2017 OBIA classified image.

Classified Data	TBS	Barren Land	Built up Area	Water Bodies	Row total	User's Accuracy
TBS	22	0	1	0	23	96%
Barren Land	0	23	3	0	26	88%
Built up Area	0	2	21	2	25	84%
Water Bodies	3	0	0	23	26	88%
Column total	25	25	25	25	100	---
Producer's accuracy	88%	92%	84%	92%	---	89%

Overall Kappa ($\hat{K}$) = 0.8864

For the 2017 image of Rustenburg the overall classification was 91% ($\hat{K}$ = 0.9069). The highest user's accuracies were for the classes TBS, at 96%, and water bodies at 100%. The built up area and barren land yielded user's accuracies of 87% and 82%, respectively.

5.3.3. Accuracy assessments for Klerksdorp town land-use/land cover maps

The confusion matrices of classification of the images of Klerksdorp are shown in Tables 16, 24 and 32. The overall accuracy of the 1999 thematic map was 75% ($\hat{K}$ = 0.7441). Barren land was had a user's accuracy of 61%, built up area had 82% user's accuracy, TBS had 76%, and water bodies 86%. However, some of the built up areas were misclassified as TBS (8%) and barren land (16%). This is mainly because the roofing material used for buildings in this area has an almost similar spectral reflectance of TBS and barren land. The tin roofing (especially for low cost government-built RDP houses) and wall building materials exhibit similar reflectance with opencast mines and quarries and barren land.

For the 2013 image the overall classification was 82% ($\hat{K}$ = 0.8149). Barren land had a user's accuracy of 71%, and 76% for the built up area class. At user's accuracy of 100%, TBS was the most accurately classified land cover was the TBS class, due to its contiguous nature that exhibited a unique spectral signature. Water bodies had user accuracy of 86%. This could be attributed to the high growth of thickets, bushes and shrubs along the water bodies. The overall classification accuracy of the 2017 thematic map of the study area was 83% ($\hat{K}$ = 0.8251). Barren land had a user's accuracy of 80%, and built up area had 72%. Water bodies were classified with a user's accuracy of 100%, and the TBS class had a user's accuracy of 86%.

5.3.4. Accuracy assessments for Potchefstroom town land-use/land cover maps

The error matrices of classification of the images of Potchefstroom are shown in Tables 18, 26 and 34. The overall classification of the 1999 thematic map was 77% ($\hat{K}$ = 0.7644). The Barren land had a user's accuracy of 70%, while classification of the built up area yielded a user's accuracy of 81%. The classification of the TBS class resulted in a user's accuracy of 71%, and it was 87% for water bodies.

For the 2013 image the overall classification accuracy was 86% ($\hat{K}$ = 0.8557). Barren land had user's accuracy of 78%, whereas the built up area had 79%. The most carefully classified land cover was the TBS class, which had user's accuracy of 95%. This high TBS user's accuracy could be because of its contiguous nature that exhibited a unique spectral signature. The water body class, on the other hand, had a user's accuracy of 96%.

For the 2017 image of Potchefstroom the overall accuracy was 89% ($\hat{K} = 0.8864$). The barren land class had a user's accuracy of 88%, while the built up area had 84%. The water bodies class was classified with a user's accuracy of 88%, while the TBS class produced a user's accuracy of 96%, which was the highest out of all the four classes.

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5.4. Optimised methodology for monitoring urban sprawl in towns in the North West Province

From the results in Sections 5.2 – 5.4, the nature of the optimal methodology for monitoring urban sprawl in the towns of the North West Province of South Africa can be derived. This section summarises the methodology and its optimal characteristics, on the basis of the metrics of the features that characterise urban land in the province.

5.4.1. Methodology

Figure 21 summarises the methodology that was developed. The methodology is a process flow chain with flexibility of inputs at each of the stages. The first stage is to select the imagery to use. At this stage high spatial resolution is fundamental, due to the small nature of the urban metrics that define urban land (e.g. the shacks (Figure 1), gravel roads, houses, etc.). There is flexibility of choice of imagery at this stage. In this study SPOT imagery was used, but there is scope for use of imagery with higher spatial resolution depending on the timescale of the analysis of urban sprawl in relation to the program history of the imagery.

The use of the 10 m spatial resolution scale in this study meant that small features that define urban land were not adequately discriminated on the imagery. Examples of these are roads that are only about 5 m wide and the shacks that were only about 2 m wide. However, the emphasis on the use of texture during image classification enabled urban land to be mapped accurately even at the low spatial resolution of 10 m, since such land was texturally different from the surrounding vegetation without built up surfaces.

Once the appropriate imagery has been selected the next stage is radiometric pre-processing. In this stage of the methodology it is essential to reduce the differences in radiometric resolution if the selected imagery is from multiple sensors. In this study the imagery used was acquired by three different SPOT sensors: HRV, HRVIR and NAOMI. Given inherent differences in radiometric resolution the image data were converted to at-sensor radiance. The next step is the geometric pre-processing. In order to enable accurate change detection, it is essential to work at the same spatial resolution and map projection for the multitemporal images. In this study the 10m resolution and the UTM projection were used. The pixel size selected has to be as high as allowed by the image dataset. Pan-sharpening using a technique that preserves the spectral integrity of the data can also be used to enhance the spatial resolution. Then the images must be registered to the same map frame using image-to-image registration. One of the dates on the multitemporal image dates needs to be selected as the reference image. The spatial extent of the towns concerned can then be extracted by subsetting.

Object based image analysis to generate a thematic layer of the urban areas is the next stage in the methodology. In this study, the multiresolution segmentation algorithm was found to be quite accurate as the preliminary step to the classification of the resulting segmented image. In order to extract the urban land, the fundamental specification for multiresolution segmentation was to emphasise image texture ('shape') over the spectral characteristics ('colour'). This enabled urban land with small metrics such as shacks and gravel roads to be accurately delineated, in comparison with the use of a parametric classifier like the Maximum Likelihood Classifier. The scale parameter in the multiresolution segmentation specification was set to be high, at 160. After generating the segments that sufficiently delineated urban features the next stage is to use a non-parametric classifier. In this study the decision tree-based Random Forest classifier was found to be adequate. There is scope to use newer object-based nonparametric classifiers in future applications of the methodology.

Once satisfactory accuracy from the resulting classification is achieved, particularly amounting to overall accuracy higher than 80% and user's accuracy for the urban land class higher than 80% as well, the next step in the methodology is to implement change detection to determine the extent of urban sprawl. Boolean GIS overlay analysis is recommended for the detection of urban sprawl. For this, numeric codes that yield unique numbers that are indicative of change or no change in urban land need to be devised. This is a particularly important stage and is flexible depending on the number of dates of imagery. In this study three dates were used, and the numeric coding shown in Table 10 was designed and implemented.

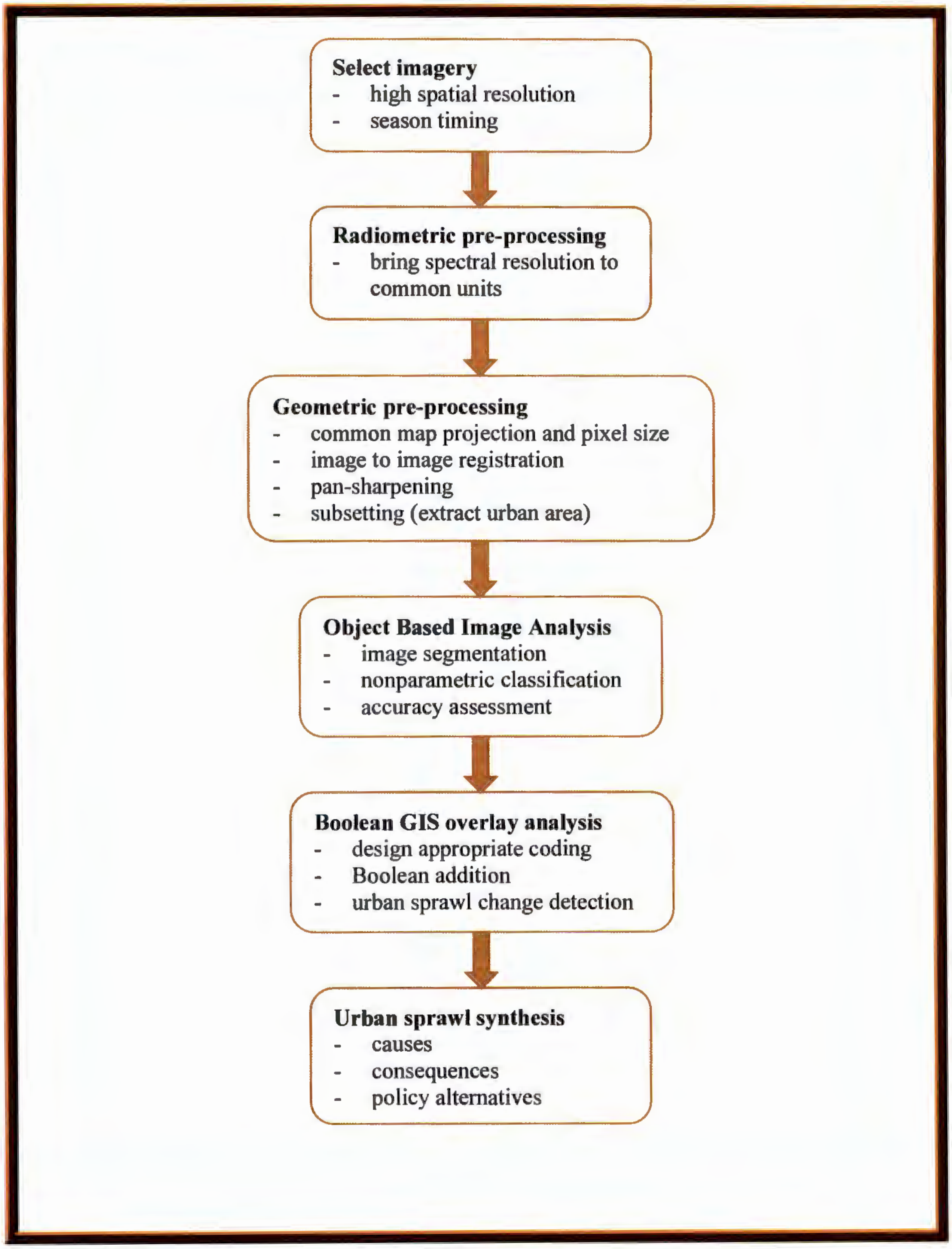

Figure 21: Diagrammatic summary of the Remote Sensing and GIS methodology developed for monitoring urban sprawl in the major towns of the North West Province of South Africa.

Once the urban sprawl has been quantified and mapped, the results need to be analysed for meaning. The location of the sprawl can be identified by the municipal authorities. The causes and consequences (social, economic, environmental) then need to be assessed. This makes the methodology developed in this study useful for use by the authorities in the North West Province of South Africa, as well as any other province or country in which the urban metrics are similar. The methodology has scope for application in town and country planning.

5.4.2. Optimisation

The methods procedures that form the methodology that was developed for monitoring urban sprawl, as summarised in Figure 21, are commonly used in Remote Sensing and GIS. However, they have been optimised in this study. The following are the aspects which are peculiar to this study and, therefore, which constitute optimisation:

1) ***Choice of image classification algorithm***

This study compared the performance of the widely used and accurate parametric of the Maximum Likelihood Classifier approach to mapping urban land. In comparison with the newer object based Random Forest classifier, which is nonparametric, it was established in this study that nonparametric approaches would be better in mapping the urban metrics of the towns of the North West Province of South Africa. The towns in the study area have the common phenomenon of urban areas being characterised by the combination of bare soil, informal settlements with the peculiar buildings called Shacks, gravel roads, as well as tar roads and the formal buildings of suburbs and the central business district. In these circumstances the parametric MLC was less accurate at delineating the urban land, resulting in a salt-and-pepper mapping of the urban land. The nonparametric approach based on image objects generated homogenous blocks of pixels in the urban land, resulting in higher classification accuracy.

2) ***Change detection using Boolean GIS overlay analysis***

GIS overlay analysis by Boolean addition proved to be particularly useful in detecting change or no change in urban sprawl. This was because it enabled the isolation of the urban land, per given classified image, from the other classes. With the urban land extracted from the other classes the amount and location of change in its extent over the years could accurately be quantified and mapped. Therefore, as long as the algorithm used for image classification produces high accuracy, Boolean GIS overlay analysis by addition is a useful method for quantifying and mapping urban sprawl.

Chapter 6

URBAN GROWTH CHANGE DETECTION USING OPTIMISED REMOTE SENSING AND GIS METHODOLOGY

6.1. Introduction

This chapter addresses Objective 3 of the study. The optimal methodology for monitoring urban sprawl in the four towns studied was selected and implemented. Therefore, in this chapter an interpretation of the findings based on the analysis and results in the context of the third objective of the study are presented. The essence of the analysis is to assess the extent of urban growth in the study areas.

Change detection also known as Digital Change Detection is one of the processes of identifying or highlighting significant differences in the state of an object or phenomenon by observing it at different times (Pathak, 2014; Singh, 1989; Sudhira *et al.*, 2004). The process encompasses the quantification of multi-date imagery to derive changes over two times (Coppin *et al.*, 2004). A wide range of approaches to change detection analysis have been reported (Hamandawana *et al.*, 2005; Shalaby & Tateishi, 2007). For this study, post-classification comparisons were applied to assess the amount of change in urban extents in the study areas. Classified image pairs of two different time periods were compared using cross-tabulation in order to determine qualitative and quantitative aspects of the changes for the periods from 1999 to 2017. A change matrix (Weng, 2001), as well as change maps, was produced with the help of ERDAS Imagine software. Quantitative areal data of the overall land use/cover change as well as gains and losses in each town between 1999 and 2017 were then compiled.

6.2. Change detection using optimal methodology for urban sprawl monitoring

Results from post-classification analysis are presented using a series of change maps for visualisation and statistical tables to provide quantitative measures of change. The change maps use the colour *from-to* indices of change defined in the tables. A pixel-by-pixel comparison procedure was done for the study year images through post-classification comparison. The emphasis in this study is on built up area in terms of location and direction of change. Measuring the extent of the built up area helps in analysing population density and urban growth, which provides some evidence that sprawl, is taking place as a pattern of development (Frenkel & Ashkenazi, 2008; Jiang *et al.*, 2007).

6.2.1. Change detection in Mahikeng town

Table 35 shows that there was a general increase of 2% in the built up area between 1999 and 2013, and then 2013 and 2017. TBS land cover decreased by 6% between 1999 and 2013 while between 2013 and 2017 there was a minor decrease of 7%. Since the declaration of Mahikeng as the capital city of the North West Province and the government's decision to create a political and economically fast-growing city, Mahikeng's built up area has cumulatively increased by 5%. This is a consequence of significant investment in real estate, large-scale retailing and public institutions. Between 1999 and 2013 barren land cover had a 2% increase as compared to the 2013 and 2017 barren land cover, which had 3% increment. This could be attributed to the shift away from farming towards a polycentric model, which attracted many people from farming to white-collar jobs in Mahikeng town. The extent of water bodies remained below 0.9% over the years though there are slight differences in the total hectare between these periods.

Table 35: Trend changes in Mahikeng land cover categories.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-3 326.49	-5.9	-3 883.32	-6.9
Barren Land	+1 100.65	+2.0	+1 856.57	+3.3
Built up Area	+1 011.84	+1.8	+1 526.75	+2.7
Water Bodies	+1 214	+2.2	+500	+0.9

Each year change takes place; hence, an annual rate of change had to be calculated from the trend change analysis using percentage change between two numbers on the basis that the outcome is considered either a reduction or an increase in rate. Between 1999 to 2013 and 2013 to 2017 for TBS the annual percentage change was -0.4 and -2 respectively. This result implies that the TBS land cover class decreased at a rate of 2% per annum. The barren land had an annual rate of change of 0.1% between 1999 and 2013 whilst the rate of increase of barren land accelerated by 0.8% in the 2013 and 2017 period. Built up area increased over the 14-year period at the rate of 0.1% between 1999 and 2013, which could be associated with migration pull into the urban area of Mahikeng. Consequently, an important driver of change to the increase of barren and built up area cover categories could be attributed to the simultaneous decrease of TBS land.

Table 36: Annual rate of change in land cover categories for Mahikeng.

Land cover categories	**1999 – 2013**		**2013 – 2017**	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-237.61	-0.4	-970.83	-1.7
Barren Land	+78.62	+0.1	+464.14	+0.8
Built up Area	+72.27	+0.1	+381.69	+0.7
Water Bodies	+86.71	+0.2	+125	+0.2

The quantitative evaluation of the space-time transformations of land use is a fundamental stage in understanding the dynamics of the processes that lead to urban landscape change. Between 1999 and 2017, Mahikeng town experienced transformation in its land cover classes as shown in Table 37. An analysis of temporal changes can be utilised to reveal trends in land cover change throughout the study period, while analysis of changes in land cover types can identify specific transitions in each class. Finally, the analysis of changes in land cover by location can be used to show the positions of the most significant changes in land cover. The total area in the four towns with a change of land cover is presented for each year in Tables 39 to 42. The total area of changed is different in years and increases with time. Changes in land cover can result in gains in certain classes, losses in certain classes or a combination of both.

TBS had a net loss of 7 943.03 ha (-14.2%) while barren land had a net gain of 3 342.74 ha. The transition of land use between 1999 and 2017 was mainly from TBS and barren land to built-up area. Figure 22 shows the overall changes in Mahikeng town between 1999 and 2017. Between 1999 and 2013 there appears to be an equal amount of change in the land use and land cover classes, with a few unchanged areas. In comparison, between 2013 and 2017 most of the land covers increased over the 4-year period, with fewer patches of decreased land cover.

Table 37: Total area net change detection from 1999 to 2017 for Mahikeng.

	Total area in land class at 1999 (ha)	The total area changed to per land class (ha)	Net gain/Loss (ha)	Net change (%)
TBS	+32189.21	+24246.18	-7943.03	-14.2
Barren Land	+22189.22	+25531.96	+3342.74	+6.0
Built up Area	+1089.75	+3937.75	+2848.00	+5.1
Water Bodies	+637.49	+2389.78	+1752.29	+3.1
Total area	+56105.67	+56105.67	------	------

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Burchfield *et al.* (2006), stated that cities would sprawl more if they were built for the dependence on the use of private vehicles rather than around public transport and were not surrounded by high mountains. This scenario could be related to Mahikeng town which is characterised by a flat and low lying terrain and is thus more likely to expand in every direction depending on migration and other factors which will be in play.

Table 38: Area changed into built-up from 1999 to 2017 for Mahikeng.

Land cover categories	Area changed to built-up land (ha)			% change per class		
	1999	**2013**	**2017**	**1999**	**2013**	**2017**
TBS	445.1	288.3	620.8	3	2	4
Barren Land	160.3	378.5	418.4	2	4	3
Water Bodies	56	20	14	3	2	0
Total area	661.4	686.8	1053.2	8	8	7

6.2.2. Change detection in Rustenburg town

Platinum mining is one of the driving forces, spurring urbanisation in Rustenburg town. Land cover changes reflect the dynamics observed in the socio-economic condition of a given area. Similarly, changes in the socio-economic situation trigger land cover changes through their influence on land management techniques used and other various aspects of environmental policy. Table 43 shows the different rate of change in land cover categories between 1999 and 2017.

Table 39: Trend changes in Rustenburg land cover categories.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-9 084.19	-19.6	+2 195.14	+4.7
Barren Land	+7 679.28	+16.6	-1 217.34	-2.6
Built up Area	+1 130.38	+2.4	+607.73	+1.3
Water Body	+274.53	+0.6	+370.07	+0.8

In Rustenburg, there was a general increase of 2.4% in the build-up area between 1999 and 2013 and between 2013 and 2017; the town had a 1.3% growth in built up land over a period of 4 years (Table 42). Between 1999 and 2013 water bodies had an increase of 1% while between 2013 and 2017 water bodies retained 1% in the land cover category; this could be attributed to the change in the climatic condition (318.4 mm and 255.2 mm rainfall distribution between these years) hence many water bodies have reduced in volume. The barren land cover between 2013 and 2017 had a 3% reduction while the TBS land cover increased by 5%. However, 1999 and 2013 TBS land cover had 20% reduction giving rise to other land cover classes.

Table 40: Total land cover change over time in Mahikeng

	1999 (ha)	%	2013 (ha)	%	2017 (ha)	%
TBS	32189.21	57.37	28862.72	51.44	24979.4	44.52
Barren	22189.22	39.55	23289.87	41.51	25146.44	44.82
Built	1089.75	1.94	2101.59	3.75	3628.34	6.47
Water	637.49	1.14	1851.49	3.30	2351.49	4.19
Total	56105.67		56105.67		56105.67	

Table 41: Total land cover change over time in Rustenburg

	1999 (ha)	%	2013 (ha)	%	2017 (ha)	%
TBS	29431.31	63.44	20347.12	43.86	18151.98	39.13
Barren	15268.18	32.91	22947.46	49.46	24164.8	52.09
Built	1154.26	2.49	2284.64	4.92	2892.37	6.23
Water	538.41	1.16	812.94	1.75	1183.01	2.55
Total	46392.16		46392.16		46392.16	

Table 42: Total land cover change over time in Klerksdorp

	1999 (ha)	%	2013 (ha)	%	2017 (ha)	%
TBS	27394.69	62.18	25674.13	58.28	18236.84	41.40
Barren	14465	32.83	15709.94	35.66	22258.92	50.53
Built	1495.2	3.39	1851.23	4.20	2539.54	5.76
Water	700	1.59	819.59	1.86	1019.59	2.31
Total	44054.89		44054.89		44054.89	

Table 43: Total land cover change over time in Potchefstroom

	1999 (ha)	%	2013 (ha)	%	2017 (ha)	%
TBS	45124.66	78.91	33508.03	58.60	23179.22	40.54
Barren	9378.87	16.40	19024.47	33.27	26584.63	46.49
Built	1509.5	2.64	2492.48	4.36	4907.87	8.58
Water	1169.05	2.04	2157.1	3.77	2510.36	4.39
Total	57182.08		57182.08		57182.08	

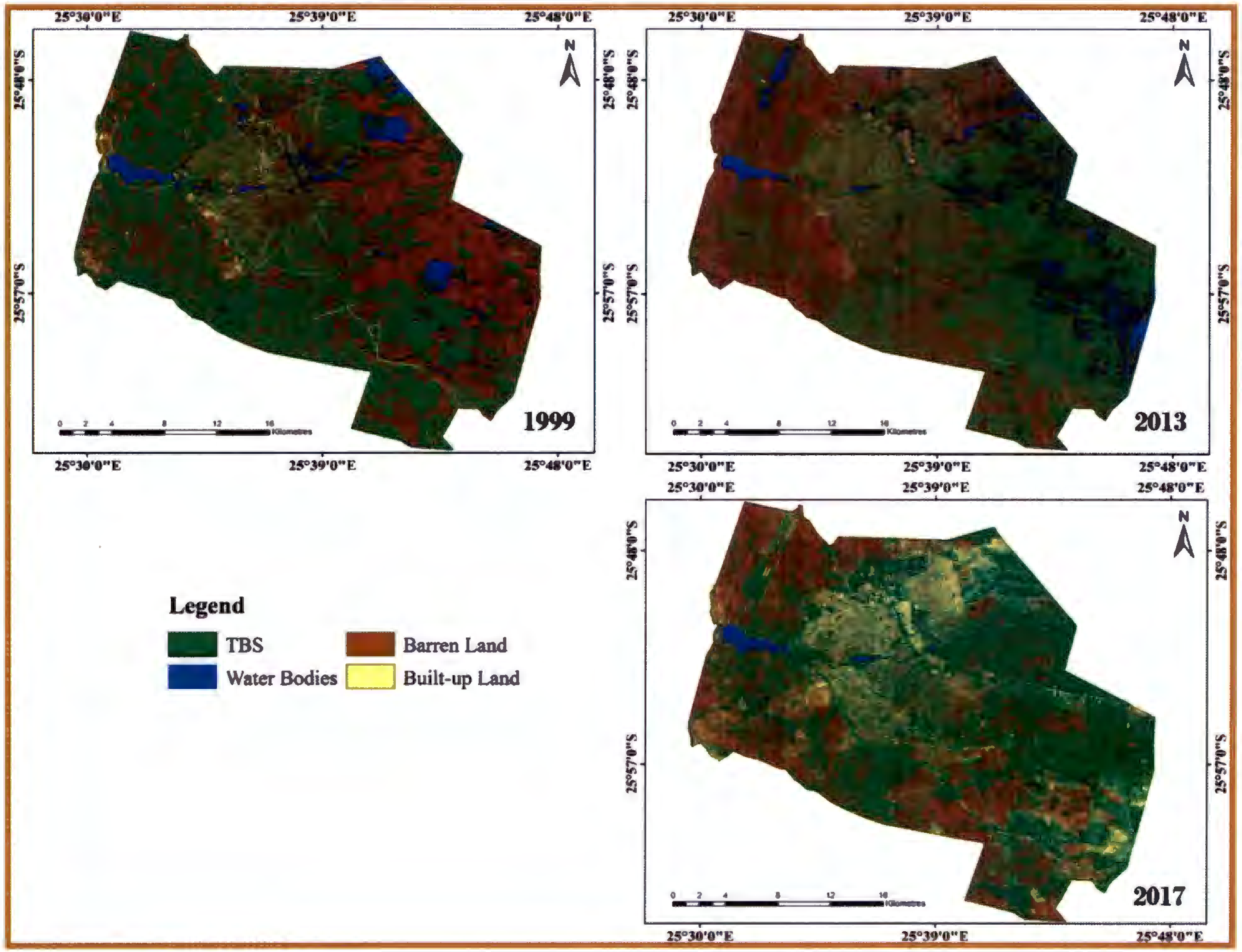

Figure 22: Land use land cover map highlighting the changes in Mahikeng, 1999-2017.

Between 1999 and 2013 barren land had an annual rate of change of 1% and the rate of increase of barren land accelerated by 1% in the 2013 and 2017 period. This could be attributed to the 1% increase in the TBS class. The annual percentages of change in the TBS class between 1999 to 2013 and 2013 to 2017 were -1.4 and -1.2, respectively. A plausible explanation could be that on the opencast mines and quarries, which were no longer in operation, woody vegetation began to sprout in those areas. Over the 18-year period, the built-up area increased at the rate of 0.5% between 1999 and 2017. The increase could be associated with migration pull into the platinum town of Rustenburg.

Table 44: Annual rate of change in land cover categories for Rustenburg.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-648.87	-1.4	-548.79	-1.2
Barren Area	+548.52	+1.2	+304.34	+0.7
Built up Area	+80.74	+0.2	+151.93	+0.3
Water Body	+19.61	+0.0	+92.52	+0.2

Table 45: Total area net change detection from 1999 to 2017 for Rustenburg.

	Total area in land class at 1999 (ha)	The total area changed to per land class (ha)	Net gain/Loss (ha)	Net change (%)
TBS	+29431.31	+18252.07	-11179.24	-24.1
Barren Land	+15268.18	+23920.62	+8652.44	+18.7
Built up Area	+1154.26	+2963.56	+1809.30	+3.9
Water Body	+538.41	+1255.92	+717.51	+1.5
Total area	+46392.16	+46392.16	------	------

Tables 44 and 45 illustrate land cover change detected between 1999 and 2017 in Rustenburg. The TBS class had a net loss of 11 179.2 ha (-24%) while the other land cover classes (barren land and water bodies) had a net gain of 8 652.44 ha and 717.51 ha, respectively.

On the other hand, built up area had a net gain of 1 809.30 ha (4%). The gain could be attributed to immigration because of mining and better job opportunities.

Figure 23 depicts the pattern of land-cover change over the three dates in Rustenburg. In all four classes, the area under TBS land and the barren category decreased followed by slight increases on the three image dates. The decrease in the TBS is an indication that the open TBS areas of the landscape are regenerating to closed TBS lands in some parts, and degrading to barren and built up area in others. Between 2013 and 2017, the water bodies increased due to the expansion of dams and man-made water features. Looking at an image of a single year the percentage of an area undergoing change does not appear to be very large, but a look at all the images from different time periods showed that the change trajectories were characteristic of a landscape that was highly dynamic.

Table 46: Area changed into built-up from 1999 to 2017 for Rustenburg.

Land cover categories	Area changed to built-up land (ha)			% change per class		
	1999	**2013**	**2017**	**1999**	**2013**	**2017**
TBS	430.4	281.9	522.6	3	2	4
Barren Land	195.1	361.8	485.3	2	3	4
Water Bodies	20.1	0	0	3	0	0
Total area	645.6	643.7	1007.9	8	5	8

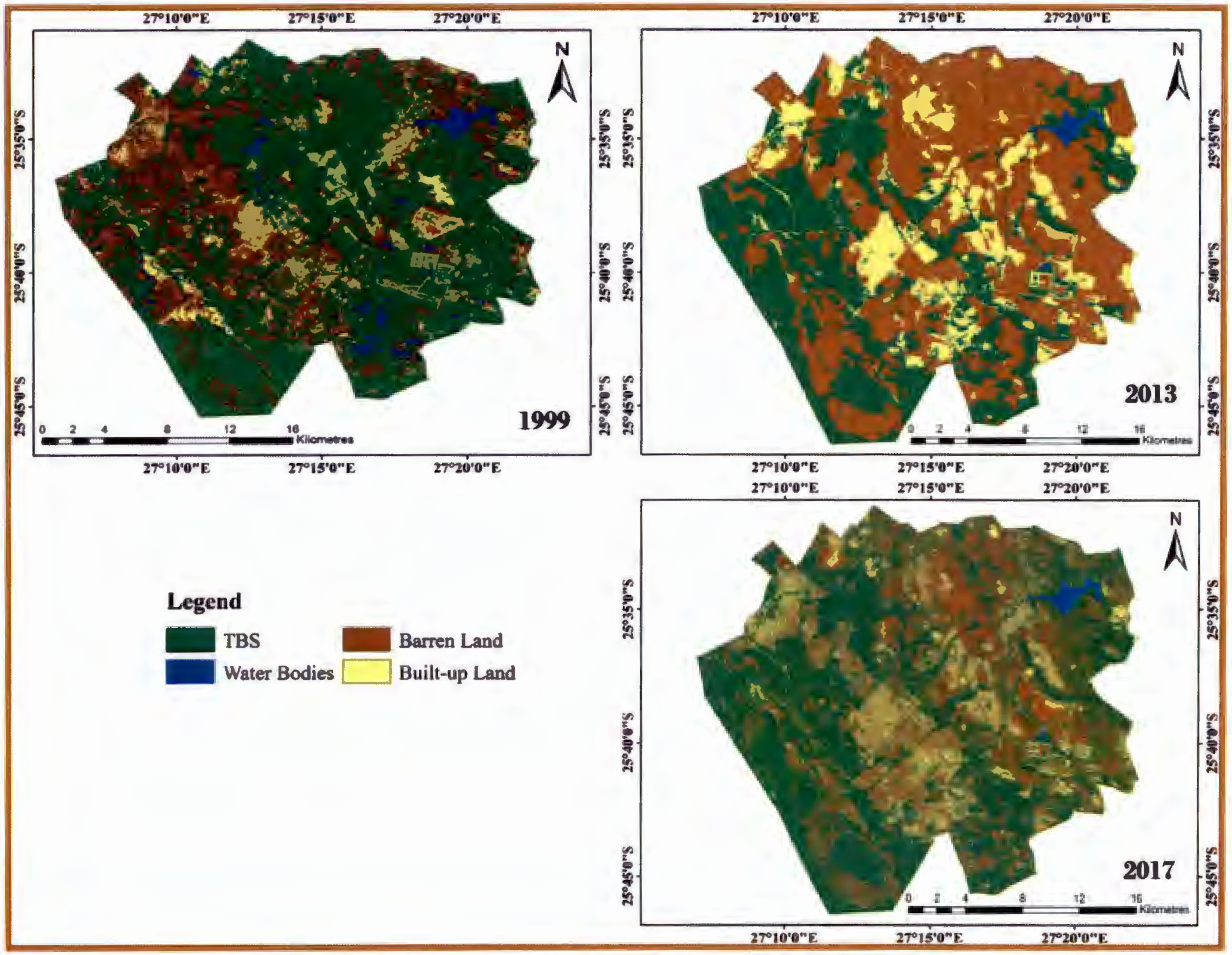

Figure 23: Land use land cover map highlighting the change in Rustenburg, 1999 - 2017.

6.2.3. Change detection in Klerksdorp town

Table 47 shows the different rates of change in land cover categories in Klerksdorp between 1999 and 2017. There was a general increase of 1% in the built up area between 1999 and 2013. This could be attributed to the shift toward white-collar jobs and the pull of many people from farming to industries. Furthermore, TBS land cover decreased by 4% between 1999 and 2013, and 17% in the period 2013 and 2017. The town experienced a 3% and a 15% increase in barren land cover between 1999 and 2013 and between 2013 and 2017, respectively. By 2017, water bodies showed a slight change even though there was a large change in the area extent (Figure 24).

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Table 47: Trend changes in Klerksdorp land cover categories.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-1 720.56	-3.9	-7 437.29	-16.9
Barren Land	+1 244.94	+2.8	+6 548.98	+14.9
Built up Area	+356.03	+0.8	+688.31	+1.6
Water Body	+119.59	+0.3	+200	+0.5

Table 48: Annual rate of change in land cover categories for Klerksdorp.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-122.90	-0.3	-1 859.32	-4.2
Barren Land	+88.92	+0.2	+1 637.25	+3.7
Built up Area	+25.43	+0.1	+172.08	+0.4
Water Body	+8.54	+0	+50	+0.1

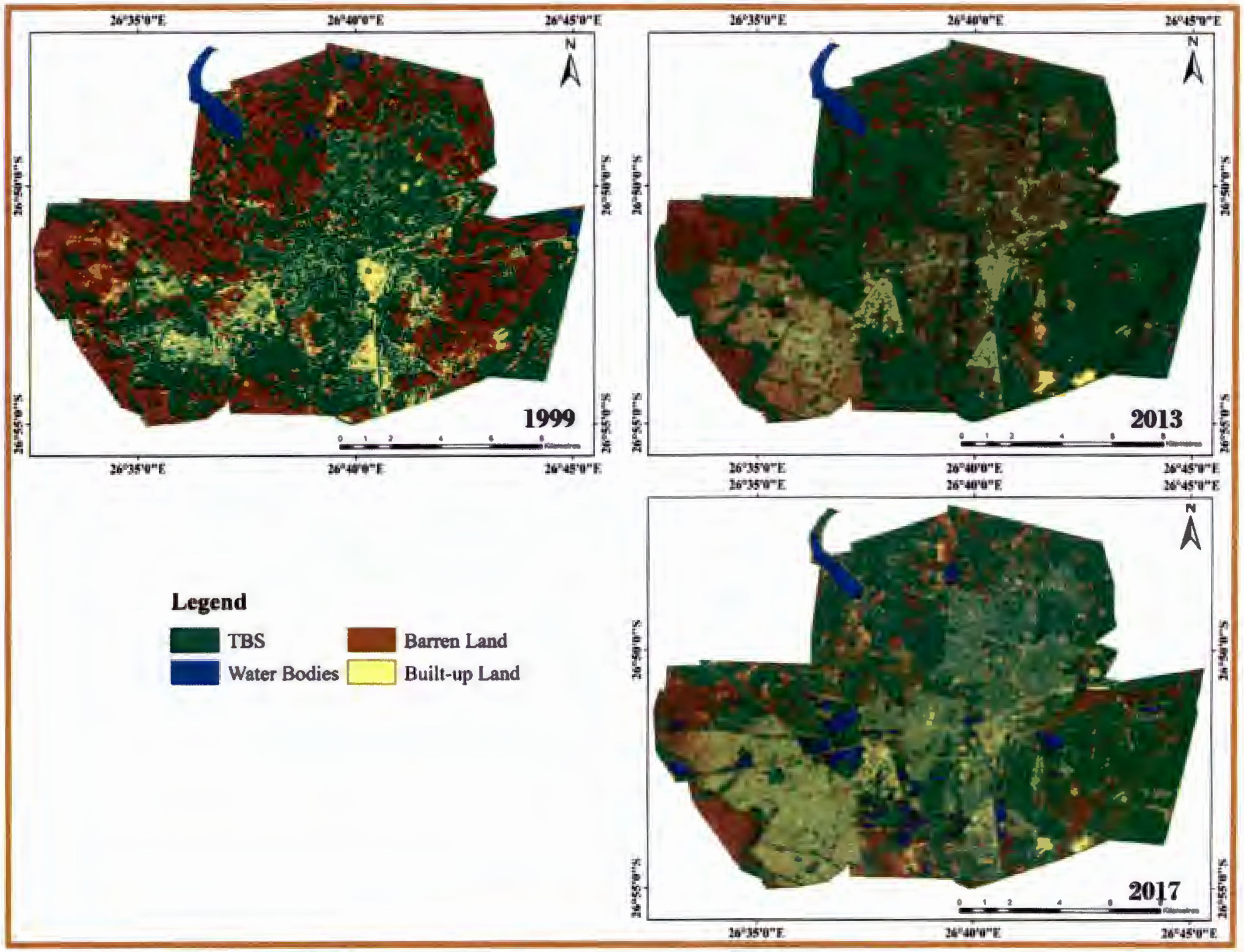

Figure 24: Land use land cover map highlighting the change in Klerksdorp, 1999 - 2017.

TBS percentage changes from 1999 to 2013 and then 2013 to 2017 were -0.3 and 4.2, respectively. Over the 18-year period, built up area increased by 0.5% between 1999 and 2017, which could be associated with migration pull into Klerksdorp town. Table 48 shows that water bodies did not change between 1999 and 2013, but changed by 0.1% from 2013 to 2017. The barren land had a change of 0.2% between 1999 and 2013 and 4% from 2013 to 2017.

Table 49: Total area net change detection from 1999 to 2017 for Klerksdorp.

	Total area in land class at 1999 (Ha)	The total area changed to per land class (Ha)	Net gain/Loss (Ha)	Net change (%)
TBS	+27394.69	+16500.41	-10894.28	-24.7
Barren Land	+14465	+23807.24	+9342.24	+21.2
Built up Area	+1495.2	+2686.19	+1190.99	+2.7
Water Body	+700	+1061.05	+361.05	+0.8
Total area	+44054.89	+44054.89	------	------

All the classes (TBS, barren land, built up area and water bodies) showed transition between 1999 and 2013 (Table 49). TBS had a net loss of 10 894.28 ha (-24.7%) while the other land cover classes (built up area, barren land and water bodies) had net gains of 1 190.99 ha, 9 342.24 ha and 361.05 ha, respectively of all the four classes, areas under the classes of TBS and barren land, as well as water bodies, increased considerably due to the expansion of the city. In many cases, urban growth is being referred to as an uncontrolled suburban development that increases traffic problems, depletes local resources and destroys open spaces (Peiser, 2001).

Table 50: Area changed into built-up from 1999 to 2017 for Klerksdorp.

Land cover categories	Area changed to built-up land (ha)			% change per class		
	1999	**2013**	**2017**	**1999**	**2013**	**2017**
TBS	289.6	376.0	582.6	3	2	4
Barren Land	109.2	467.3	673.8	2	4	5
Water Bodies	10	6	2	2	1	0
Total area	408.8	849.3	1258.4	7	7	9

6.2.4. Change detection in Potchefstroom town

Table 51 shows the different rates of change in land cover categories between 1999 and 2017 in Potchefstroom. The town experienced increases of 17% and 13% in barren land between 1999 and 2013 and between 2013 and 2017, respectively. By 2017, water bodies showed slight percentage change of 1% even though there was a large change between 1999 and 2013, amounting to 2%. There was a general increase of 2% in built up area between 1999 and 2013. This could be attributed to a shift to white-collar jobs and also people being attracted from agriculture to industries, just like in Klerksdorp. Likewise, the area under TBS decreased by 20% between 1999 and 2013 and by 18% in the period between 2013 and 2017.

Table 51: Trend changes in Potchefstroom land cover categories.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-1 1616.63	-20.3	-10 328.81	-18.1
Barren Land	+9 645.6	+16.9	+7 560.16	+13.2
Built up Area	+982.98	+1.7	+2 415.39	+4.2
Water Body	+988.05	+1.7	+353.26	+0.6

Table 52: Annual rate of change in land cover categories for Potchefstroom.

Land cover categories	1999 – 2013		2013 – 2017	
	Area (ha)	Percentage change	Area (ha)	Percentage change
TBS Land	-829.76	-1.5	-2 582.20	-4.5
Barren Land	+688.97	+1.2	+1 890.04	+3.3
Built up Area	+70.21	+0.1	+603.85	+1.1
Water Body	+70.58	+0.1	+88.32	+0.2

Table 52 shows that the annual percentage variations of TBS between 1999 and 2013, and between 2013 and 2017 were respectively -2% and -5%. During the 18-years period, the built up area increased to 1.2% between 1999 and 2017 and could be associated with migration to the town of Potchefstroom. The water bodies remained at 0.1% between 1999 and 2013, as well as 2013 and 2017, with an increase of 0.2%. The barren land recorded an annual rate of change of 1.2% and 3.3% between 1999 and 2013, respectively for the period 2013 and 2017.

Table 53: Total area net change detection from 1999 to 2017 for Potchefstroom.

	Total area in land class at 1999 (Ha)	The total area changed to per land class (Ha)	Net gain/Loss (Ha)	Net change (%)
TBS	+45124.66	+21426.78	-23697.88	-41.4
Barren Land	+9378.87	+27785.70	+18406.83	+32.2
Built up Area	+1509.5	+5441.50	+3932.00	+6.9
Water Body	+1169.05	+2528.10	+1359.05	+2.4
Total area	+57182.08	+57182.08	------	------

Table 54: Area changed into built-up from 1999 to 2017 for Potchefstroom.

Land cover categories	Area changed to built-up land (ha)			% change per class		
	1999	**2013**	**2017**	**1999**	**2013**	**2017**
TBS	320.8	261.5	487.6	4	2	5
Barren Land	203.1	479.2	456.4	3	5	4
Water Bodies	15.7	0	0	2	0	0
Total area	539.6	740.7	944	9	7	9

TBS and barren land to built-up area showed the largest transitions between 1999 and 2017 (Table 53). TBS had a net loss of 23 697.88 ha (-41.4%), while the other land cover classes (water bodies and built up area) had net gains of 1 359.05 ha and 3 932 ha, respectively. Figure 25 depicts the pattern of land-cover change overtime for Potchefstroom. The areas under the barren land and TBS classes, as well as the water bodies, increased considerably due to the expansion of the town although a lot of areas were classified as water due to spectral confusion. For instance, barren lands were misclassified as TBS due to their similar spectral characteristics in some areas and vice versa. Additionally, some of the water bodies were classified as TBS due to algae blooms, leading to them being detected as TBS. Therefore, Johnson (2001) conclusion on identifying communities whose development is the source of the sprawl phenomenon and environmental impacts of urban sprawl was accurate. The phenomenon could be identified in this study area.

6.3. Quantifying urban growth pattern using Boolean GIS overlay analysis

Figures 26 to 37 map the changes in built up area that resulted from Boolean GIS overlay analysis over time for the four towns. The result of the GIS Boolean overlay analysis was a single image that identified change trajectories or sequences of the built up area class for given image dates per town. The output is a categorical 'change image', where each pixel includes information on built up area for both dates. The output also includes unchanged built up area. Since there were three image dates for each town (i.e. 1999, 2013, 2017) the analysis results in the twelve maps in Figures 26 – 37.

In Mahikeng there was a drastic increase in the spatial expansion of the built structure between 1999 and 2013, as shown in Figures 24 and 25. The increase of built structures occurred predominantly in the north western and the south western parts of the town. The only noticeable growths are on the edges of the developed areas of 2013 built structure. The built up area has taken up much of the TBS land cover. In addition, other cleared areas are left as barren land.

In Rustenburg (Figures 29 to 31), the built up area increased in all directions as compared to Mahikeng, Klerksdorp and Potchefstroom, which expanded in predominantly one direction. This is due to the mining and industrial activity in Rustenburg, which could be linked with the inflow of labour into Rustenburg. Mines have a major role in the expansion of the town and the transformation of natural habitat. In the case of Rustenburg, mining activities have given rise to barren land on what were previously TBS areas. In addition, there is evidence of settlement growth for mine workers consequently having a negative impact on the surrounding landscape.

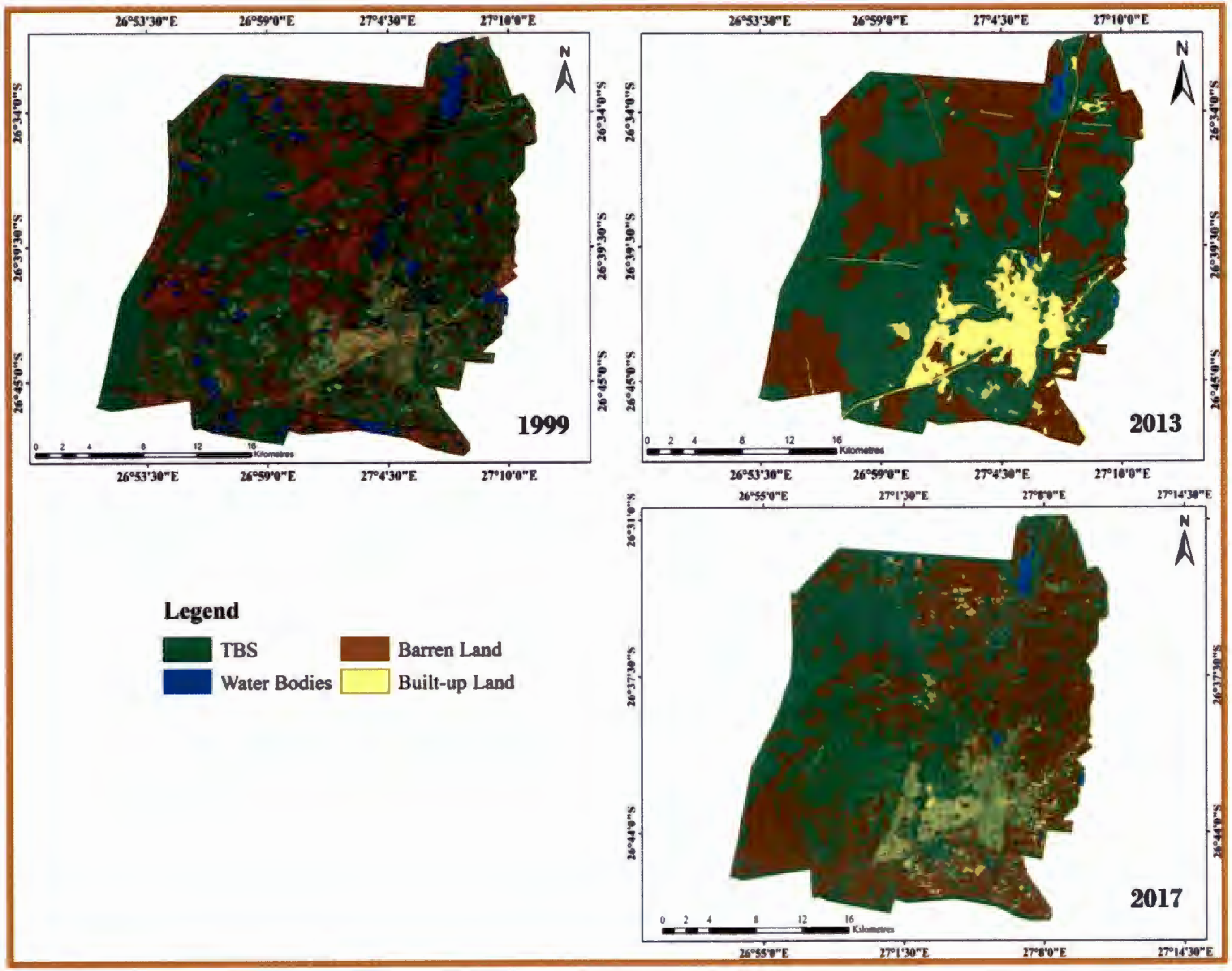

Figure 25: Land use land cover map highlighting the change in Potchefstroom, 1999 – 2017.

The expansion of Klerksdorp (Figures 32, 33 and 34) differs from Mahikeng, Rustenburg and Potchefstroom in that the town was expanding outward by filling in open land. The growth of urban areas has mainly been influenced by government initiated development policies since the end of apartheid, which aimed at undoing the effects of the apartheid city (Donaldson, 2006; Jürgens *et al.*, 2013). The Reconstruction Development Program (RDP), initiated by the government for informal settlements and the development of other physical infrastructure, has led to a significant increase in the developed area in Klerksdorp. The RDP areas are expanding in previously TBS areas, hence transforming the landscape. As the expansion takes place, much of the cleared TBS is left as barren land and, therefore, leads to ecological impacts.

For Potchefstroom (Figures 35, 36 and 37), growth in urban area was unlike the other three towns in the province in that the increase of built up area occurred predominantly within the Central Business District (CBD) and the outskirts. The growth of urban areas has mainly been influenced by commercial farming as well as mining in that area. Due to spectral confusion some of the areas were mapped as built up areas when in fact they were decommissioned mines.

6.4. Synthesis

This chapter addressed the optimal methodology for monitoring urban sprawl in the four towns studied which was selected and implemented. Therefore, in this chapter, an interpretation of the findings based on the analysis and results in the context of the third objective of the study was presented. Change detection was one of the processes used to identifying or highlighting significant differences in the state of an object or phenomenon by observing it at different times. The process encompasses the quantification of multi-date imagery to derive changes over two times. For this study, post-classification comparisons were applied to assess the amount of change in urban extents in the study areas. Classified image pairs of two different time periods were compared using cross-tabulation in order to determine qualitative and quantitative aspects of the changes for the periods from 1999 to 2017. Results from the post-classification analysis are presented using a series of change maps for visualisation and statistical tables to provide quantitative measures of change.

A pixel-by-pixel comparison procedure was done for the study year images through post-classification comparison. Thus, emphasis in this study is on the built-up area in terms of location and direction of change. In this chapter, the results further indicated that Potchefstroom is expected to sprawl the most followed by Mahikeng, Klerksdorp, and Rustenburg as the least as a result of the soil type as indicated in chapter 2. Rustenburg town has the ability to develop upwards instead of sideward due to the fact that most of its land is taken up with mining activity as compered to other towns in the province. Additionally, its sideward growth is restricted by mountenous terrain to the south and west, and mines to the north and east of the town. On the other hand, Potchefstroom town can develop sideward instead of upwards since it has abundant land to the western and northern side into tribal land with sprouts of informal settlements. Mahikeng town is more or less like Potchefstroom town in that it can develop outward to the eastern and southern side. As for Klerksdorp town, it has the ability to expand upward, because of the type of soil that is clay loam. The results for this chapter were an overlay of the built-up area showing the location of the change from 1999 to 2017 for all the four study towns based on Boolean GIS overlay analysis.

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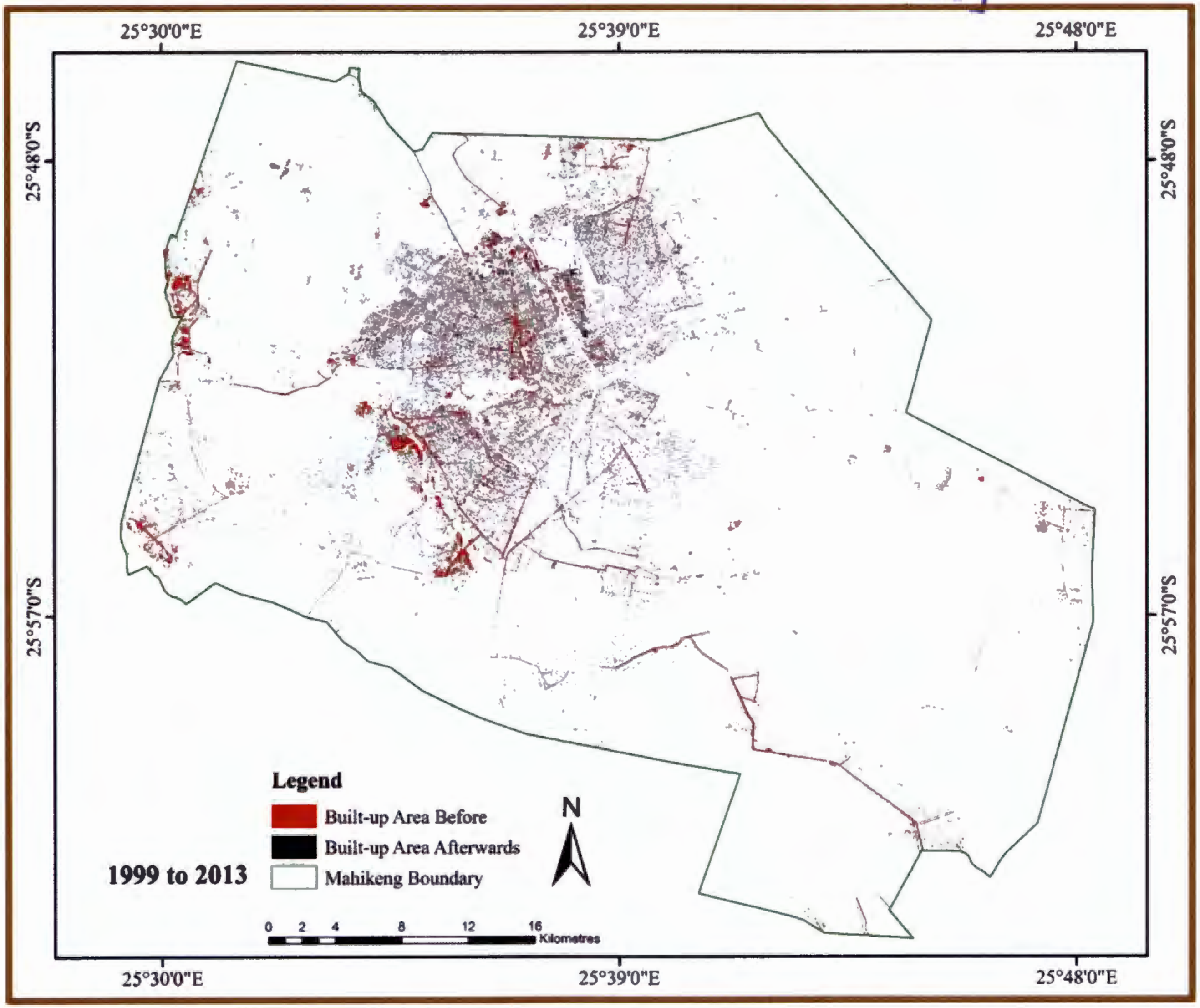

Figure 26: Overlay of built-up area showing the location of the change in 1999 to 2013 for Mahikeng.

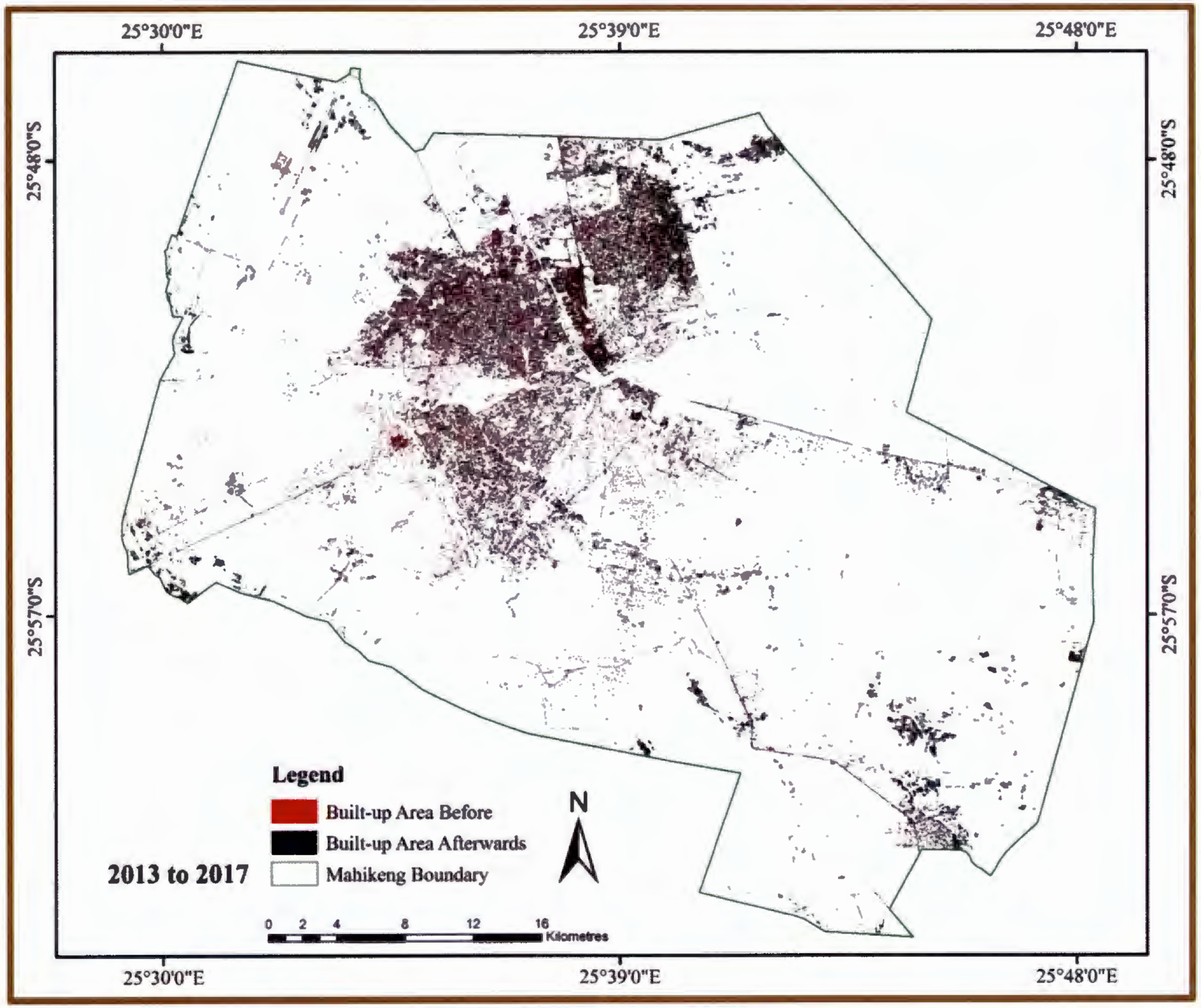

Figure 27: Overlay of built up area showing the location of the change in 2013 to 2017 for Mahikeng.

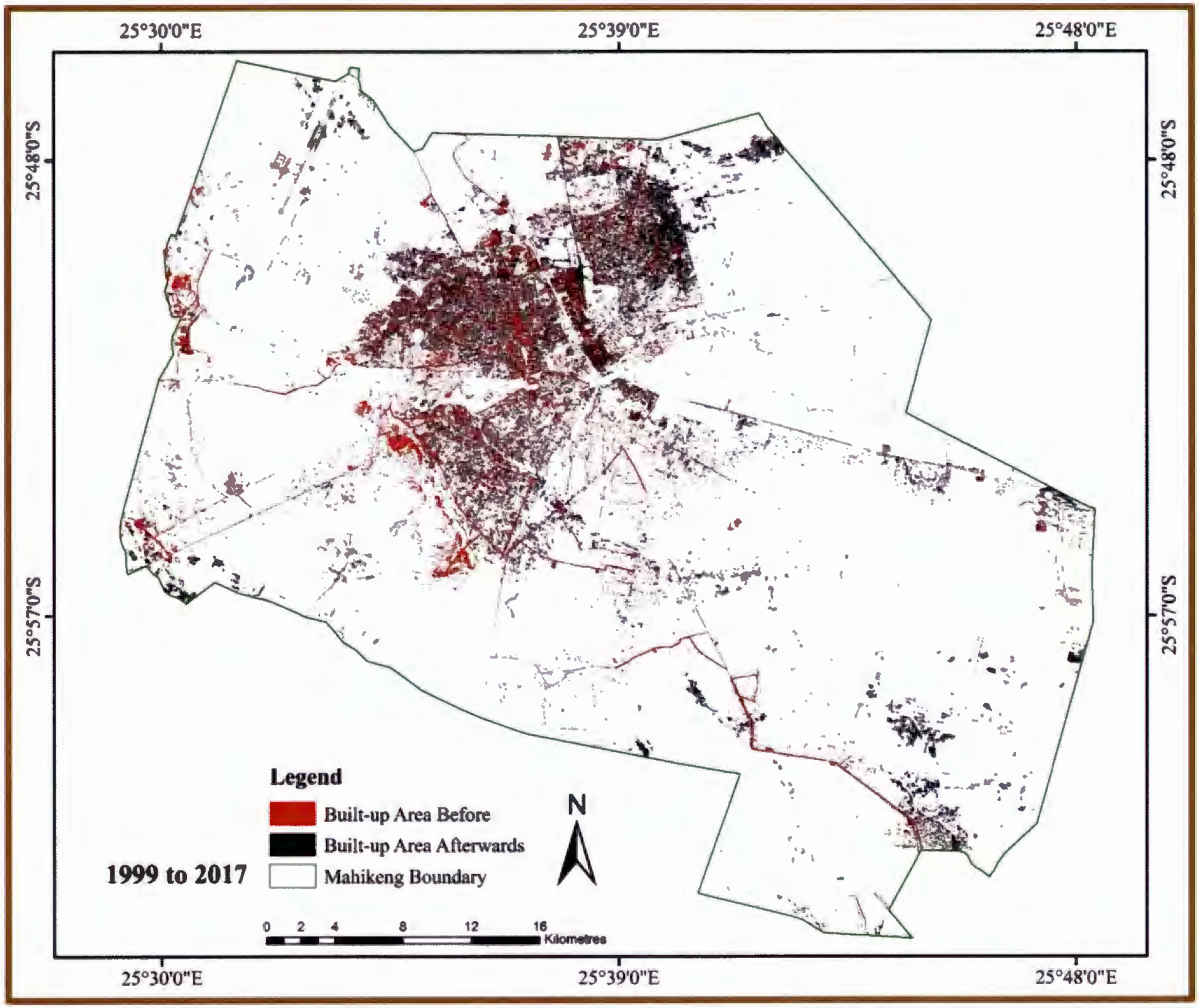

Figure 28: Overlay of built up area showing the location of the change in 1999 to 2017 for Mahikeng.

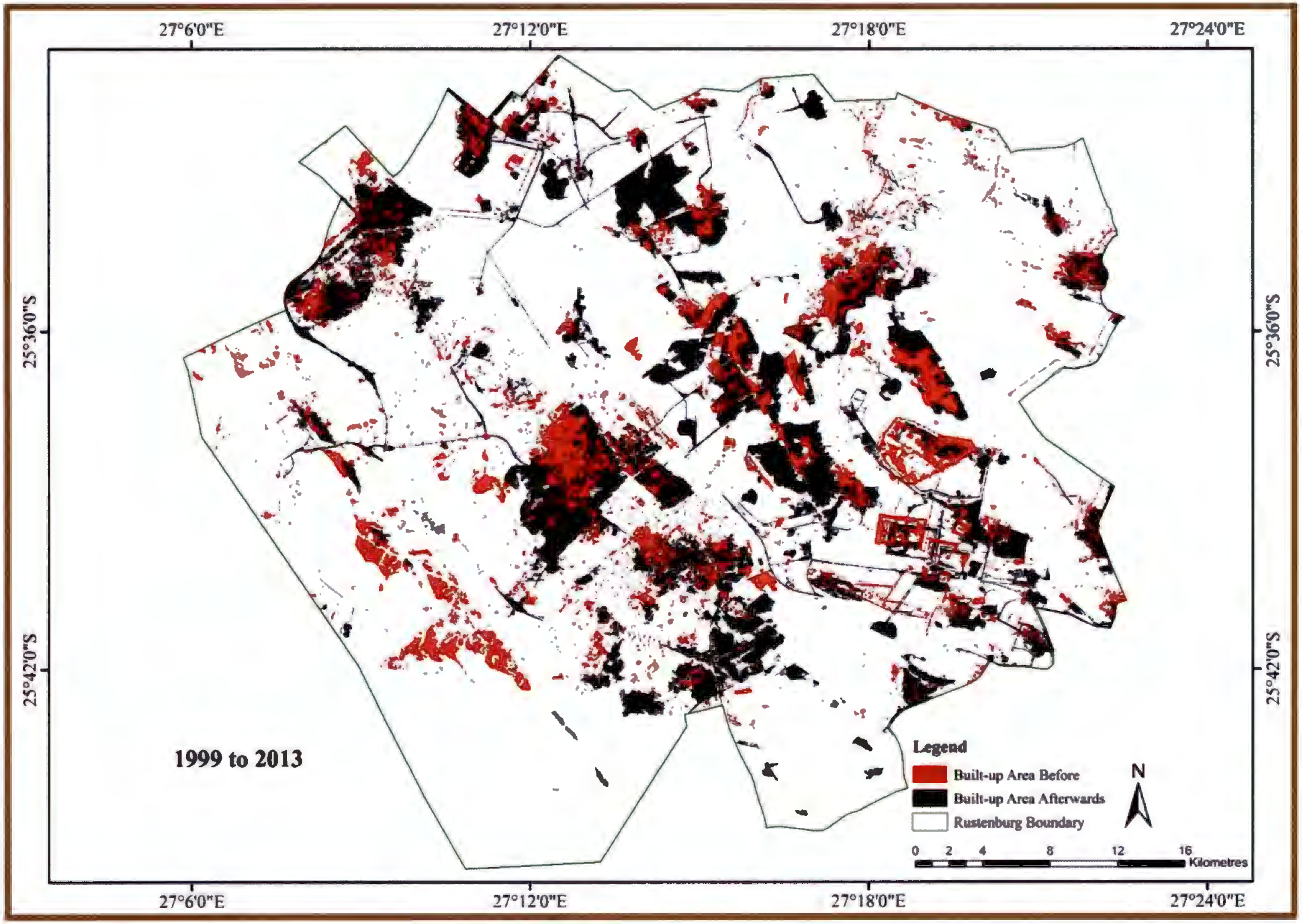

Figure 29: Overlay of built up area showing the location of the change in 1999 to 2013 for Rustenburg.

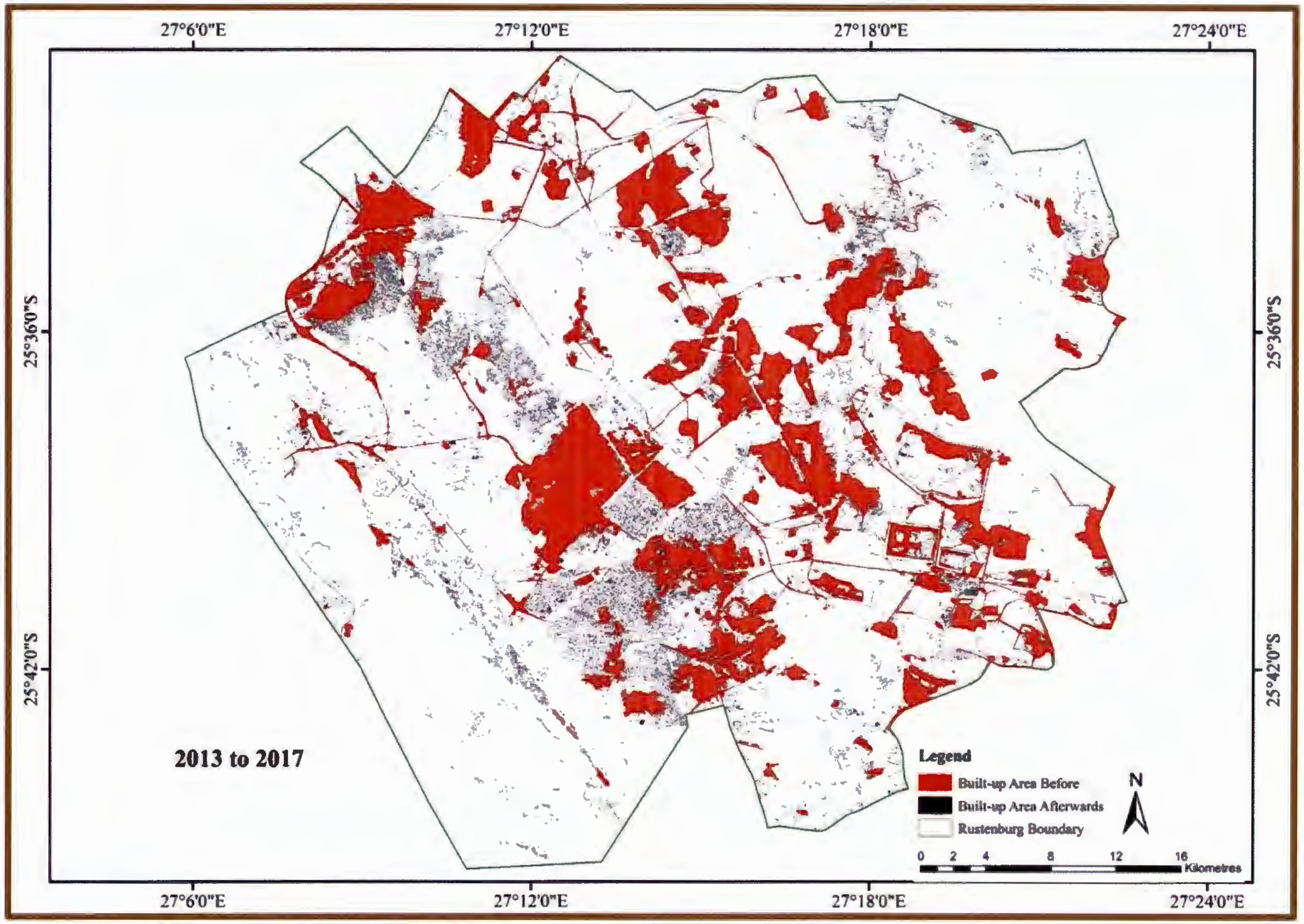

Figure 30: Overlay of built up area showing the location of the change in 2013 to 2017 for Rustenburg.

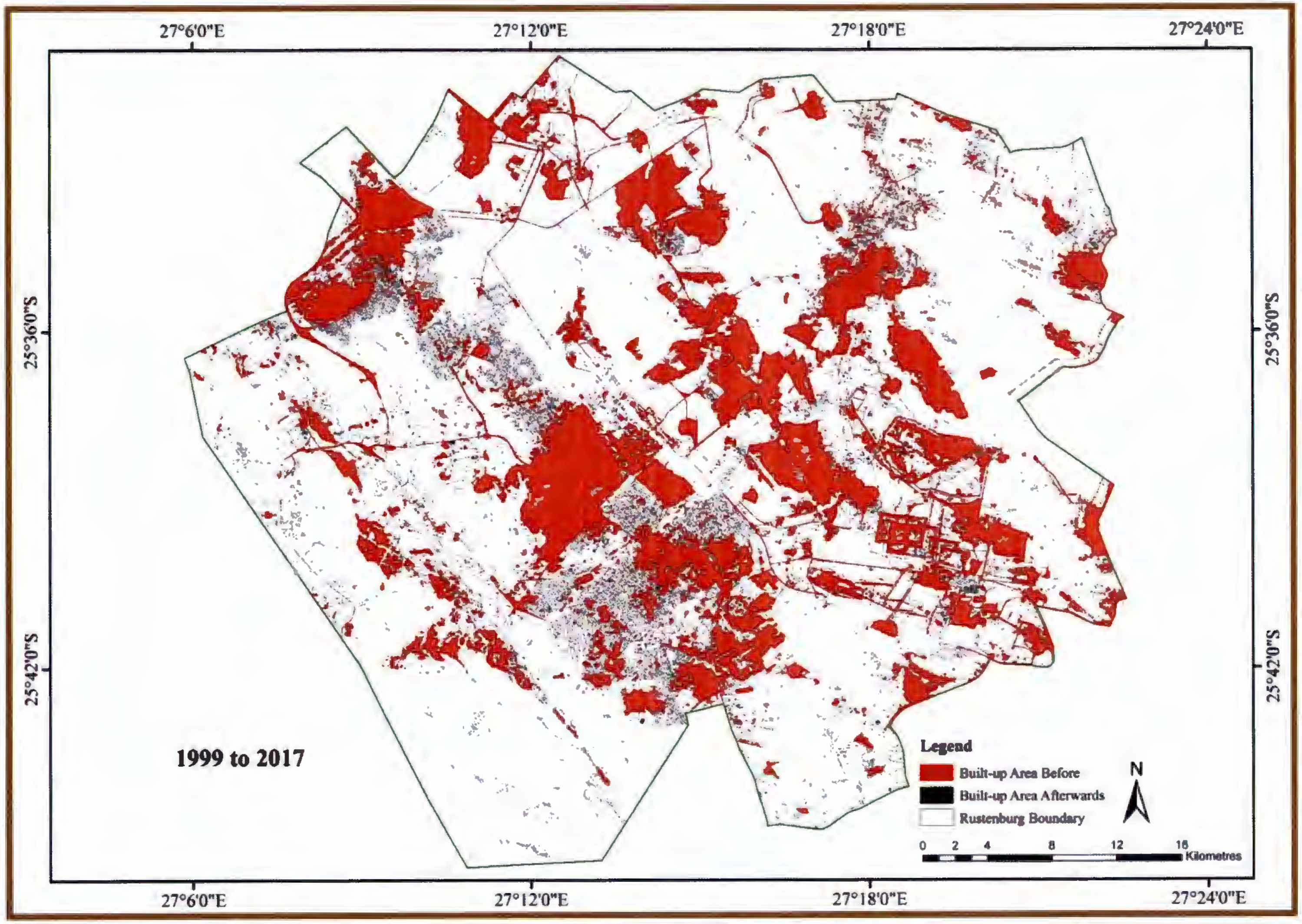

Figure 31: Overlay of built up area showing the location of the change in 1999 to 2017 for Rustenburg.

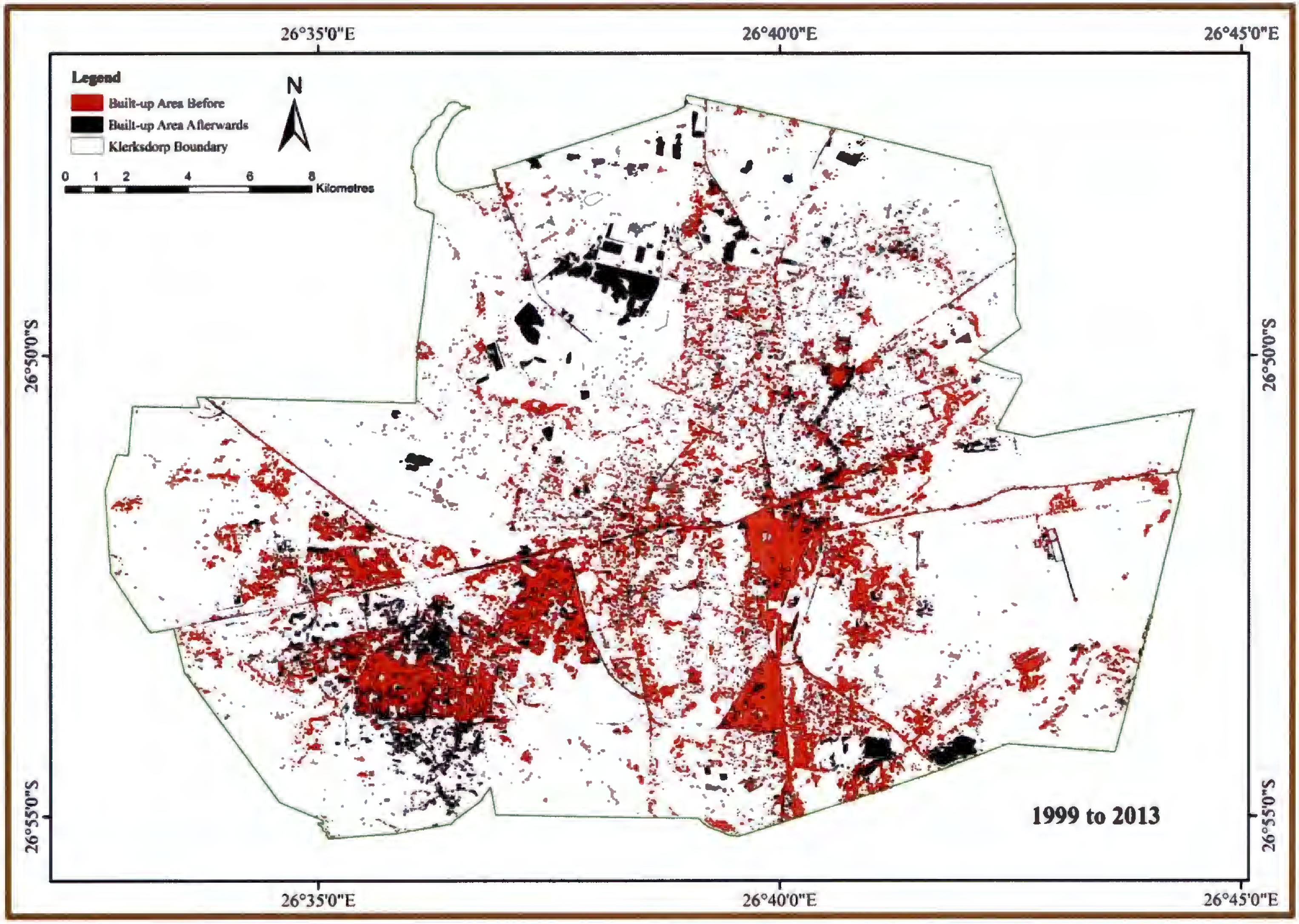

Figure 32: Overlay of built up area showing the location of the change in 1999 to 2013 for Klerksdorp.

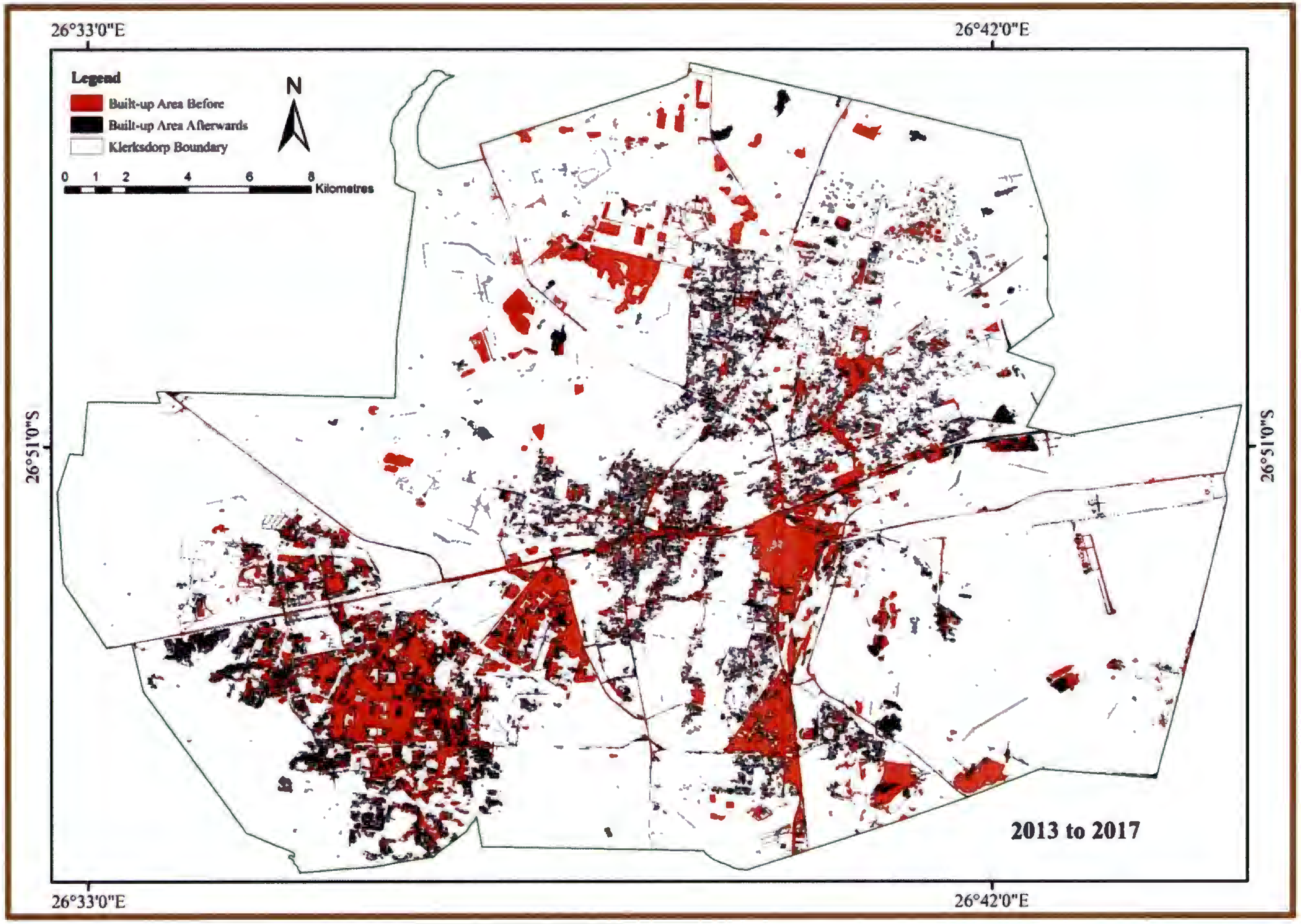

Figure 33: Overlay of built up area showing the location of the change in 2013 to 2017 for Klerksdorp.

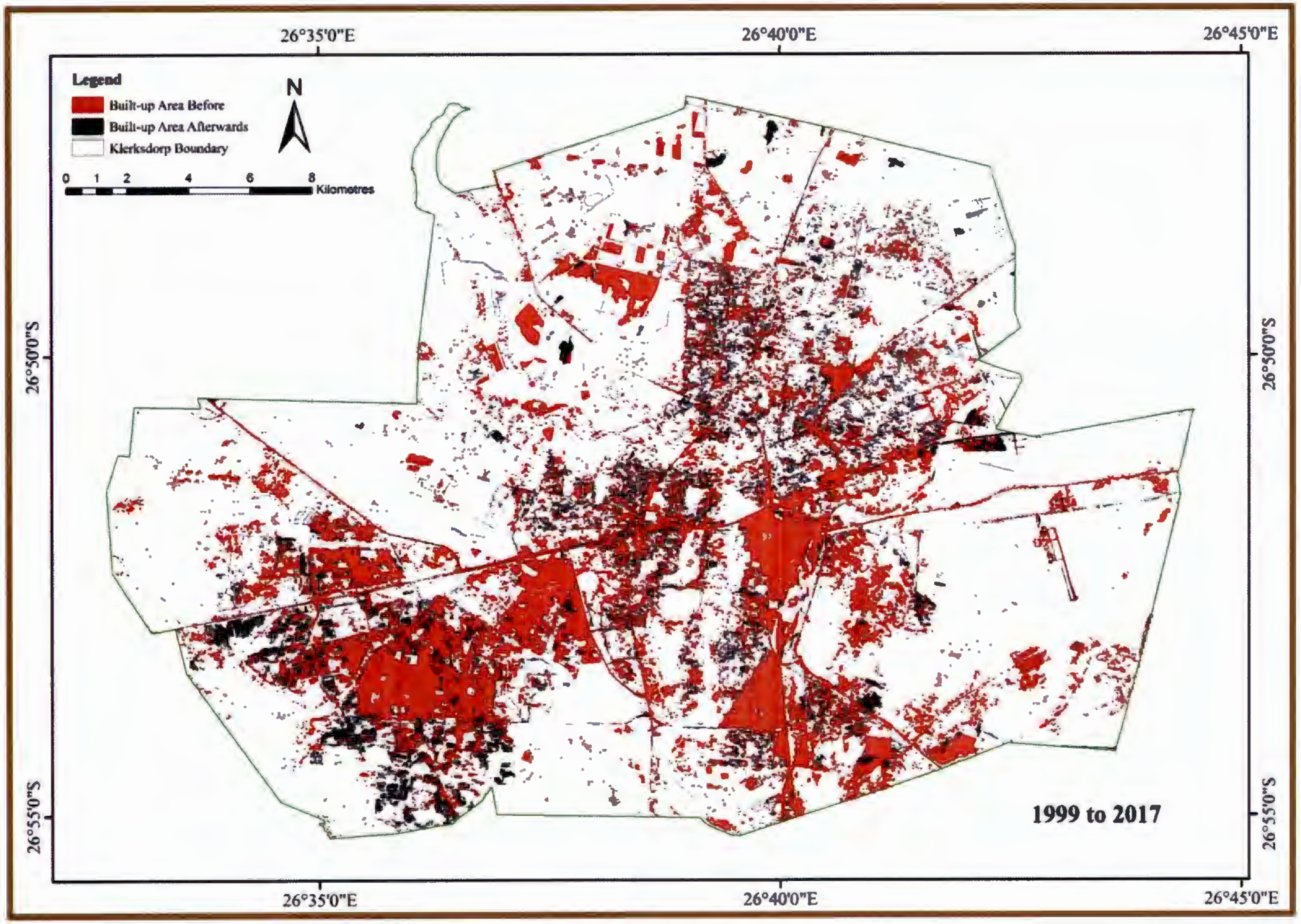

Figure 34: Overlay of built up area showing the location of the change in 1999 to 2017 for Klerksdorp.

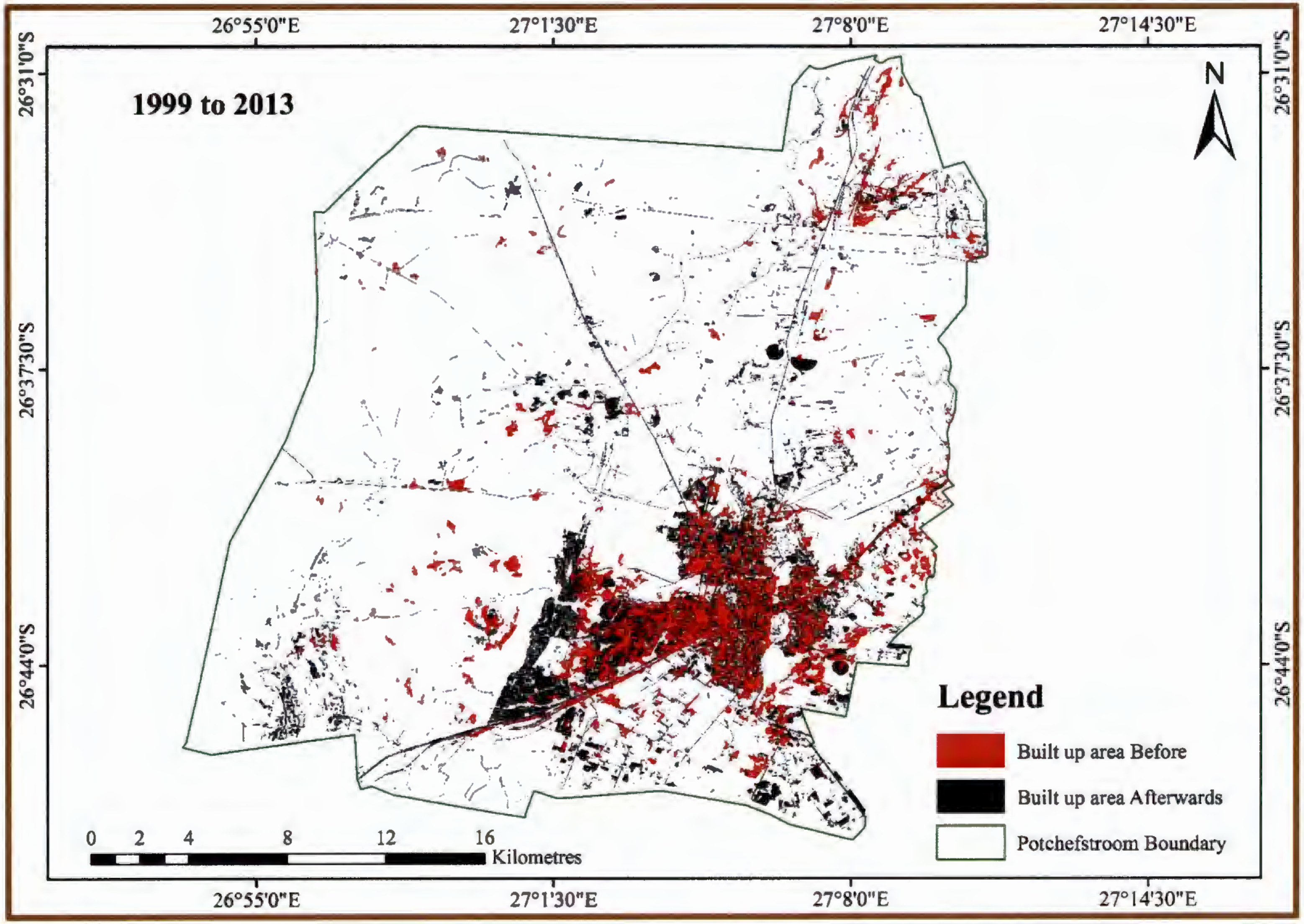

Figure 35: Overlay of built up area showing the location of the change in 1999 to 2013 for Potchefstroom.

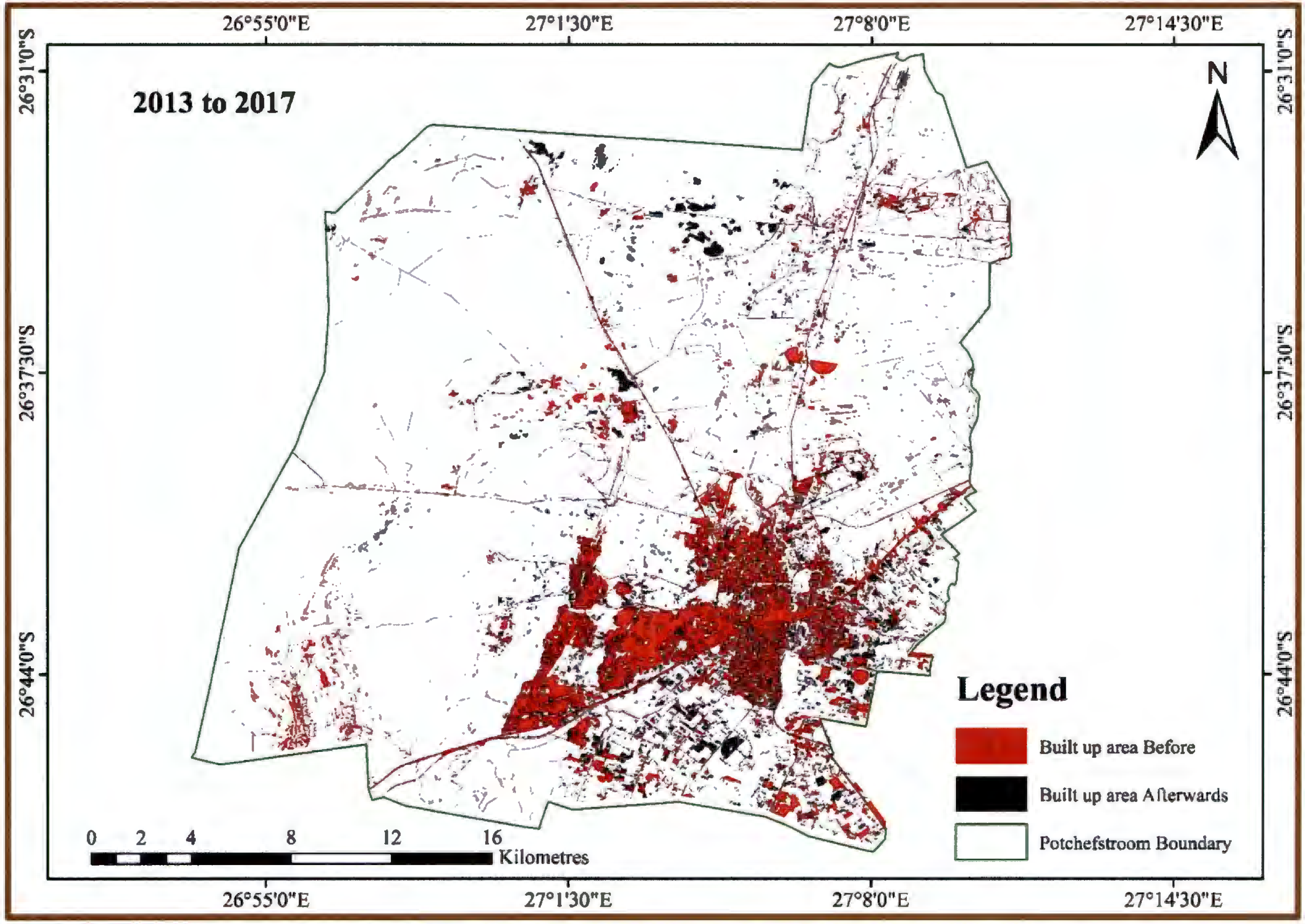

Figure 36: Overlay of built up area showing the location of the change in 2013 to 2017 for Potchefstroom.

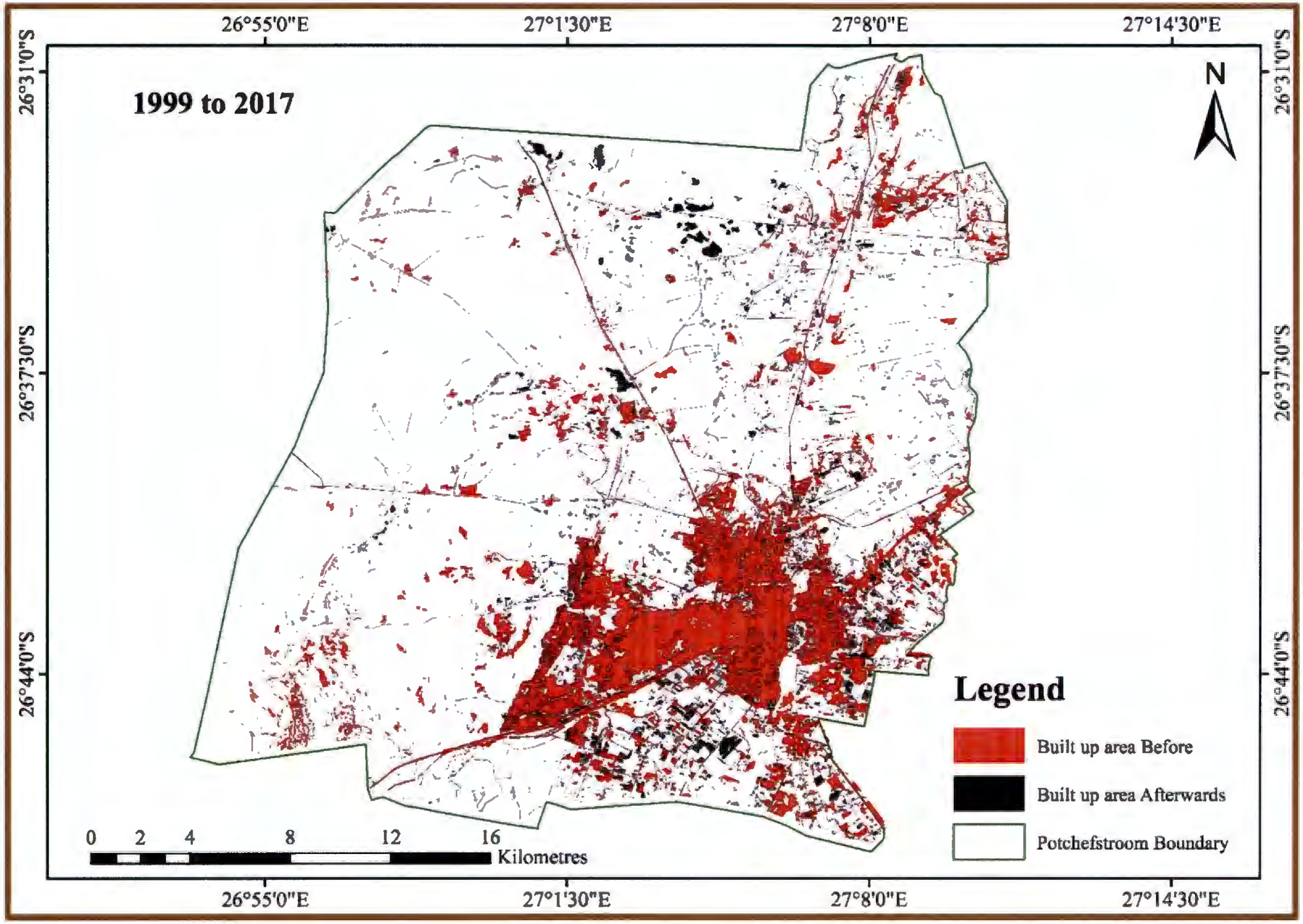

Figure 37: Overlay of built up area showing the location of the change in 1999 to 2017 for Potchefstroom.

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1. Introduction

This study sought (i) to establish the spatial scale of the field features that constitute urban growth in the North West Province, (ii) to determine the appropriate digital image-processing algorithm that can detect the spatial elements of urban growth, (iii) to operationalise the identified algorithm in change detection for monitoring urban growth, using common optical satellite imagery and GIS, and (iv) to determine the overall suitability of Remote Sensing for monitoring urban growth in towns of the North West Province of South Africa. This chapter presents a summary of the results against these objectives, limitations of the study, recommendations from the study, the study's contribution to knowledge, suggestions for future research and the overall conclusions arising from the study.

7.2. Summary of results

This study established an optimal methodology for monitoring urban sprawl in towns with similar urban metrics to the four towns studied. The methodology was then implemented to determine urban growth. Post-classification comparisons were applied to assess the amount of change in urban extents in the study areas. Results from the post-classification analysis indicated that between 1999 and 2017 built up area in Potchefstroom increased by 8.5%, by 6.47% in Mahikeng, 6.25% in Rustenburg and by 5.76% in Klerksdorp.

This study compared the performance of the widely used and accurate parametric of the Maximum Likelihood Classifier approach to mapping urban land. In comparison with the newer object based Random Forest classifier, which is nonparametric, it was established in this study that nonparametric approaches would be better in mapping the urban metrics of the towns of the North West Province of South Africa. The towns in the study area have the common phenomenon of urban areas being characterised by the combination of bare soil, informal settlements with the peculiar buildings called Shacks, gravel roads, as well as tar roads and the formal buildings of suburbs and the central business district. In these circumstances the parametric MLC was less accurate at delineating the urban land, resulting in a salt-and-pepper mapping of the urban land. The nonparametric approach based on image objects generated homogenous blocks of pixels in the urban land, resulting in higher classification accuracy.

GIS overlay analysis by Boolean addition proved to be particularly useful in detecting change or no change in urban sprawl. This was because it enabled the isolation of the urban land, per given classified image, from the other classes. With the urban land extracted from the other classes the amount and location of change in its extent over the years could accurately be quantified and mapped. Therefore, as long as the algorithm used for image classification produces high accuracy, Boolean GIS overlay analysis by addition is a useful method for quantifying and mapping urban sprawl.

7.3. Objectives revisited

Objective 1 was to establish the spatial scale of the field features that constitute urban growth in the North West Province. The study derived that the spatial scale of urban features ranges from 3 m to ≥100 m, indicating small urban features such as informal dwellings known as "shacks" and roads (Figure 1), and large paved surfaces such as parking lots and large blocks of buildings like shopping malls and sports stadiums. The building up of informal settlements occurs very rapidly and without monitoring them using special data and purpose-specific image classification protocols, they become very difficult to characterise. Hence, the nature of the characteristics of urban development in South Africa makes it difficult to monitor urban growth by multitemporal image classification.

Objective 2 was to determine the appropriate digital image-processing algorithm that can detect the spatial elements of urban growth. Therefore, in chapter 5, objective 2 of the study was addressed by making a comparison of classification of the urban land using the Random Forest classifier based on Object-Based Image Analysis (OBIA) with the supervised Maximum Likelihood Classifier (MLC). The multi-resolution segmentation technique was used to construct a hierarchical network of image objects that allowed the definition of relationships between contiguous objects of different sizes. In this study, the segmentation level 3 at the scale parameter 160 was selected for its classification, since it gave the best result in the visualization of the urban classes based on the colour and homogeneity. From the results relating to this objective, the OBIA approach was proposed as an alternative analysis framework that can mitigate the salt-and-pepper classification deficiency associated with the MLC approach. The OBIA classification approach proved to be a very effective tool for producing LULC thematic maps of towns with urban metrics such as those in the towns of the North West Province of South Africa.

Objective 3 was to operationalise the identified algorithm in change detection for monitoring urban growth, using common optical satellite imagery and GIS. Change detection to map urban sprawl was implemented by Boolean GIS overlay analysis to address objective three. The built up area thematic class per image date (1999, 2013 and 2017) for Mahikeng, Rustenburg, Klerksdorp, and Potchefstroom, was subsequently combined for each town to provide a single image that identified change trajectories using the Boolean analysis. This highlighted urban growth, using spatial metrics that quantify and classify the complex landscape structure into simple and identifiable models using Boolean GIS overlay analysis. Thus, emphasis in this study is on the built-up area in terms of location and direction of change.

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Objective 4 was to determine the overall suitability of Remote Sensing for monitoring urban growth in towns of the North West Province of South Africa. This study demonstrated the efficacy of object-oriented classification in delineating urban and non-urban features as shown by the high classification accuracies. Using a post-classification change detection technique, the study indicated that there was a significant urban expansion in all the four study towns. Therefore, this work shows the value of satellite imagery in examining urbanisation trends in developing cities. Overall, the urbanisation spatial trends established in this study will provide valuable information required for municipal planning in the four towns.

7.4. Limitations of the study

One of the main limitations to this study was obtaining a long archive of imagery going back as far as 1985 during the apartheid period. Between the Landsat and SPOT programs, which have the longest image archive, SPOT images were preferred due to high spatial resolution. High spatial resolution was a cardinal requirement because some of the urban metrics that would indicate urban sprawl are small in size, for example, shacks and tar roads (Figure 1b). Therefore, SPOT imagery was ideal for this study. The ideal dates of imagery selected were between May and July to help ensure consistency in cover classes and phenology. For the historical analysis of change in urban sprawl, imagery dating back as far as possible where needed. The SPOT programme commenced in 1986 with the launch of SPOT 1. However, although listed on the SANSA catalogue, imagery from the sensors on SPOT 1, SPOT 2 and SPOT 3 were not available due to technical problems. Therefore, only images from the SPOT 4 High-Resolution Visible Near Infrared (HRVIR) were obtained. Based on these considerations, images from April and May 1999, 2013 and 2017 were obtained from SANSA.

7.5. Recommendations from the study

It is recommended that the government budget for capital developments to exploit benefits of Remote Sensing and GIS to town planning, by (i) integrating spatial planning at all governmental levels: national, state and city, (ii) creating a stable policy framework for private investment in urban infrastructure, and (iii) approving plans for urban growth through privet and higher learning institutional research. In doing so, the government should propagate policies on open space preservation in the inner city. This could alleviate many of the problems faced by towns and cities in South Africa, and should be implemented for environmental management and natural resource harmony. Introduction of the environmentally friendly city as opposed to compact cities would have a positive impact on people, such as having parks for people to rejuvenate during breaks and after work, reduce noise pollution and air pollution. Having urban structures with vegetation around them helps alleviate the destruction of the ecology. Finally, the expansion of cities or towns requires that ecology knowledge be better integrated into urban planning. To achieve this goal understanding of ecological patterns and processes in urban ecosystems is needed.

GIS and Remote Sensing methodology, such as the one illustrated in this study, needs to become integral procedure in municipal management of urban growth as well as town and country planning. The methodology has shown that answers about the location and size of urban growth can be derived rapidly using the integration of GIS and Remote Sensing. National and local government agencies can help by passing and enforcing laws and ordinances that promote the use of better technologies in support of decision-making with regard to managing urban sprawl. The spatial technologies of GIS and Remote Sensing are recommended technologies in this regard.

7.6. Contributions to knowledge

The main contribution of the study is the development of an optimised GIS and Remote Sensing methodology for detecting change in urban settings of the South African context, where what constitutes 'urban' is different from the developed world setting. Thus, the study has significant contribution in the following areas:

1) Development of optimised GIS and Remote Sensing methodology for establishing the spatial scale of the field features that constitute urban growth in South African cities and similar developing world settings.

2) Determining the appropriate digital image-processing algorithm that can detect the spatial elements of urban growth.

3) Operationalisation of the identified algorithm in change detection for monitoring urban growth, using common optical satellite imagery and GIS.

7.7. Suggestions for future research

Future similar studies can be made more accurate by considering the following:

(1) To avoid misclassification other sources of satellite images can be used that are of much higher resolution, such as QUICKBIRD, IKONOS and SPOT 6 and 7 Multispectral images with less than 1.5 m.

(2) Conduct this study in other towns of South Africa to determine whether the methodology developed would perform equally well.

(3) Use a longer time frame for the analysis (e.g. back to the 1980's).

7.8. Overall conclusion

The results from this study lead to the following conclusions:

1) The nonparametric classification approach using a nonparametric classifier like Random Forest is more accurate for delineating the urban metrics of the towns in the North West Province of South Africa, whose urban land is characterised by a mixture of formal built up areas and the scantly built informal settlements with gravel roads and small dwellings made from iron roofing sheets ('shacks').

2) The overall suitability of monitoring urban growth in towns of the North West Province of South Africa through the use of Remote Sensing has demonstrated the efficacy of object-oriented classification in delineating urban and non-urban features as shown by the high classification accuracies. Therefore, this work shows the value of Remote Sensing satellite imagery in examining urbanisation trends in developing cities.

3) SPOT images are suitable in studying urban sprawl in towns of the developing world structure and are ideal for identifying small features that define urban land.

4) GIS overlay analysis by Boolean addition is particularly useful in detecting change or no change in urban sprawl.

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