MONITORING AND MODELLING SETTLEMENT GROWTH USING OBJECT-BASED CLASSIFICATION TECHNIQUES:

A CASE STUDY OF PRETORIA NORTH, SOUTH AFRICA

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DECLARATION

I, the undersigned, hereby declare that this research submitted for the degree of Master of Science in Geographical Information Systems and Remote Sensing, at the University of the Witwatersrand, Johannesburg, is my own original work and has not been previously submitted to any other institution of higher education. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

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October 2022

ABSTRACT

Accurate and up-to-date maps of settlement distribution are critical for urban planning, monitoring, and management decisions. Remote sensing is useful for monitoring the dynamics of urban growth over large areas. Over the year's urban built-up areas have rapidly increased in Pretoria North. Built-up layers for 1990 and 2017 were used to model settlement growth for 2025 using cellular automata (CA) incorporated with the artificial neural network (ANN) model within modules for land use change simulations (MOLUSCE) QGIS plugin. A rule-based classification object-based image analysis (OBIA) approach was used for extracting built-up and settlement types from high-resolution SPOT multispectral imagery. A total of seven SPOT images for the period 1990 to 2017 with a five-year interval were used to assess and quantify built-up area growth. The results from the study indicated urban increases from 65.2 km^2 in 1990 to 144.4 km^2 in 2017. Post-classification change detection technique was used to quantify built-up area growth. The results from the study also showed a significant urban expansion of 44.34 km^2, which represents a 47.3% growth that occurred during the period between 1994 and 2000. The overall accuracies from images for years 1990 – 2017 ranged from 80% to 87%. Settlement growth was measured by examining changes in built-up areas over the years. The study showed an increase in formal and a decrease in informal areas during the period 2005 to 2017 as a result of housing upgrades. The projected results for 2025 revealed that built-up areas will increase in the coming years. It was found from the results that SPOT satellite imagery and OBIA are valuable for modelling urban growth. Information derived from the study can be used by decision makers for planning and management purposes.

Keywords: object-based image analysis (OBIA), SPOT, settlement, urban growth, built-up areas, thresholding

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DEDICATION

It is a great honour to achieve this prestigious qualification; I thus dedicate this achievement to my late little brother. Blessings Oliphant “Smile a little more”.

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ABBREVIATIONS AND ACRONYMS

CA	cellular automata
CoT	City of Tshwane
CoGTA	Cooperative Governance and Traditional Affairs
DEM	digital elevation model
ENVI	Environment for Visualizing Images
FLAASH	Fast Line-of-sight Atmospheric Analysis of Hypercubes
GIS	geographic information systems
GLCM	Global Local Co-occurrence Matrix
SANLC	South African National Land Cover
MOLUSCE	Modules for Land Use Change Simulations
MRS	multi-resolution segmentation
NDVI	Normalized Difference Vegetation Index
NIR	near infrared
OBIA	object-based image analysis
SACN	South African Cities Network
SANSA	South African National Space Agency
SDGs	Sustainable Development Goals
SML	Symbolic Machine Learning
SPOT	Satellite Pour l’Observation de la Terre
StatsSA	Statistics South Africa

CHAPTER 1: INTRODUCTION

1.1 Background

Globally, cities are facing excessive urban growth with about 55% of the population living in urban areas globally (United Nations, 2015, 2019; Mudau and Mhangara, 2021). Urban areas cover a small area of the world's overall landmass (Bhatti and Tripathi, 2014). However, urban growth is one of the main challenges faced by both developed and developing countries, although developing countries are experiencing higher urban growth rates (Hegazy and Kaloop, 2015). As one of the processes of urbanisation, urban growth occurs mostly on the outskirts of cities, thereby causing development pressure for cities (Kemper et al., 2015).

Factors such as population growth, economic development, government policies, reclassification of cities, rural–urban migration for employment prospects, and access to better service delivery all contribute to urban growth. Urban areas are characterized by tall buildings/skyscrapers generally referred to as "built-up areas". Such areas occur as an outcome of urban growth occurring towards the urban fringe. This results in a rise in congestion levels, scarcity of open space, demand for new infrastructure, and transport (Broere, 2016).

When population and income increase; the demand for housing and other service delivery increases. Subsequently, land and housing prices increase, causing the shifting of lower and middle-income people to move to the suburban areas due to the lower cost of residential properties in these areas (Amato et al., 2015; Rahman, 2016). The demand for housing increases the cost of housing and land in city centres and areas around or near the city causing poor people to be unable to afford decent housing.

Currently, developing countries continue to face shortages of low-cost housing for the urban poor population, resulting in increased numbers of urban dwellers living in informal areas (Ren, 2018). This is evident in areas like Rio de Janeiro with 22% of the population staying in informal settlements. Other such areas are Guangzhou, South China 35% and Mumbai, India with 41% of its population staying in informal settlements (Ren, 2018).

In South Africa, it has been reported that there has been an increase in the population of urban dwellers from 52% in 1990 to 62% in 2011 (South African Institute of Race Relations, 2013) and with about 42 million people living in informal areas (Kemper et al., 2015). The Gauteng City-Region Observatory (2018) indicated that city-region settlements in Gauteng are rapidly increasing, with 51% being informal dwellings and 38% formal dwellings. The City of Tshwane (CoT) Metropolitan Municipality is one of Gauteng province’s fastest-growing municipalities in terms of population and urban settlement. The increase in urbanisation calls for a need to study urban growth in the area and how it has developed over time and how it may grow in future.

Built-up areas are rapidly expanding, especially in urban areas due to migration and population growth. According to a United Nations report, 68% of the world’s population is estimated to be living in urban areas by 2050 (United Nations, 2019). An understanding of urban spatial distribution and growth is crucial for urban planning, resource management and urban development (Mubea and Menz, 2014). A fundamental activity that is required in urban spatial distribution is the accurate and timely mapping of built-up areas (Bhatti and Tripathi, 2014; Roy Chowdhury et al., 2018). This is required to evaluate the spatial and temporal landscape of urbanisation occurring across urban areas by city managers, decision makers, and researchers (Zhang et al., 2014).

Globally, built-up areas have expanded extensively in urban regions as a result of population. The expansion of built-up areas to accommodate a rising population leads to lasting impacts on landscapes and livelihoods (Güneralp et al., 2020). Loss of agricultural land, climate change, reduction in wildlife habitat, the spread of human settlements in disaster-prone areas and the loss of biodiversity are some of the impacts of increasing built-up areas(Ehrlich et al., 2018; Fafchamps and Shilpi, 2021; Williams et al., 2019).

Understanding the trends of built-up areas is crucial, as this helps with understanding the impacts of built-up area expansion, it provides an understanding of the proportion of built environment compared to other land uses and the rate of land consumption over time. Additionally, pro-active planning, policy-making and decision-making require an understanding of the changes in built-up areas to develop indicators that can be used as measures to support policy-making, allocation of resources and planning for the future. Knowledge of spatial information concerning spatial patterns of built-up landscapes is now one of the most critical criteria for tracking Sustainable Development Goals (SDGs) globally (Kemper et al., 2015; Corbane et al., 2017; Mudau et al., 2020b; Vivekananda et al., 2020).

Traditionally, field surveys have been used extensively to study urban expansion (Pissourios, 2019). However, these survey methods are labour-intensive, time-consuming and pricy (Su et al., 2020; Adeyemi et al., 2021). Field surveys provide insufficient coverage, cannot meet the demand for understanding rapid urban land development, and are ineffective in providing frequent built-up information on built-up areas (Mudau and Mhangara, 2021; Wang et al., 2022).

Remote sensing satellite data, as opposed to traditional field survey approaches, provides large area coverage, and repetitive data acquisition; further, it is reliable, effective, and relatively economical, and it can easily be combined with other datasets such as censuses, thereby improving accuracy (Ahmad and Goparaju, 2016). Remote sensing has been proposed as an efficient tool for extracting and classifying land cover. Recently, object-based image analysis (OBIA) has been extensively applied in remote sensing for mapping land use /land cover (Zheng et al., 2016; Phiri et al., 2019; Mugiraneza et al.,2019; Rasouli et al., 2021; Idowu et al., 2022; Killeen et al., 2022; Qin and Liu, 2022); these studies showed that object-based methods are more accurate, successful and visually superior in terms of boundary consistency than other methods in mapping land cover, especially in urban areas using high-resolution satellite images. Additionally, OBIA has increasingly made the method of identifying land cover types faster and more reliable (Samal and Gedam, 2015; Kutz et al., 2022).

Numerous studies on monitoring and modelling settlement growth have been conducted using remote sensing data such as Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), and Satellite Pour l'Observation de la Terra (SPOT). Additionally, remote sensing techniques have been applied to distinguish formal and informal settlements within urban areas. However, to the best of my knowledge, there are limited studies on monitoring and modelling settlement growth using SPOT have been conducted. In addition, with the increase in urbanisation spatial information on settlement is required for urban planning. Hence, this study aims to monitor and model settlement growth using SPOT and object-based image classification.

1.2 Problem statement

In recent years, Gauteng province has undergone rapid urbanisation, with urban land cover increasing from 12.6% to 18.36% between 1991 and 2009 (Mubiwa and Annegarn, 2013). The rapid increase in urbanisation has been due to population growth. It is projected that Gauteng's urban population will have doubled by 2055 (Mubiwa and Annegarn, 2013; Wray and Cheruiyot, 2015). According to the South African Cities Network (SACN) (2022), large metropolitan areas are currently experiencing the most rapid population and urban growth. This is evident in the CoT Metropolitan Municipality, where urbanisation is increasing as the population grows (SACN, 2016; CoGTA and CoT, 2020). As a result, there is a significant increase in both formal and informal settlements. The majority of the growth in both settlements is taking place on the city's outskirts near or within townships owing to a shortage of residential space in inner cities and insufficient available land in the cities overall (Wray and Cheruiyot, 2015).

According to 2011 statistics, Pretoria North (Region 1) of the CoT Metropolitan Municipality has the highest population density of all the regions in the city (CoGTA and CoT, 2020). Approximately 27.7% of Tshwane's population lives in Region 1 townships (Soshanguve, Mabopane and Winterveld); this has been complemented by a steep increase in the number of informal settlements. The 2020 CoT report stated that the difficulties in overcoming housing and service delivery backlogs are exacerbated by the ever-increasing demand for housing that results from rising population and increasing urbanisation. As a result, it is essential to monitor and model settlement growth in this region.

Ground surveys, aerial photography and unmanned aerial vehicles have been used in mapping urban growth in the CoT (CoT, 2022). Nevertheless, survey methods are strenuous, expensive and time-consuming. Although both aerial photography and unmanned aerial vehicles are remote sensing techniques, data acquisition using these two approaches is limited to a small area and is expensive for large areas, making them less viable for regularly obtaining data (Richards, 2013). Remote sensing satellite imagery, in contrast, offers a viable reliable source of information for understanding urban growth; it has been utilized to map, monitor and model the growth of settlements. However, most estimations of settlement growth have been conducted using traditional classification methods, which focus mainly on pixel-based methods that map the spatial extent. With the increase in urban growth, it is crucial to classify settlements in the urban built-up environment, to monitor the changes over time and model potential areas of growth. This information is crucial for decision-making and development planning.

1.3 Research aim

This research aims to model and monitor settlement growth using SPOT satellite images in Pretoria North, South Africa from 1990 to 2017.

1.4 Objectives

The objectives of this study are:

- To map and assess the spatial extent of built-up areas in Pretoria North, Tshwane, from 1990 to 2017 with five-year intervals using object-based classification techniques.
- To distinguish between formal and informal settlements from 2005–2017.
- To model the settlements growth in 2025 using the cellular automata (CA) modelling technique.

1.5 Research questions

This study seeks to answer the following questions:

- What is the spatial growth of built-up areas in Pretoria North, South Africa from 1990–2017?
- What is the spatial growth of formal and informal settlements from 2005–2017?
- Where are areas of potential settlement growth in 2025?

1.6 Structure of the research report

This study comprises five chapters

- Chapter one consists of an introduction to the study, background, problem statement, aim of the research, objectives, and research questions.
- Chapter two reviews the literature associated with the scholarly work that has been conducted on urban growth, settlement mapping, object-based mapping and CA models for mapping urban growth.
- Chapter three focuses on a description of the study area, data collection and processing and classification methods.
- Chapter four describes the results.
- Chapter five discusses the research findings.
- Chapter six provides a conclusion, limitations and recommendations.

CHAPTER 2: LITERATURE REVIEW

2.1 Urban growth globally

Abdullahi et al. (2017) define urbanization as the transformation of natural areas into build-up areas for residential, industrial and commercial use. The United Nations defines urbanization as the process of areas transitioning from being rural to being urban (United Nations., 2015). Urbanization is also defined as the increasing number of people living in cities (McGranahan and Satterthwaite, 2014). Urbanization is a major concern in many cities around the world as cities are drastically increasing in extent (Vigneshwaran and Vasantha Kumar, 2018). Urban growth is a result of several steering forces that influences socioeconomic, and environmental conditions (Chen et al., 2014). Although urban growth is important, its growth is associated with huge negative impacts on other ecosystems such as water, air and land; which is mainly due to changing of natural lands into water-resistant surfaces (Patra et al., 2018; Viana et al., 2019).

According to a United Nations population division report, 54% of people worldwide resided in urban areas in 2014, and that figure is anticipated to rise to 61% by 2025 (Nauman et al., 2015; United Nations, 2015). Presently, on a global scale most cities are rapidly urbanizing, with 55% of the world’s population now living in cities. This represents an increase from the 2014 United Nations report (United Nations, 2015, 2019).

Globally, urbanization has been accelerating over the past three decades. The rapid growth over the decades was expected by developed countries; unfortunately, developing countries were not expecting such rapid urbanization (Wang et al., 2020). Research has shown that the focus on global urbanization is shifting from developed to developing countries (Chen et al., 2014). Africa is one of the fastest-urbanizing regions, despite it being largely rural, and it is estimated that the urban population will triple in the coming years (Güneralp et al., 2017). Additionally, it is anticipated that population growth in urban areas will have risen dramatically by 2050, with much of that growth occurring in Africa and Asia (United Nations, 2019).

Rapid urban growth has become a major problem in developing countries and it is often linked with the development of informal development patterns, such as informal settlements (Avis, 2016; Dadi et al., 2016; Jones, 2017). Research shows that informal settlements make up approximately 30% of urban settlements in developing countries (Jones, 2017) and development of these settlements is one of the pressing challenges facing developing countries. This is seen in Rio de Janeiro, where 22% of the residents live in informal settlements (Snyder et al., 2014), Guangzhou (South China) where 35% of the population lives in informal settlements, and Mumbai, where half of the residents live in informal settlements (Friesen et al., 2018). In South Africa, 63% of the population stays in urban areas, with 13,6% living in informal settlements. City-region settlements are increasing rapidly in Gauteng, with 51% being informal dwellings and 38% being formal dwellings (Kemper et al., 2015; Gauteng City-Region Observatory, 2018).

Townships have been identified as important drivers of urban growth in both developing and developed countries (Abdullahi et al., 2017).Worldwide, the rapid increase in urbanization has resulted in a concentration of people in townships on the peripheries of major cities; this development is frequently in the form of informal settlements.

Local authorities in city areas in developing countries have tried several housing plans to eradicate informal settlements by methods such as demolition and upgrading the informal settlements (Ren, 2018). Linard et al. (2013) indicated that Africa’s population will double in the next 40 years and it is crucial to prepare for the growth by providing spatial detail maps that will assist decision makers in managing infrastructure and land productivity and will enable proper planning of basic facilities.

2.2 Remote sensing for urban growth

Remote sensing is defined as the science and art of gathering information without physically coming into contact with the object under observation (Lillesand et al., 2015). The availability of remote sensing sensors that provide satellite imagery datasets at various spatial, temporal, and spectral resolutions offers vast opportunities for mapping urban growth. With the rapid expansion of urban areas, the establishment of accurate information on the urban built-up area is important for urban planning, disaster management and resource management; it also serves as a key for studying urban geography, and the proper planning of urban infrastructure and basic facilities (Linard et al., 2013; Wray and Cheruiyot, 2015; Hussain and Shan, 2016;Vigneshwaran and Vasantha Kumar, 2018).

The use of earth observation satellite data has largely overtaken field survey approaches for identifying urban built-up areas, owing to developments in remote sensing and geographic information systems (GIS) technology. The advantages of remote sensing data and technology are that it offers capability of mapping and monitoring ecosystem health at various temporal and spatial resolutions, and provides data coverage over large/inaccessible areas (Li et al., 2014). Furthermore, it provides historical data that helps in monitoring, mapping and estimation of urban growth at different scales through the use of various remote sensing algorithms, technologies and images. Owing to these advantages, remote sensing is now recognized as an important tool for understanding urban growth, with several studies using remote sensing technology and data to map, monitor, and predict urban growth patterns, thus yielding useful results (Kemper et al., 2015; Kadhim et al., 2016; Lal et al., 2017; Shaw and Das, 2018; Melchiorri et al., 2019; Samper et al., 2020).

The improvement in remote sensing data accessibility and image resolution has resulted in an increase in the availability of urban information for a wide range of spatial, spectral, and temporal resolutions, making urban growth models more realistic (Aarthi and Gnanappazham, 2018; Ma et al., 2019). There is a rise in the use of high-resolution images obtained by sensors such as SPOT and WorldView resulting from high spatial resolution satellite data providing crucial detailed information on the built-up area (i.e., settlement areas), which serves as important evidence of the status of settlement types and distribution, especially in regions that are strongly affected by ongoing population growth (Gxumisa and Breytenbach, 2017; Aravena Pelizari et al., 2018; Cai et al., 2019). Furthermore, it has enabled settlement monitoring through the provision of continuous spatially explicit and temporal data related to the land surface (Hegazy and Kaloop, 2015; Ahmad and Goparaju, 2016; Ngcofe et al., 2017; Chen et al., 2017, 2020; Mudau et al., 2020a).

Remote sensing image classification methods have been applied to the mapping of urban growth. Some of these classifications are based on mono-temporal images that analyse settlements based on a single date image (Zoungrana et al., 2015), while other classifications rely on multi-temporal images with varying spatial resolutions. Pixel-based methods, machine learning classifiers, visual image interpretation, and object-based image analysis are examples of such methods (Boori et al., 2015; Schug et al., 2020). Ezimand et al. (2018) developed a novel index using visible blue band and first shortwave infrared(VbSWIR1-BI method) to detect built-up land areas through the thresholding of various spectral indices that separate built-up from non-built-up areas. The first shortwave infrared index showed improved overall accuracy in extraction. Hoffman-Hall et al. (2019) used a random classifier to map rural settlements; the results showed that the random classifier can be used to map settlements in remote areas. Patel et al. (2015) and Kar et al. (2018) extracted urban areas using the Normalized Difference Spectral Vector indices from Landsat 5 and Landsat 7 imagery and topographic sheet; the results showed an increase in urbanization ascribed to an increase in population and migration.

Although different methods have yielded high accuracies in mapping urban areas and settlement growth, there are still challenges in mapping settlement types. Mudau and Mhangara.(2021) indicated that it is not feasible to detect settlement types using spectral characteristics only. Mapping of settlements does not solely depend on the spectral information, due to varying building materials used in building settlements such as the roof (Fallatah et al., 2019; Mudau and Mhangara, 2021). While these methods improve the mapping of built-up areas, most of them are based on the use of the pixel-threshold-based algorithm methods; meanwhile, advanced, and automatic methods have been developed to map built-up areas. Although less often applied than pixel-based analysis, OBIA is already popular in discussions on monitoring of urban growth. This interest stems from the growing number of high-resolution images that are available and improved access to software. Unlike the pixel-based classifier, OBIA incorporates analysis of spectral information with shape, texture and brightness that allows the detection of settlement types. Table 1 summarises studies conducted on settlement growth using remote sensing. The studies show that remote sensing can successfully monitor settlement and that there is an increase in settlements both in urban and rural areas. Therefore, it is essential to monitor settlement growth and detect settlement types, as these factors strongly influence urban development.

Table 1: Summary of studies previously done on remote sensing of settlement growth

Author/s and year	**Study area**	**Data**	**Methods**	**Main findings**
Mahmoud et al. (2016)	Abuja, Nigeria	Landsat	Support Vector Machine classifier was used for the classification of the settlement layer IDRISI software package was used to model growth	Overall accuracy above 82% was obtained Between 2001 and 2014, there was an increase from 11% to 17% in urban built-up areas A growing trend in settlement expansion was projected
Mudau et al. (2020a)	Tshwane, Johannesburg, Polokwane and Rustenburg, South Africa	SPOT6/7	Trimble eCognition software and ArcGIS software were used for analysis and classification Canny edges, Soil Adjusted Vegetation Index and spectral properties were used for classification	Overall accuracy obtained was above 75% for formal and 45% for informal settlement
Chen et al. (2020)	Beijing, Shanghai & Guangzhou, China	MODIS Landsat Mobile phone location	Normalized Difference Vegetation Index (NDVI) and location-based were used to map the extent of human settlements	The overall accuracy obtained was 95.2%
Al-Bilbisi(2019)	Amman, Jordan	Landsat	Maximum Likelihood Algorithm and PCI software were used for classification	Urban land increased from 149.08 to 237.86 km^2 in 1987 and 2017 respectively Overall accuracy was above 85%
Corbane et al. (2019)	Qalubiya, Egypt	Landsat GHS_LDSMT_201	Symbolic Machine Learning (SML) classifier	The overall accuracy was above 86% The study showed that it is possible to assess human settlements from rural hamlets to megacities using SML
Kemper et al. (2015)	South Africa	SPOT5 South African National Land Cover SPOT Building Count (SBC)	Multiscale textural and morphological features were used for mapping settlements	The overall accuracy was 97% A new workflow was developed for mapping settlements in South Africa The study proved that the Joint Research Centre methods for Global Human Settlement Layer could be used in South Africa
Ngcofe et al. (2017)	KwaZulu Natal, South Africa	SPOT5	eCognition software and ERDAS were used for analysis and classification	Overall accuracy was 70.7% in mapping settlements using GEOBIA

2.3 Object-based image analysis for detecting and monitoring built-up areas

The OBIA is a remote sensing image analysis paradigm that examines image objects based on their morphological, spectral and textural features (Blaschke, 2010). These image objects are made through the grouping of pixels with homogeneous properties that represent real-world geographic objects that form the basis for image analysis (Nussbaum and Menz, 2008; Ye et al., 2018); this helps the classifier to differentiate spectrally similar land cover types (Akar et al., 2017). Research has shown that OBIA reduces spatial noise, thus increasing classification accuracy (Mahdianpari et al., 2020); it performs better than the traditional pixel-based classification techniques that operate on a single pixel without considering the size and morphology of an object (Blaschke, 2010; Myint et al., 2011; Ye et al., 2018).

Satellite images are a valuable source of information for monitoring urban built-up areas. Classification of land use/cover types in urban environments is very challenging owing to the spectral heterogeneity of images in these areas (Wurm et al., 2011). The development of, and access to, earth observation technology has facilitated mapping land covers more accurately, thereby facilitating the better detection of surface features (Amini et al., 2018). Further, the use of data with high spatial, spectral, and temporal resolution has enabled the classification of heterogeneous urban environments (Hussain and Shan, 2016).

To provide up-to-date maps and databases on urban expansion, land cover data must be collected regularly (Hussain and Shan, 2016). Extensive classification of land cover types in urban areas has been done using OBIA, as it decreases image complexity (Amini et al., 2018). Further, there is a strong correlation between OBIA classification techniques and urban forms, with its key variables being shape, size, texture, settlement intensity and spatial distribution of different urban features (Al-sharif, et al. 2017).

Recently, OBIA has been widely applied to the extraction of urban and rural features. In addition, it has been used for the classification and trend analysis of urban areas. Several studies have attained highly accurate classification results when utilising OBIA for urban growth and settlement mapping (Akar et al., 2017; Gianinetto et al., 2014; Mudau et al., 2014; Ngcofe et al., 2017). Mapping land cover types (i.e., built-up, vegetation and water) using high-resolution satellite images is effective using OBIA (Rossi et al., 2019; Sreekesh et al., 2020). In addition, the integration of morphological, textural, and spectral attributes used in the OBIA approach increases image classification accuracy. This method of classification has been selected for this study.

2.4 Application of a cellular automata technique for urban growth modelling

Models of urban growth attempt to predict future urban growth. Numerous studies articulate that urban form and patterns significantly affect social, environmental, and urban sustainability. Therefore, assessing future trends in urban areas is essential for succeeding in urban sustainability plans (Al-sharif et al., 2017). To model urban growth, several models such as support vector machine (Samardžić-Petrović et al., 2016), agent-based models, Markov chain models and CA have been developed.

One of the widely used methods effective for simulating spatial dynamic urban growth is CA modelling. In predicting urban growth, CA models are known to be a powerful tool that performs well (Aarthi and Gnanappazham, 2018). These models have been widely used because of their flexibility, self-organisation characteristics, ability to reproduce the dynamics of complex systems and compatibility with raster data.

According to Naghibi et al. (2016), the CA model comprises five components, namely (i) cell space where the automaton is present; (ii) cell state, which refers to the land use category occupied by a cell at a set time; (iii) cell neighbourhood, which includes surrounding cells; (iv) time; and (v) transition rule where cells change their state depending on neighbourhood cells in discrete time steps. The transition rule determines the performance of CA (Naghibi, et al., 2016). Transition rules are used in CA to provide spatial patterns of urban growth and trends over time; because of heterogeneity and non-linearity that exist amongst urban growth driving forces, determining the optimum CA, transition rule is a critical step.

2.5 Summary of lessons learnt from the literature review

This section reviewed the literature on the use of remote sensing, OBIA and CA techniques for monitoring and modelling urban (built-up) growth. It has been outlined in the literature that urban areas are dominated by built-up areas. Urban growth is linked to migration and population growth.

The literature has shown that challenges in monitoring urban growth can be solved using remote sensing, as it has been acknowledged as an effective technique for gathering spatial information for urban growth monitoring and assessment for planning purposes. Unplanned urbanization damages natural resources and affects the quality of human livelihoods. Urban form and pattern have an impact on social, environmental, and urban sustainability, thus affecting any plans for urban sustainability.

Urban growth prediction models will assist decision makers to identify potential areas of growth and plan the development of their cities. The literature outlines that the availability of high-resolution satellite datasets helps in making urban growth models more realistic. Authors have also described the use of high spatial resolution satellite data enables the detection of built-up areas and distinct dwelling units.In developing countries, urban expansion is often linked with the development of informal settlements. It is evident that as demand for spatial information increases, the acquisition of spatial data must be timely, reliable and easily accessible.

The literature also recommends that high spatial resolution images are useful for mapping built-up areas using OBIA. In addition, the literature has also shown that OBIA increases classification accuracy. This study will investigate the use of OBIA to map built-up and non-built-up areas.

Several studies have demonstrated that urban growth can be monitored and modelled using OBIA and CA techniques. Traditional pixel-based methods have been extensively used, whereas OBIA and CA techniques which improve accuracy remain largely unexplored. Hence, this study will investigate the use of OBIA and CA techniques for monitoring and modelling settlement growth.

CHAPTER 3: METHODOLOGY

3.1 Study area

The study area is Pretoria North, Gauteng Province, South Africa. It comprises Region 1 townships in the City of Tshwane Metropolitan Municipality, namely Soshanguve, Mabopane and Winterveld. The Soshanguve, Mabopane and Winterveld townships were developed in the late 1960s (Mosiane, 2022). Figure 1 shows the locality of the study area.

Geographically, Region 1 of Pretoria North lies between 25°29' south and 28°06' east at 1 182 m above sea level. Geologically, the area is located in the bushveld complex group. Region 1 townships fall within the summer rainfall region of South Africa, and it experiences 4 to 6 months (October to March) of hot, wet summer where temperatures can reach as much as 34 °C, and a dry frosty winter (May to September) where temperatures can be as low as −2 °C. During the summer season, the region receives an average annual rainfall of 463 mm.

In the CoT context, Region 1 has the highest social vulnerability to impacts from climate change and is characterized by extremely populated areas situated within informal settlements with the lowest levels of access to basic services (CoGTA and CoT, 2020). The CoT is one of the three administrative capital cities of South Africa, and is bordered by three provinces, namely, Limpopo, North West and Mpumalanga. The CoT is home to many national departments and state entities, and over 100 embassies are located in the city. There are four public universities located in CoT, namely, Tshwane University of Technology, University of South Africa, University of Pretoria and Sefako Makgato Health Life University. The CoT Metropolitan Municipality's population was 2 921 488 in 2011 and 3 275 152 in 2016, making it Gauteng's district with the greatest percentage increase in population (StatsSA, 2016).

The population growth in CoT has been strongly influenced by the flow of people coming for jobs, services and education opportunities. Consequently, over the years Pretoria North Region 1 has been experiencing a rise in urban growth with an increased number of informal settlements; furthermore, is designated in terms of the National Department of Human Settlement as a Human Settlements and Housing Development Area. Consequently, the area was chosen for this research.

It is reported that most of Region 1 of CoT Metropolitan Municipality is densely populated. According to the CoT Metropolitan Municipality Report (2020), approximately 27.7% of the Tshwane population live in its Region 1 townships (Soshanguve, Mabopane and Winterveld). These areas have CoT's highest social vulnerability to climate change impact and are characterized by extremely populated informal settlements with the city's lowest levels of access to basic services (CoGTA and CoT, 2020).

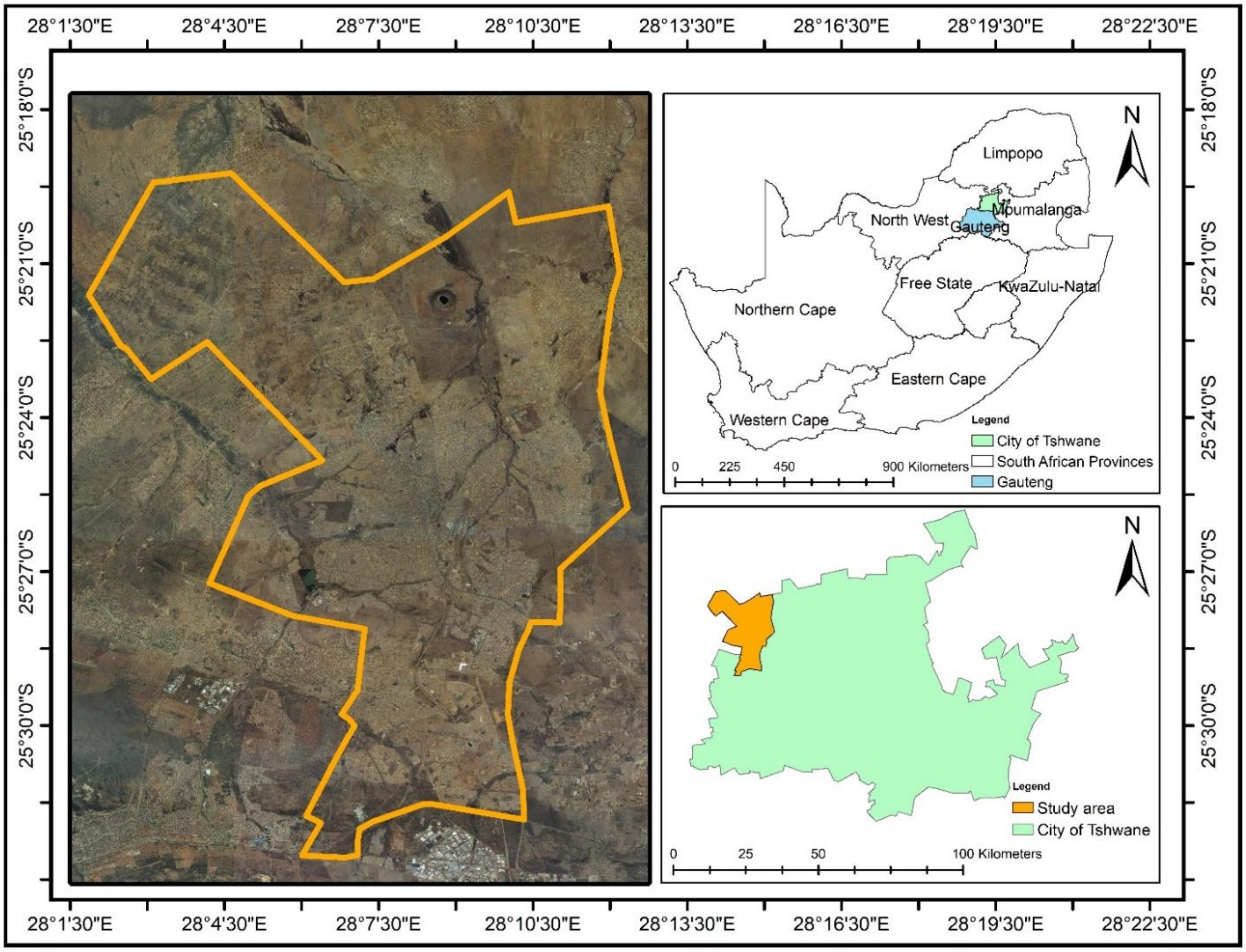


Figure 1: Study area in Pretoria North (Region 1) in the City of Tshwane (CoT) situated in Gauteng province, South Africa.

3.2 Data acquisition

The cost of remote sensing data, necessary processing software and hardware, image spatial, temporal and spectral resolution are fundamental factors, which determines the choice of selection of datasets (Adam et al., 2014). Cloud-free SPOT satellite multi-temporal images for the years 1990, 1994, 2000, 2005, 2010, 2015 and 2017 were acquired from the South African National Space Agency (SANSA) (Table 2). SPOT satellite images were selected since they are available at no cost for academic research in South Africa; SPOT provides high spatial resolution for the years chosen for the study, allowing for the quantification of distinct spatial, spectral, and geometric characterisation of different land cover types.

SPOT2 satellite images were obtained for the years 1990 and 1994, while SPOT4 data was used for 2000 and 2005. SPOT5 data was used for 2010 and SPOT6/7 images were used for 2015 and 2017. This study used five-year intervals between the years 2000 and 2015 to show any changes in built-up areas and settlements, and an interval of two years was used for the 2015–2017 period. However, owing to the unavailability of SPOT imagery for the year 1995, an interval of four and six years was allowed for the years 1990–1994 and 1994–2000, respectively. Table 2 lists the datasets used and their sensor specifications. A digital elevation model (DEM) of 20 m acquired from SANSA’s Fundisa disk was used for the modelling of settlement growth.

Table 2: Remote sensing data acquisition

Year	Sensor	Date of acquisition	Spatial resolution	Spectral resolution
1990	SPOT2	01 July 1990	10 m Pan 20 m MS	Pan: 510–730 nm Green: 500–590 nm Red: 610–680 nm Near infrared (NIR): 780–890 nm
1994	SPOT2	18 June 1994		
2000	SPOT4	26 July 2000	10 m Pan 20 m MS	Pan: 610–680 nm Green: 500–590 nm Red: 610–680 nm NIR: 780–890 nm Shortwave infrared (SWIR):1580–1750 nm
2005	SPOT4	22 September 2005	10 m Pan 20 m MS	
2010	SPOT5	05 December 2010	2.5 m Pan 10 m MS	Pan: 480–710 nm Green: 500–590 nm Red: 610–680 nm NIR: 780–890 nm SWIR:1580–1750 nm
2015	SPOT6	10 February 2015	1.5 m Pan 6 m MS	Pan: 450–745 nm Blue: 450–520 nm Green: 530–590 nm Red: 625–695 nm NIR: 760–890 nm
2017	SPOT6	17 June 2017		

3.3 Data pre-processing

Remote sensing data is one of the most frequently used primary data sources for change detection. Many applications have arisen as a result of the availability of large archives of remote sensing data, such as monitoring and modelling of different land cover types (i.e., built-up areas and water). However, several factors affect the remote sensing data acquisition process, and this lowers image quality and affects image analysis. When working with multi-temporal data from different sensors, date and time, as well as image pre-processing are needed to rectify geometric and radiometric distortions in sensors and platforms caused by changes in scene illumination, geometry, atmospheric effects, sensor noise and topography (Lu et al., 2004).

Before extracting information from multiple temporal data, it is essential to pre-process the images so that there can be conformity in the datasets allowing spatial comparison (Baboo and Devi, 2011; Otunga et al., 2014). For this study, SPOT satellite images were radiometrically and atmospherically corrected in Environment for Visualizing Images (ENVI) 5.3 software using the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) method. FLAASH was used to correct the surface reflectance and to remove unwanted errors and noise from the images in the visible to NIR wavelengths of SPOT as recommended by Siregar et al. (2018) and Guo and Zeng (2012). The images were also geometrically corrected using the image-to-image registration on ArcMap10.3 software.

The Gram-Schmidt pansharpening technique in ENVI software was used to sharpen the multispectral images using the high spatial resolution panchromatic band. The Gram-Schmidt pansharpening technique was selected, as it is one of the best pansharpening techniques for SPOT satellite images (Siregar et al., 2018; Mhangara et al., 2020). Images for the years 2005, 2010, 2015 and 2017 were pansharpened. These images were pansharpened to 10 m, 2.5 m and 1.5 m to enhance the spatial resolution of the multispectral imagery. Additionally, the images were subset to the study area to minimise processing time and computational demand.

3.4 Reference data

There are numerous methods for collecting reference data, including high-resolution images and ground truthing. Expert knowledge for visual interpretation is also used as a source of reference data. For this study, reference point data was generated using random sampling on QGIS3.18.2 software and validated using very high-resolution images on Google Earth. Google Earth provides an archive of coarse to very high-resolution images that are very useful for validating urban extent and accurate assessment of land cover (Jacobson et al., 2015). For the years 1990, 1994 and 2000, reference points were validated using SPOT images because higher-resolution images were no longer available for that year and the study area had poor coverage on Google Earth.

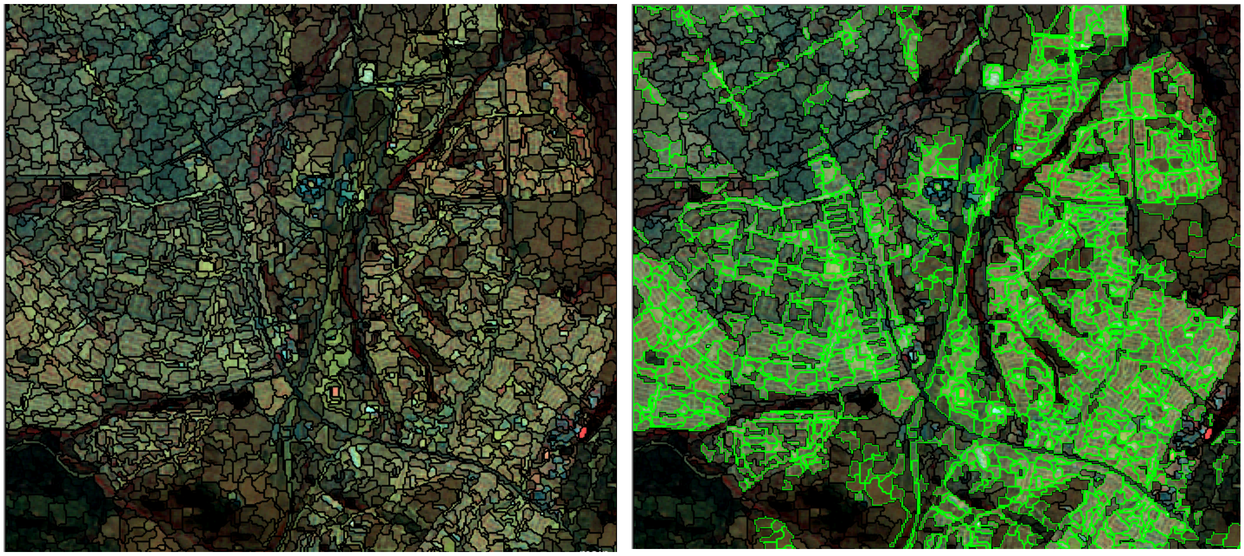
3.5 Image classification

OBIA is a method of classifying pixels into recognizable objects based on the textural, spectral, and morphological properties of the objects. Its primary analysis takes place at the image object level, which is achieved by segmentation. These image objects are created by grouping pixels with similar properties representing real-world geographic objects, and which serve as the foundation for image analysis. The benefit of OBIA stems from the spatial relationships between pixels; the between-pixel areas contain a wealth of information that aids in the creation of an object. OBIA was used for the classification of images for the present study.

3.5.1 Image segmentation

Image segmentation is the key step in OBIA, as it determines the quality of classification. The image segmentation algorithm divides homogeneous image pixels into objects with similar properties which are used in the classification and analysis of images (Blaschke et al., 2004). The image segmentation method is based on three factors, namely: the scale parameter, shape and compactness (El-naggar, 2018). These three factors are crucial as they determine the quality of image objects used for processing and classification (Dekavalla and Argialas, 2018). Although all the factors are important; scale is considered the most crucial parameter for segmentation, especially for remote sensing data (Kim et al., 2011). The scale factor controls the average size of objects and the number of objects to be segmented. Shape determines the weight of the spectral and shape information of segments, while compactness controls the homogeneity of image objects at different scales; thus shape and compactness controls homogeneity (Salehi et al., 2012; Johnson and Jozdani, 2018).

In this study, a multi-resolution segmentation (MRS) algorithm on Trimble eCognition Developer 9.0 software was used for assessing and classifying built-up areas, non-built-up areas, and formal and informal settlements. The MRS algorithm is one of the most widely applied segmentation algorithms that uses a bottom-up region merging technique (Dekavalla and Argialas, 2018; Munyati, 2018); MRS uses shape, scale and compactness parameters to partition single pixels into objects that have the same properties. A scale parameter of 5, shape set to 0.3 and compactness of 0.5 were used for segmentation in this study; these parameters were selected using a trial-and-error approach until suitable built-up objects were achieved. A small-scale value was chosen so as to construct homogeneous segments and reduce the impact of mixed land cover artefacts (Qian et al., 2015). The segmentation process is depicted in Figure 2(a) and (b) which accurately delineates built-up clusters in the study area.



(a) **(b)**

Figure 2: (a) Multi-resolution segmentation (MRS) of SPOT image (b) Building clusters outlines

3.5.2 Rule-based classification method

The second step in OBIA is the classification of the image objects. A rule-based classification method was selected and used for this study. Rule-based classification is a thresholding classification method which divides image objects into classes based on statistics from different object features. The rule-based method was selected because, with some modifications on object features, the rulesets developed in one area can automatically be applied to multi-temporal data and study areas. Further, the transferability of rulesets is important for the automation of a classification method (Demers et al., 2015; Bangira et al., 2019). The study used the indicators listed in Table 3 to determine built versus non-built areas. Classes of investigation for this study are shown in Tables 3 and 4.

Table 3: Indicators for built-up and settlement areas extraction

Feature		Thresholds for the features
Normalized Difference Vegetation Index	NDVI $= \frac{(NIR - Red)}{(NIR + Red)}$	$\geqslant -0.07 \leqslant -0.02$
Simple ratio	$\frac{Red}{Green}$	> 0.89 built-up ⩽ 0.89 non-built-up
Mean value of SPOT bands was used for classification	NIR, red and green	Green ≥ 400 NIR: > 161 and NIR < 300 Blue ≥ 350
Brightness	mean intensity of the bands of an image object (NIR, red, green, blue)	Brightness ⩾ 200
Max difference	Max difference of the spectral bands	⩾ 0.7 built-up
Global Local Co-occurrence Matrix (GLCM)	Dissimilarity	⩾ 0.7 built-up

Table 4: Classes and description

Class Name	Description
Built-up areas	Residential areas (formal and informal), construction sites, industrial areas, administrative areas, commercial, roads, impervious surfaces, and other infrastructure
Non-built-up	Agricultural land, irrigated areas, vegetation, shrubs, bushes, grasslands, open landscapes, mountains, and water (rivers, water reservoirs and dams)
Formal settlements	Settlements that have been planned and constructed in large numbers includes construction sites, industrial areas, administrative areas, commercial (often with backyard shacks)
Informal settlements	"An unplanned settlement on land which has not been surveyed or proclaimed as residential, consisting mainly of informal dwellings (shacks)" (StatsSA, 2001;Sahondo et al., 2020)

3.5.2.1 Detection of built-up and non-built-up areas

Numerous studies have used vegetation indices together with other features to extract buildings (Elshehaby and Taha, 2009; Singh et al., 2012). The Normalized Difference Vegetation Index (NDVI) was calculated using formula (1) below (Braun and Herold,2004): where NIR is reflectance in the NIR band and Red is reflectance in the red band (used to classify features into built-up and non-built-up areas). In this research, we used the NDVI instead of built-up indices for the assessment of built-up areas owing to the spectral limitation of SWIR (shortwave infrared) bands in our SPOT2 and SPOT6 datasets.

$$\mathbf{NDVI} = \frac{(\boldsymbol{NIR} - \boldsymbol{Red})}{(\boldsymbol{NIR} + \boldsymbol{Red})} \quad (1)$$

Although NDVI is designed for extraction of vegetation, it can be used as an index to extract other land cover classes such as buildings; lower values of the NDVI represent objects such as buildings and water while higher values represent vegetated areas. It has also been shown that buildings and paved surfaces have low NDVI values.

In addition to the NDVI, Global Local Co-occurrence Matrix (GLCM) dissimilarity values obtained from the spectral bands were used to classify built-up and non-built-up areas. The GLCM is a texture matrix developed by Haralick et al. (1973) as a grey-level image that displays the joint likelihood of distribution of a pair of grey levels separated by a specific distance and orientation. GLCM quantifies spatial relations of image pixels. Mudau et al. (2020) stated that texture is one of the most crucial attributes used in identifying similar patterns in images, and it is effective in mapping settlements (Ngcofe et al., 2017; Mudau et al., 2020). The study visually inspected GLCM-dissimilarity textural values to determine threshold values for built and non-built-up areas using SPOT6 imagery. Built-up areas have high textural values owing to various features, whereas non-built-up areas have low textural variation.

Furthermore, object spectral: mean value and brightness of spectra band (red, green, NIR and blue), were used in the ruleset to classify built-up and non-built-up areas on level 1 derived image objects from MRS. The NIR, blue and green bands have high reflectance from buildings, and their brightness was the reason for them being the selected. These were identified using a trial-and-error threshold method for the indicators until adequate built-up and non-built-up areas had been detected.

3.5.2.2 Detection of formal and informal settlements

Informal settlements are the greatest source of urbanization in the world. However, there is no consistent method for mapping where this informal development exists and how this is spreading. Understanding the distribution of settlements and monitoring of urban expansion is essential for several purposes, such as infrastructure planning, disaster planning, urban development, and biodiversity conservation. Remote sensing technology allows for the low-cost mapping and classification of settlements based on the settlement morphology; it enables separability of classes of data on settlements. Formal and informal settlements can be detected and discriminated from other land uses through the use of spatial, texture, geomorphic properties and landscape metrics from remote sensing image data (Zheng et al., 2016; Shabat and Tapamo., 2017). Several studies have indicated that there is insufficient knowledge of the spectral properties of urban structures and the lack of discernible spectral signatures makes mapping informal areas challenging.

Various methods have been used to map settlement such as visual interpretation, machine learning, pixel and OBIA (Mudau and Mhangara, 2021). For this study, OBIA was applied to the mapping of formal and informal settlements. The classification of formal and informal settlements was done on level 1 image objects (built-up layer) using the assign class by thematic layer algorithm, thresholding, and visual interpretation to partition formal and informal settlements from the built-up area. South African national land covers corresponding to the year of analysis obtained from the Department of Environment Affairs were used as the thematic layer for this classification. The methodology followed for this study is depicted in Figure 3.

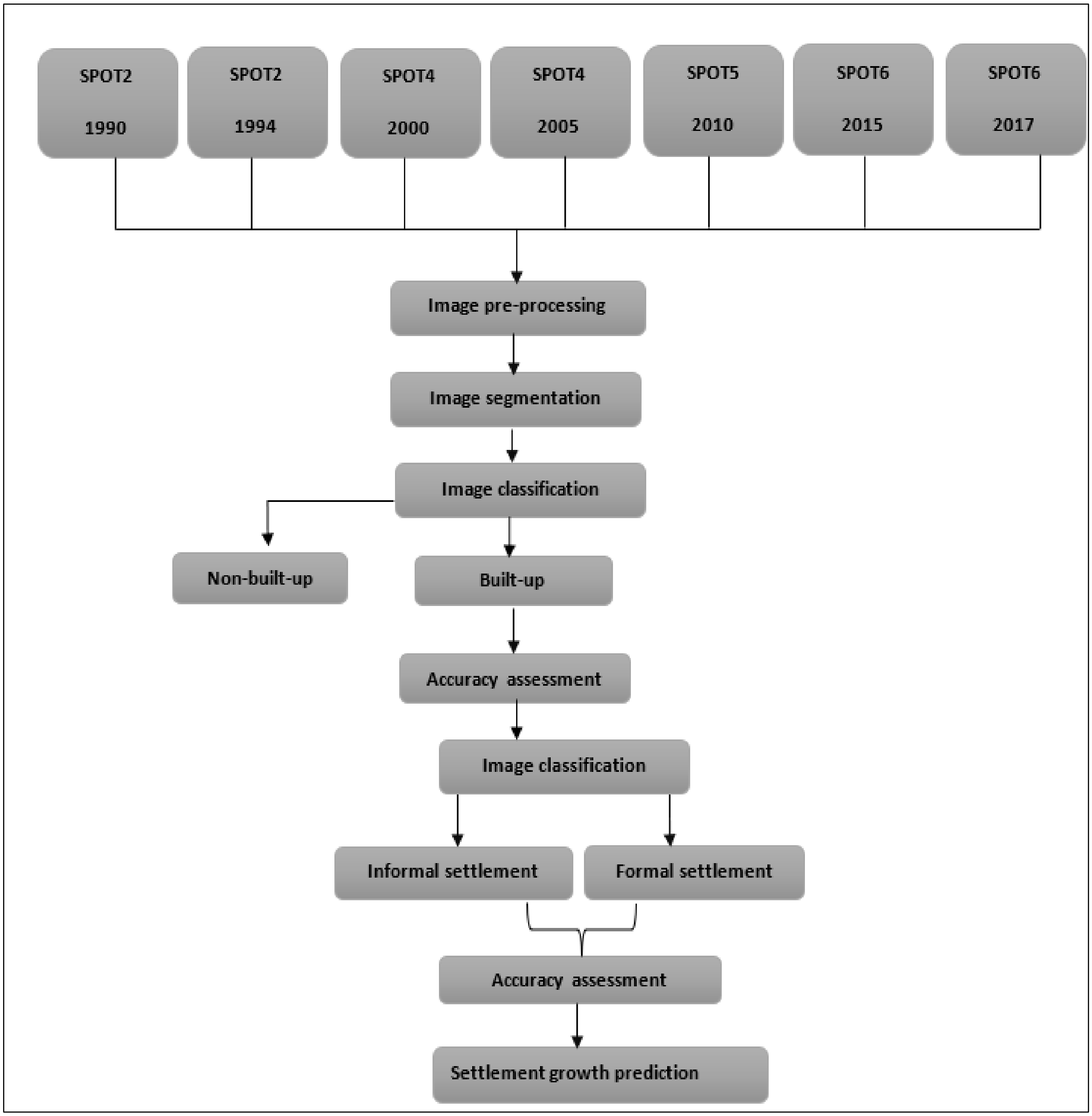


Figure 3: Methodology followed for the study

3.6 Accuracy assessment

Accuracy assessment is described as the extent to which the produced map conforms with the reference classification (Olofsson et al., 2014). It is crucial that for any GIS and remote sensing derived product, an accuracy assessment must be done to validate the product. Bharath et al. (2020) specified that until an accuracy assessment is done, classification is not complete. Additional accuracy assessment must be done to validate the correctness of the classification methodology, identify the source of uncertainty and evaluate if the derived maps are fit for purpose (Morales-Barquero et al., 2019). For accuracy assessment, one compares mapped features to higher quality reference data. Confusion matrix (which measures the degree of misclassification between classes) was used to measure the accuracy of built-up classification; the confusion matrix compares classified classes versus actual land cover classes obtained from corresponding ground truth data. The kappa coefficient was used to evaluate the accuracy of the classification.

3.7 Change detection

Change detection is a method of detecting dissimilarities in a phenomenon by observing it over different times (Singh et al., 2012). Change detection is a crucial process in monitoring urban development, as it provides an analysis of the spatial distribution of the phenomenon under observation. The increase of multi-temporal remote sensing data allows the detection and assessment of urban cover in a timely and cost-effective way (Al-doski et al., 2013); this makes remote sensing a critical technique in change detection. For this study, a post-classification change detection analysis was performed on the classified image. The analysis of post-classification change detection entails comparing classified images to detect areas of change which result in a “from-to” change matrix of the transitions between each class compared (Mudau et al., 2014; Vivekananda et al., 2020). In this study, post-classification analysis was used to calculate changes. A change detection analysis was performed in ArcGIS 10.3 by use of the overlay toolset to identify built-up areas that overlap in the following periods: 1994–2000, 2000–2005, 2005–2010, 2010–2015, and 2015–2017. “Change” was defined as the built-up areas that did not overlap in the layers. Settlement growth was measured by examining changes in built-up areas from 1994 to 2017.

3.8 Modelling future settlement growth

Urban planners require reliable data on the existing settlements, how they have changed in the past, and how they may change in the future for urban planning and land management. In this study, Modules for Land Use Change Simulations (MOLUSCE) plugin within QGIS software was used to model future settlement growth in 2025. MOLUSCE is a CA-based model designed to analyse and predict current and future land use and land cover changes (Guidigan et al., 2019). Artificial neural networks (ANNs), Monte Carlo CA, weights of evidence, and multi-criteria evaluation modelling technique are some of the algorithms included in MOLUSCE plugin (Abbas et al., 2021; Alam et al., 2021; Muhammad et al., 2022). A DEM of 20 m covering the study area, 1990 and 2017 built-up layers were used as spatial variables for MOLUSCE to model potential future settlement growth for 2025.

CHAPTER 4: RESULTS

4.1 Mapping and assessing spatial extent of built-up area

The results demonstrate that with the application of a multi-resolution scale parameter of five together with geometric and textural information image objects were successfully classified into built-up and non-built-up areas using SPOT images for the years 1990, 1994, 2000, 2005, 2010, 2015 and 2017. Figure 4 shows the result of the extracted built-up areas on eCognition using the listed indicators in Table 5.

Figure 4: Results for extraction of built-up area using indicators

Figure 5 shows the built-up area map of Pretoria North (Region 1) in the year 1990. In 1990 the spatial extent of the built-up area was 65.2 km^2.

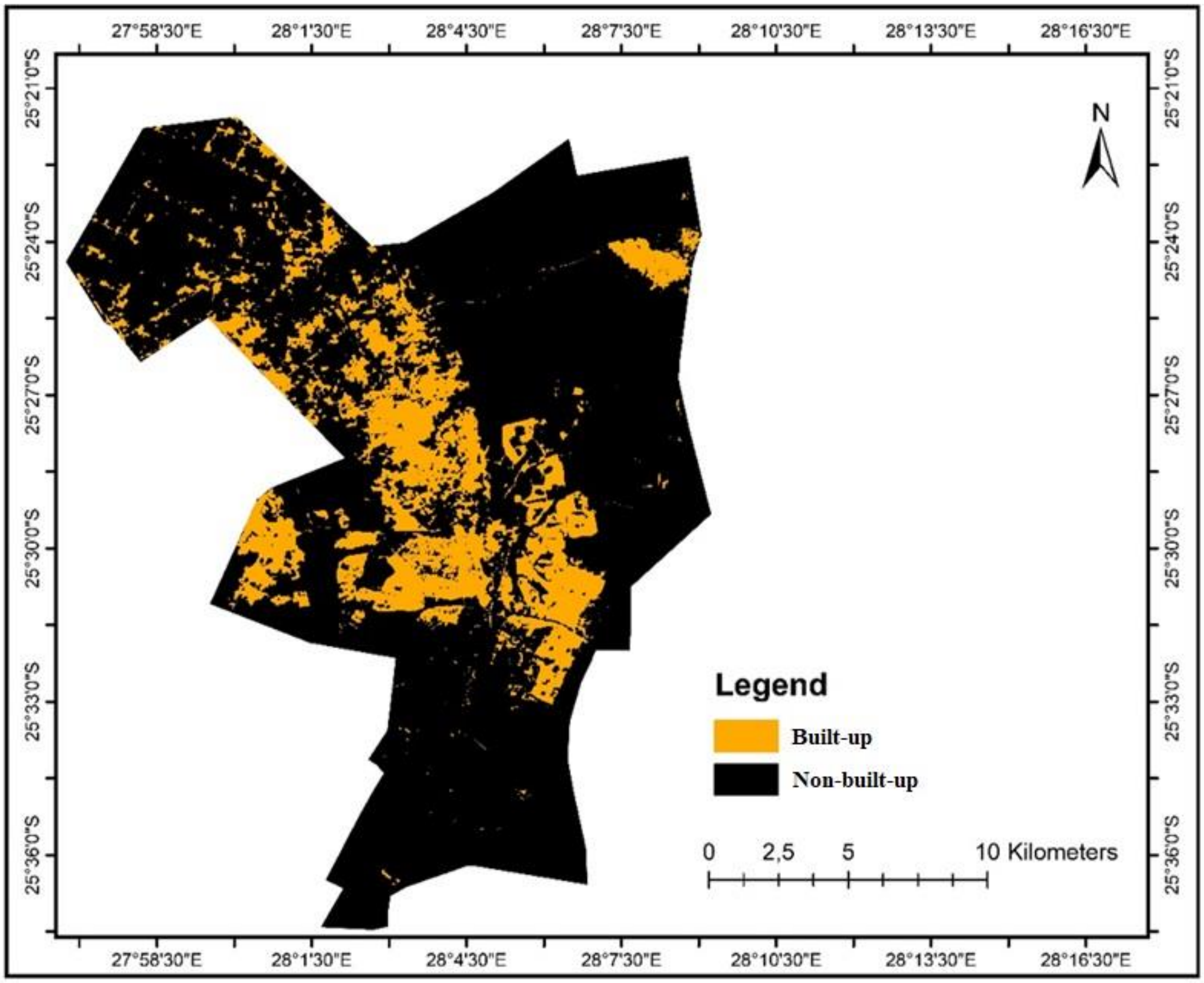


Figure 5: Pretoria North built-up areas in 1990

The built-up area map for 1994 in Figure 6 shows that built-up area covered at least 94.6 km^2 of the area. An increase in built-up area is seen in the north-eastern, western and southern parts. The total spatial extent of built-up area increased from 65.2 km^2 to 94.6 km^2 in the year 1994.

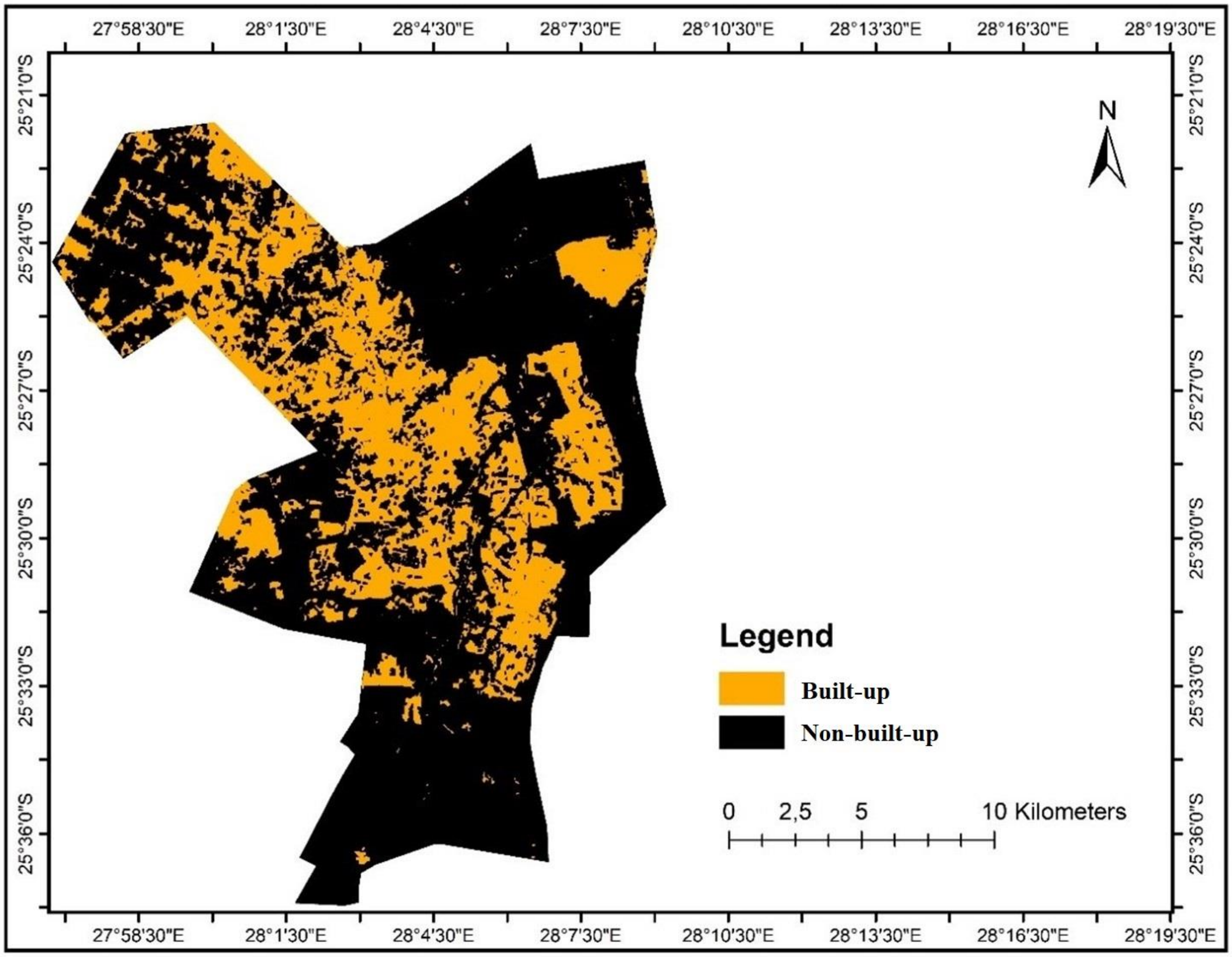


Figure 6: Pretoria North built-up areas in 1994

Figure 7 shows built-up area mapped for the year 2000. The total spatial extent of built-up area in 2000 was 139.34 km^2. Figure 7 shows that built-up area increased in the southern and north-eastern parts of the area.

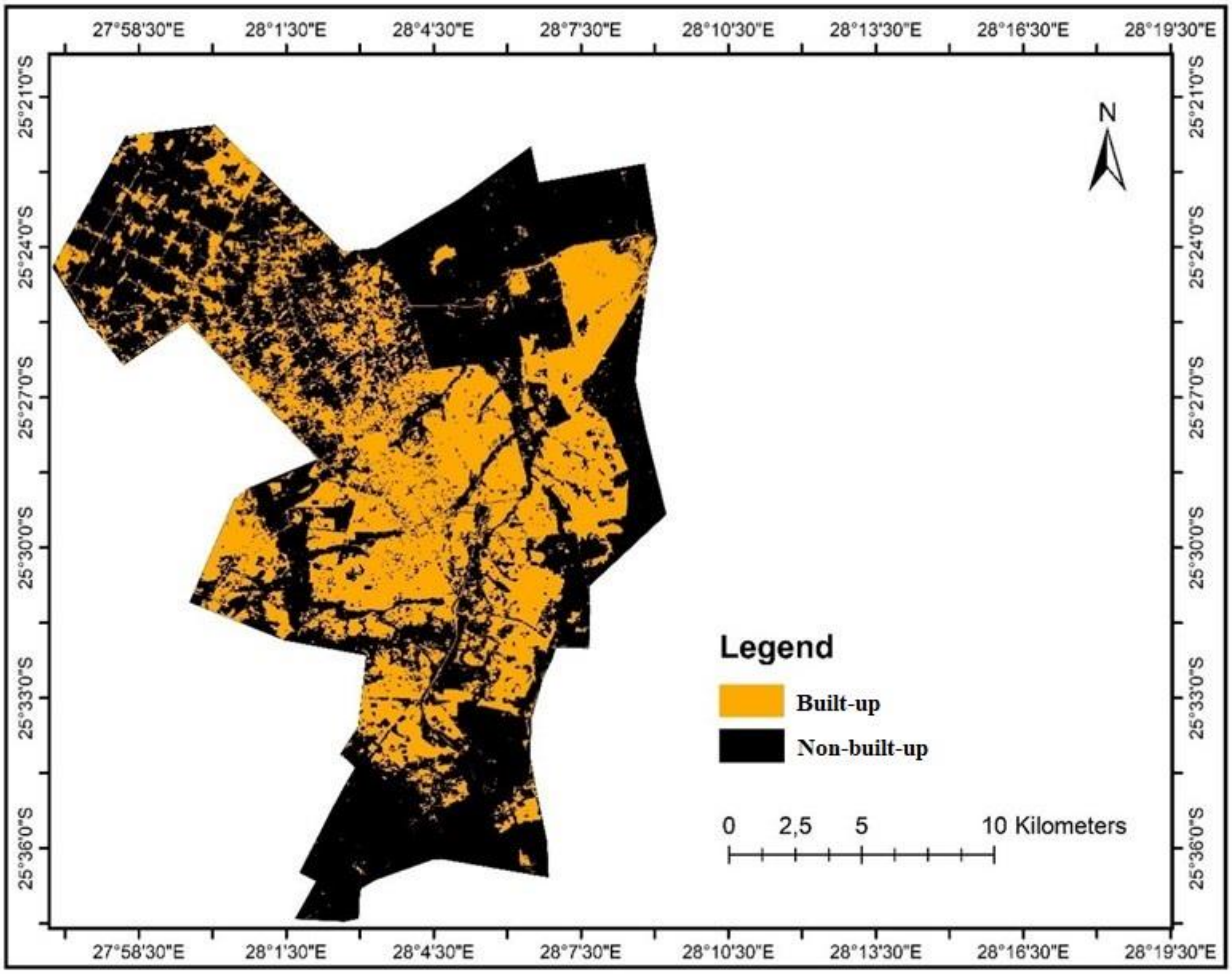


Figure 7: Pretoria North built-up areas in 2000

Figure 8 shows built-up area mapped for the year 2005. The total spatial extent of built-up area in 2005 was 157.65 km^2 and the area expanded mainly on the southern side of the study area.

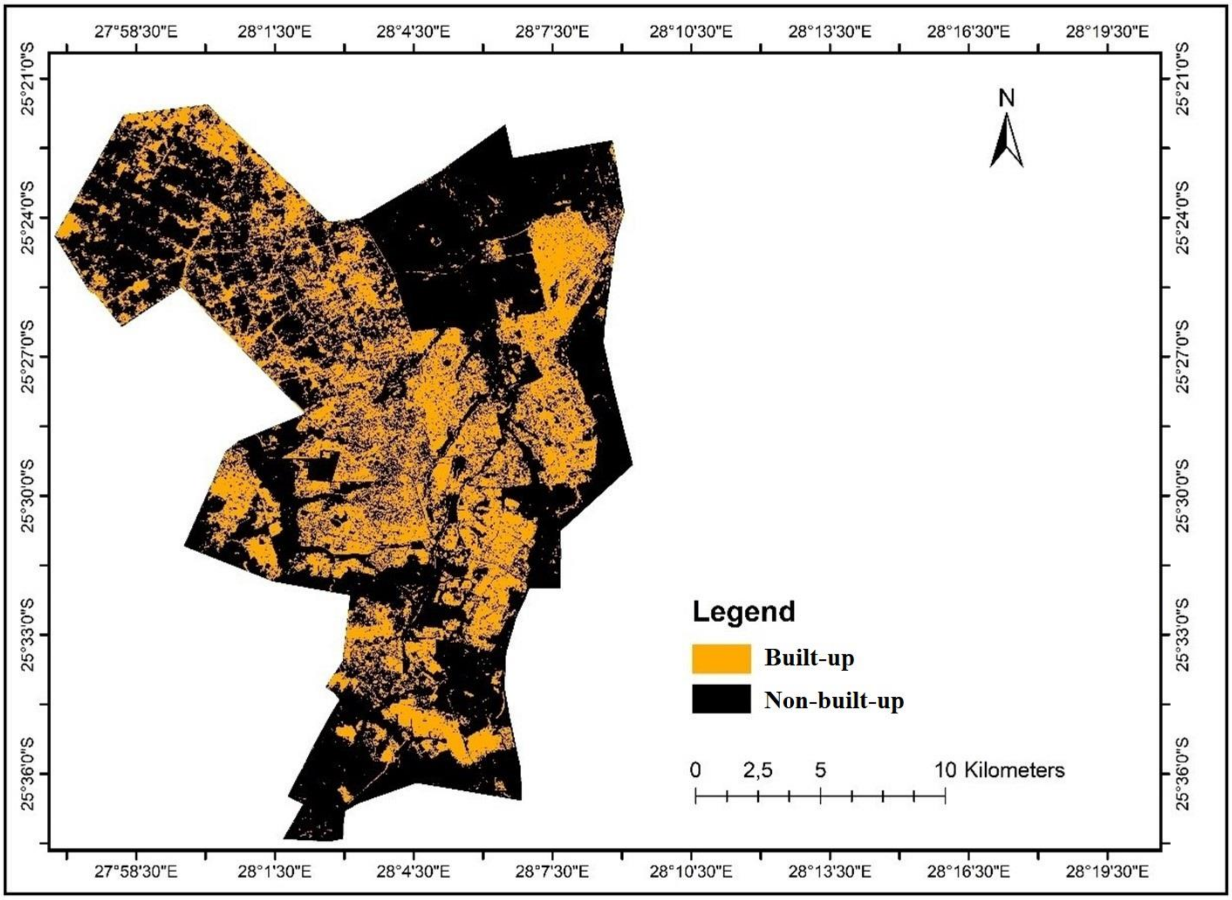


Figure 8: Pretoria North built-up areas 2005

Figure 9 shows built-up area mapped for the year 2010. The total spatial extent of built-up area was 125 km^2 and it increased mostly in the southern parts of the area.

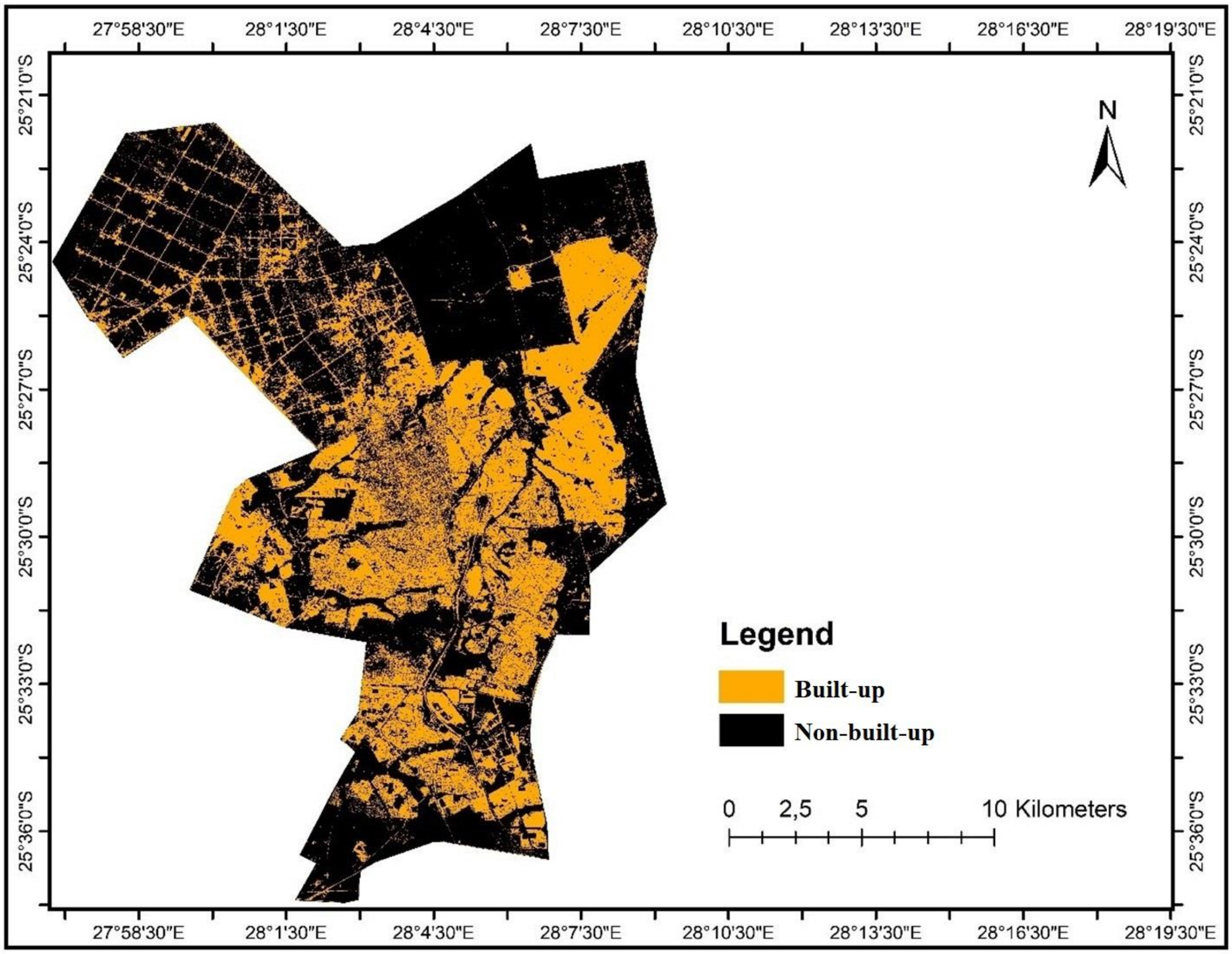


Figure 9 : Pretoria North built-up areas in 2010

Figure 10 shows built-up area mapped for the year 2015. The total spatial extent of built-up area was 117.0 km^2 for that year, and it expanded predominantly in the north-eastern and southern parts.

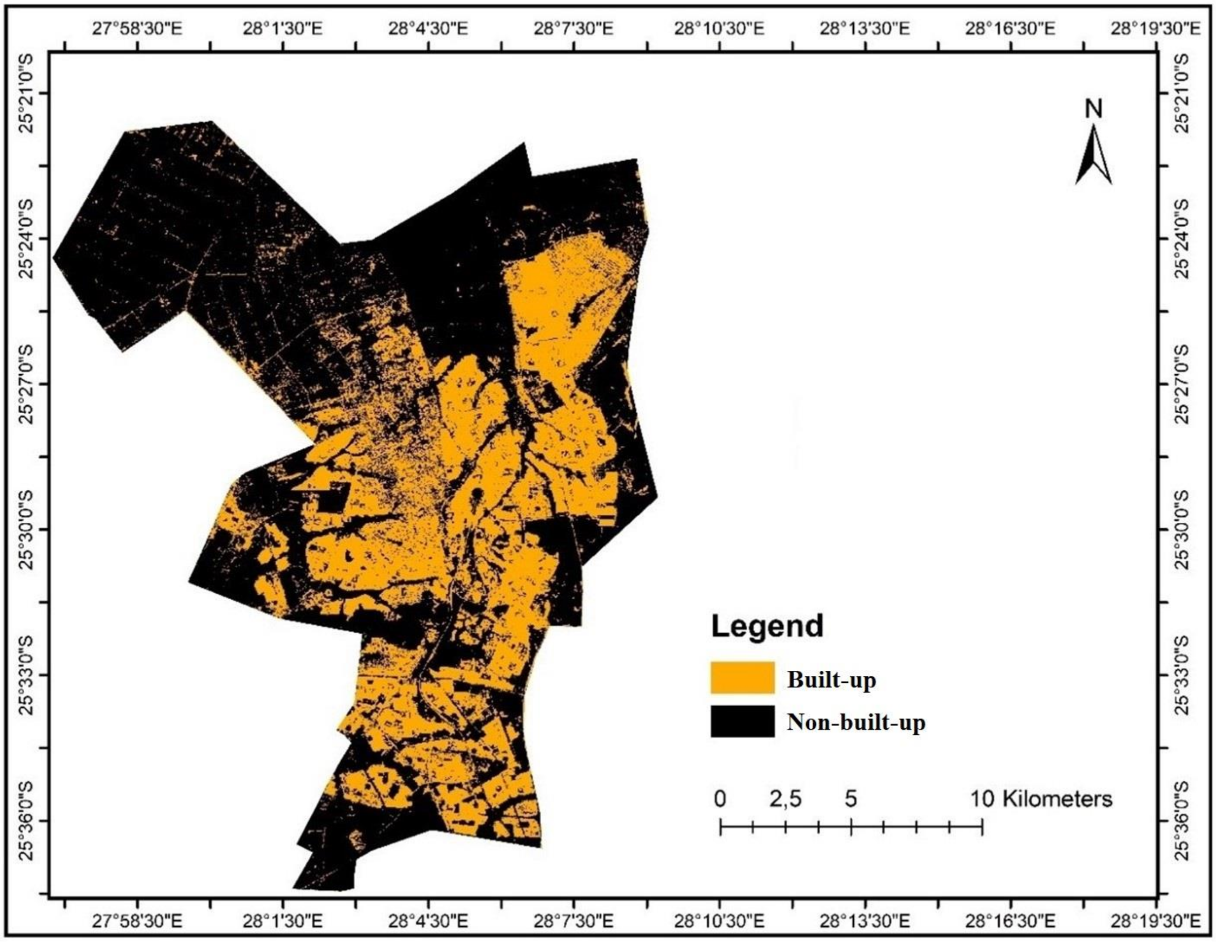


Figure 10 : Pretoria North built-up areas 2015

Figure 11 depicts the built-up area mapped for 2017. The built-up area expanded on the south and west sides of the area. For 2017, the total spatial extent of the built-up area was 144.40 km^2.

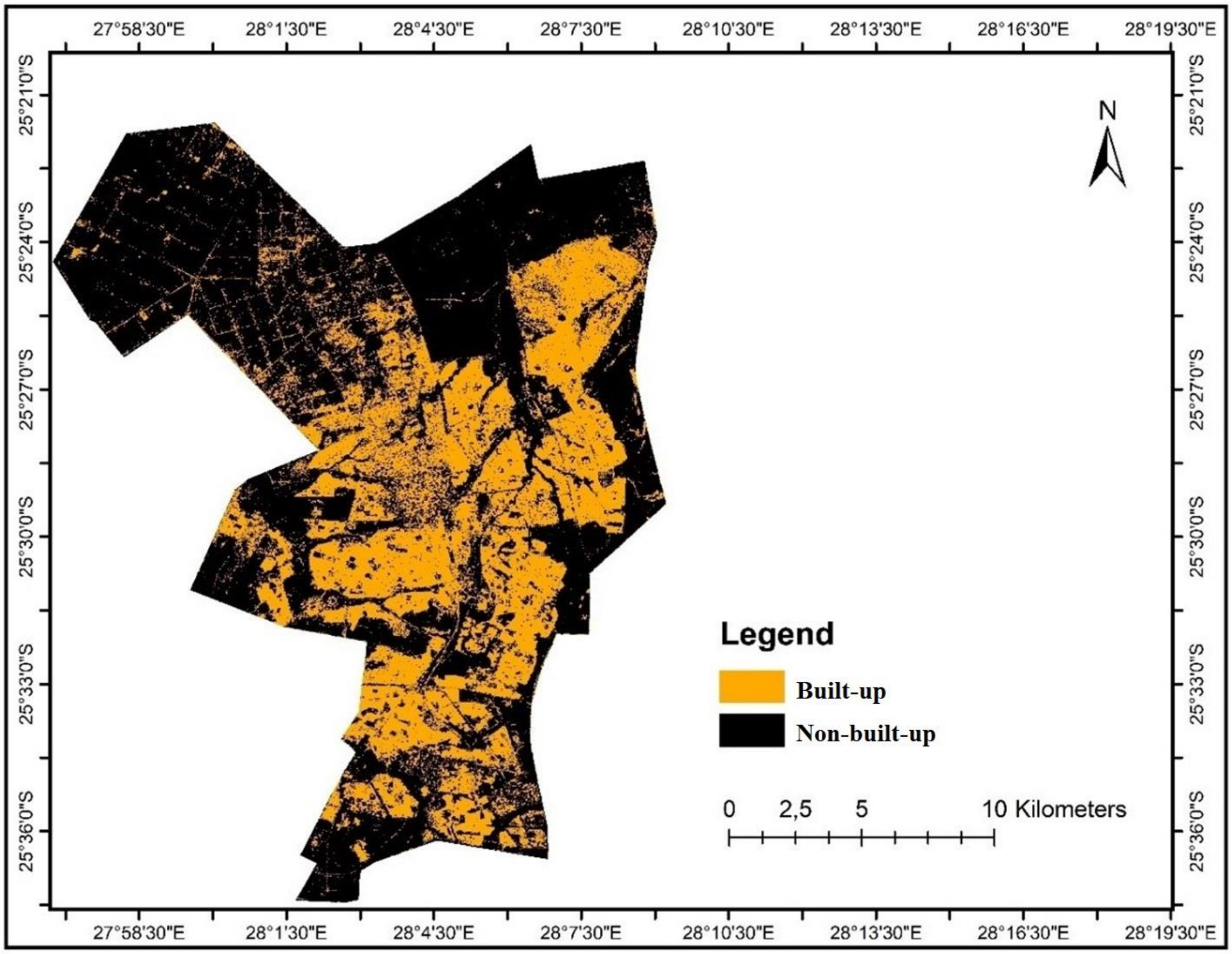


Figure 11: Pretoria North built-up areas in 2017

Table 5 illustrates the spatial extent of the mapped built-up areas from 1990 to 2017 in Pretoria (Region 1) of CoT.

Table 5: Spatial distribution of built-up area

Class name	1990 (km^2)	1994 (km^2)	2000 (km^2)	2005 (km^2)	2010 (km^2)	2015 (km^2)	2017 (km^2)
Built-up area	65.2	94.6	139.34	157.65	125	117	144.40

4.2 Discriminating between informal and formal settlements

The mapping of informal settlements is challenging since defining informal versus formal settlements needs local knowledge combined with correctly applied indicator characteristics (Fallatah et al., 2019; Samper et al., 2020). The MRS, assign class by thematic layer algorithm and mean spectral values obtained from the spectral bands were used to classify formal and informal settlements from the built-up area. Figure 12 shows the distribution of informal versus formal settlements mapped from the built-up class in the year 2005.

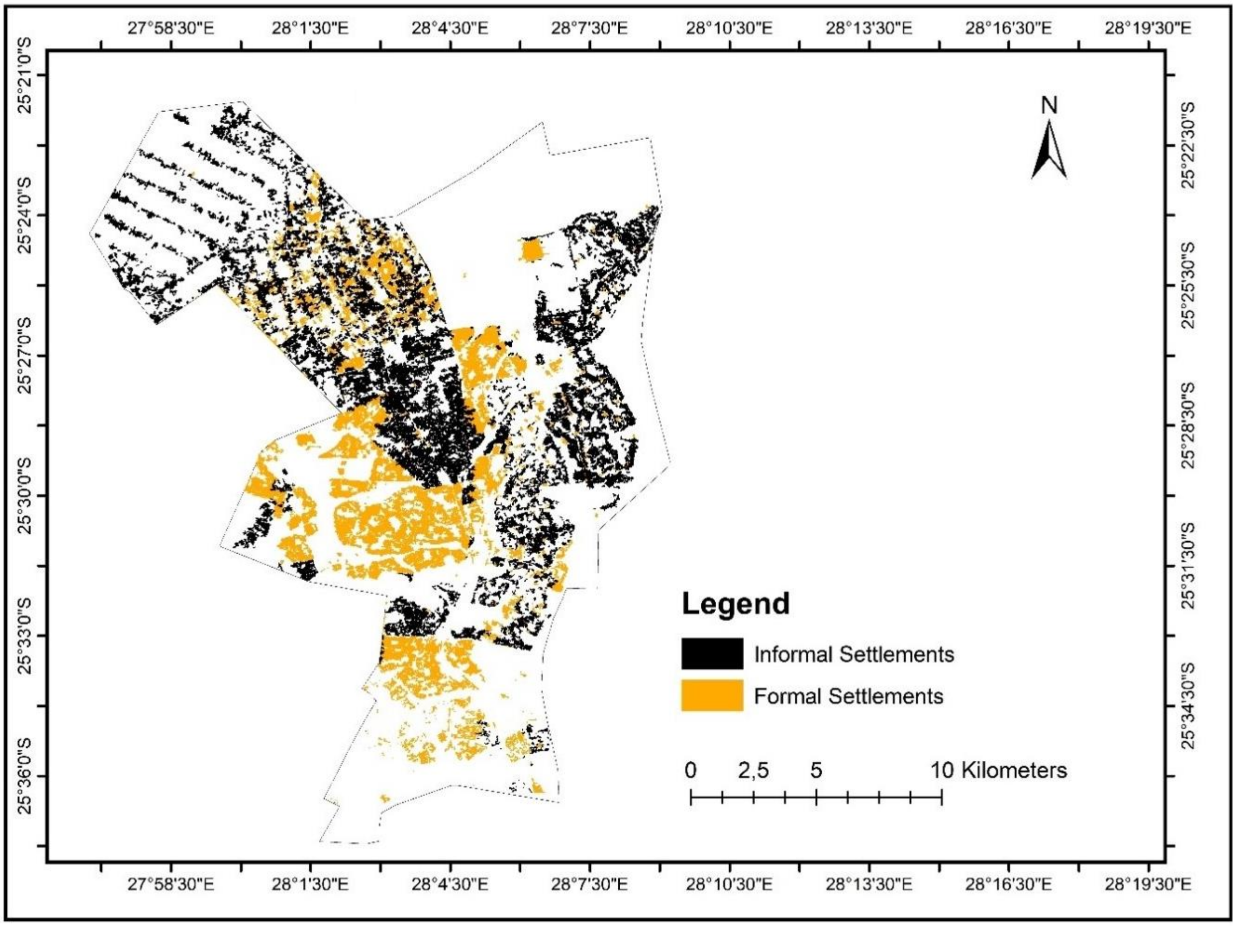


Figure 12: 2005 Settlement type map

Figure 13 The distribution of informal versus formal settlement mapped from the built-up class in the year 2017.

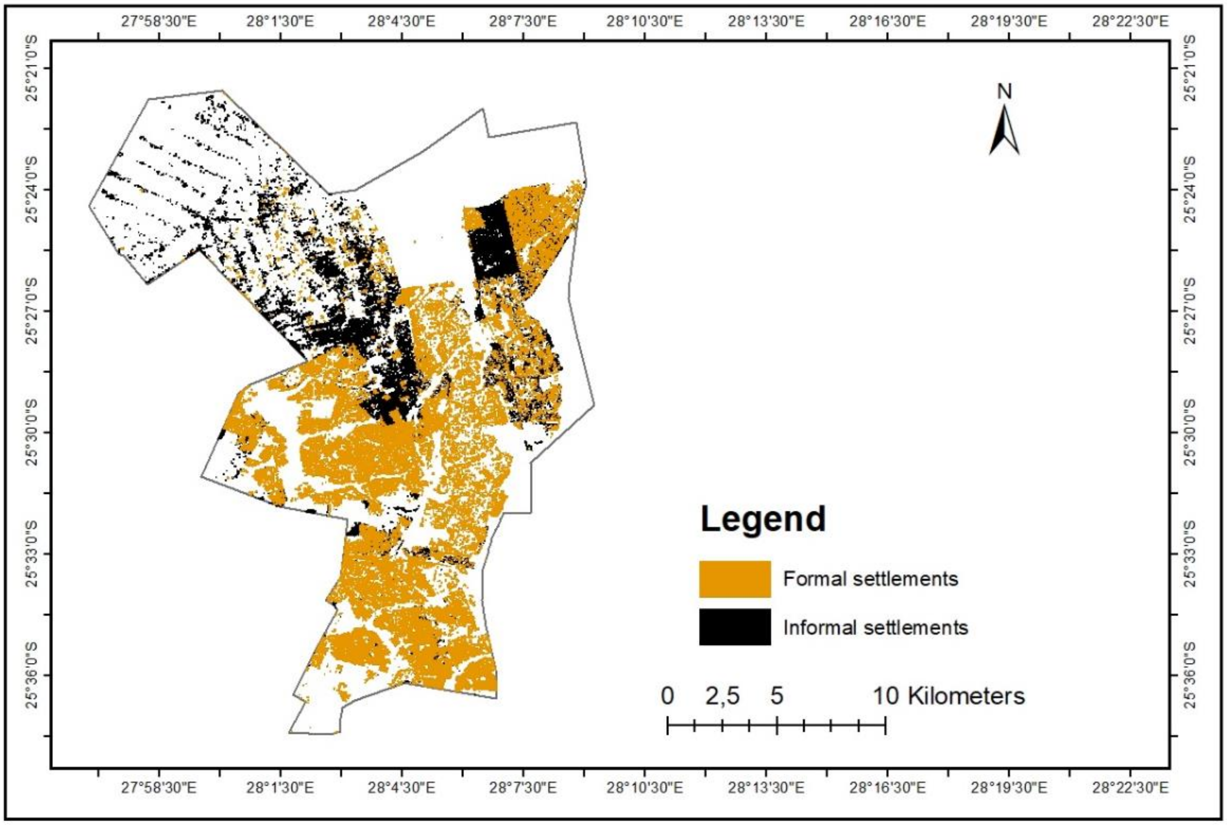


Figure 13: 2017 Settlement type map

Table 6 illustrates the spatial extent of the formal and informal settlement areas for 2005–2017 in Pretoria (Region 1) of CoT.

Table 6: Spatial distribution of settlements

Class name	2005 (km^2)	2017 (km^2)
Formal settlement	32.97	47.27
Informal settlement	46.52	19.37

4.3 Change detection

Figure 14 shows the changes in built-up areas over the years 1990,1994 and 2000. There is a significant increase of built-up areas in the north-eastern, southern and south-western parts of the study area from 1990 to 1994 and then 2000.

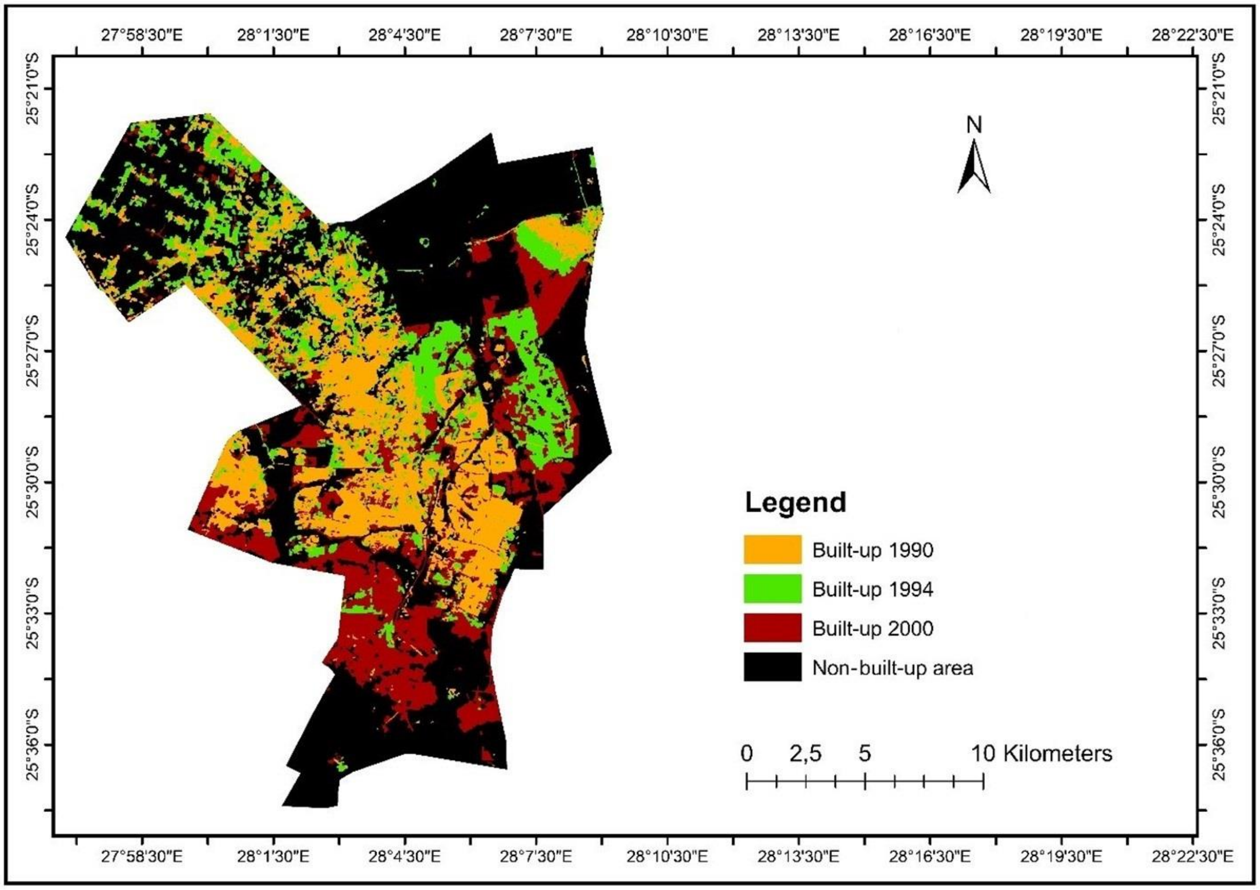


Figure 14: Settlement growth 1990–1994 to 1994–2000

Figure 15 shows changes in built-up areas over the years 2000,2005 and 2010. The results show there is a significant increase in built-up area in the southern part and major changes in the north-eastern part and on the southern side for the years 1990, 1994 and 2000.

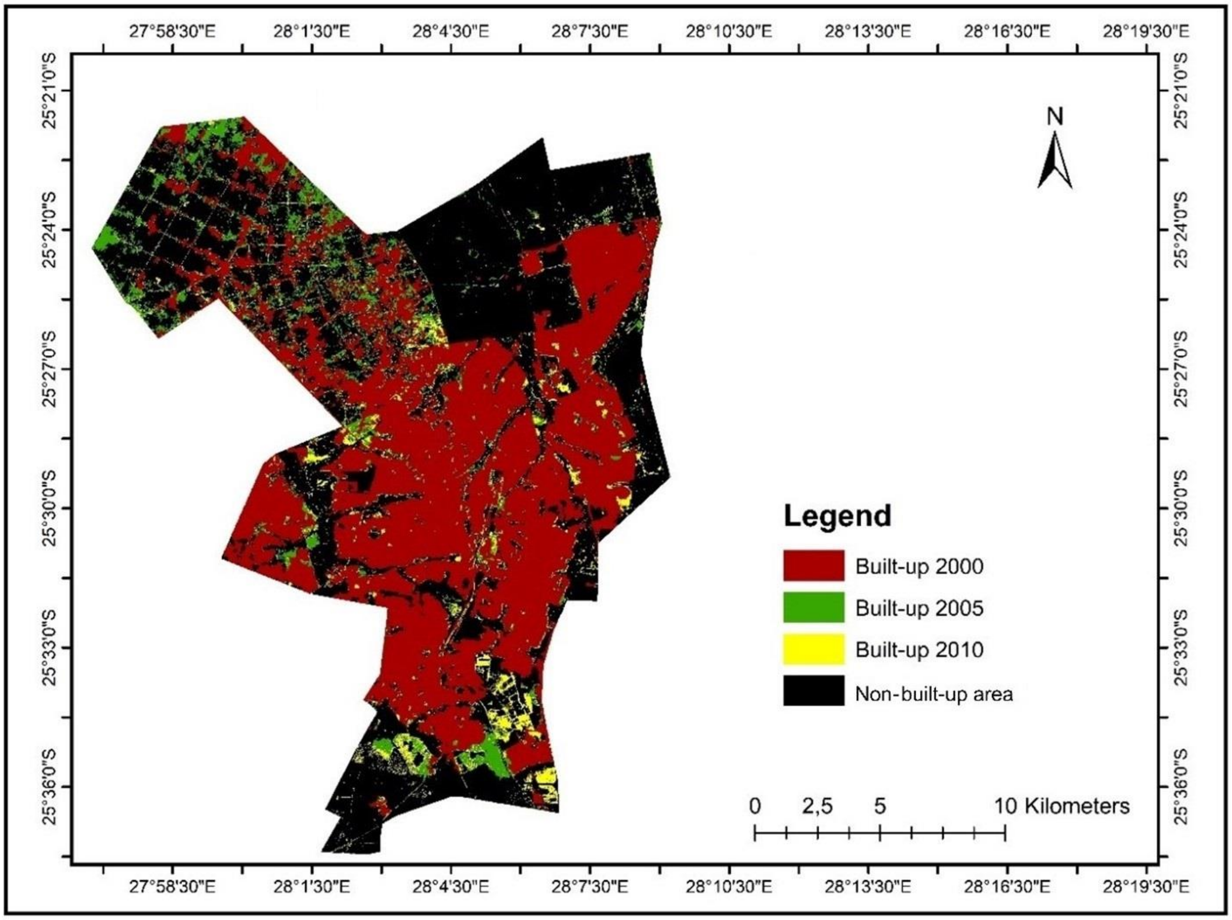


Figure 15: Settlement growth 2000–2005 to 2005–2010

Figure 16 shows changes in built-up areas over the years 2010, 2015 and 2017. The results show there is a significant increase in built-up areas in the southern part area from the years 1990, 1994 and 2000 and major changes in the north-eastern and southern parts.

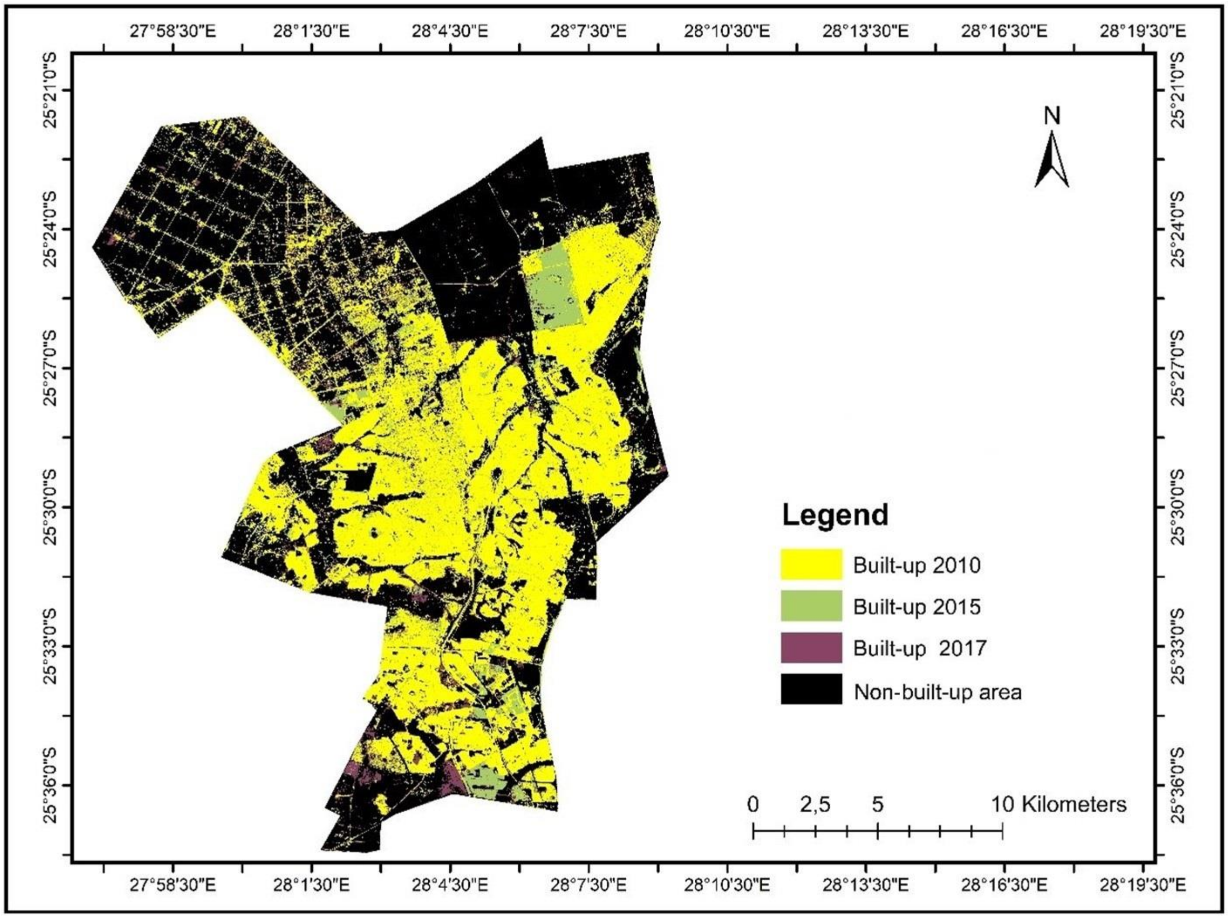


Figure 16: Settlement growth for 2010–2015 and 2015–2017

4.4 Accuracy assessment

When using satellite imagery for reference ideally the image has to be of a resolution higher than the image used for classification (FAO, 2016). According to Qian et al. (2015) the number of training samples for object-based samples is normally determined by the user based on their experience. For this study 100 ground control points were generated using random sampling on QGIS and to validate the randomly sampled points, visual image interpretation was done on Google Earth and aerial imagery. To assess the accuracy of the detected built-up, non-built-up area the points were used to visually validate the mapped area. The confusion matrix was performed using ground control points generated on QGIS and validated on Google Earth satellite imagery and SPOT images. Table 7 illustrates the overall accuracy of the images for the years 1990–2017 with overall accuracy ranging from 80% to 87% with Kappa Coefficients ranging from 0.5 to 0.6. The lowest accuracy for the mapped built-up areas was obtained in 2000 at 80% with the highest accuracy being 87% for 1990, which could be attributed to spatial resolution. Table 8 illustrates the overall accuracy of the images for the years 2005–2017 with overall accuracy ranging from 81% to 88% with Kappa Coefficients ranging from 0.72 to 0.75 for the mapped settlement areas.

Table 7: Confusion matrix table for validation of built-up area maps (1990–2017)

Year	Overall accuracy %	Kappa coefficients
1990	87	0.59
1994	84	0.61
2000	80	0.54
2005	83	0.63
2010	81	0.59
2015	84	0.65
2017	83	0.64

Table 8: Confusion matrix table for validation of settlement maps (2005–2017)

Year	Overall accuracy %	Kappa coefficients
2005	88	0.72
2017	81	0.75

4.5 Modelling of settlements growth in 2025

Settlement growth was modelled using CA-based on an artificial neural network on QGIS with the MOLUSCE plugin to simulate settlement growth in 2025. Estimating built-up areas is critical to understanding urbanization and its consequences for our rapidly changing planet. Figure 17 depicts potential growth areas; it is anticipated that settlement growth will drastically increase in the coming years, particularly in the southern part of the study area. The growth is most likely to occur because of urbanization, population growth, and the influx of people from neighbouring provinces looking for work and social amenities.

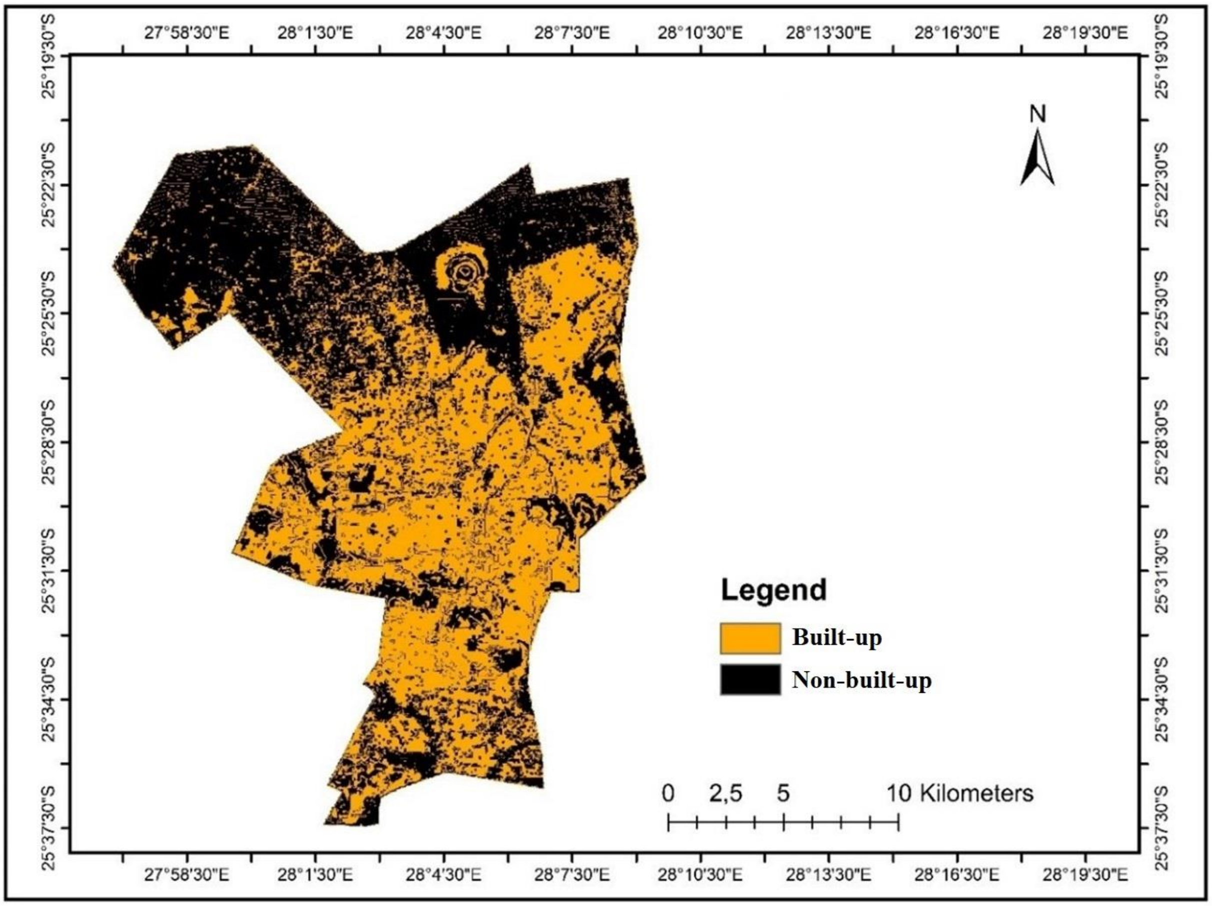


Figure 17: Projected settlement growth 2025

CHAPTER 5: DISCUSSION

This research aimed at modelling and monitoring urban settlement growth by using SPOT satellite images. This was achieved through mapping and tracking of built-up areas in Pretoria North (Region 1) CoT and by estimating areas of potential growth. The main findings from this study show the significant rise in built-up areas, which is associated with an increase in informal settlements.

The cornerstone for comprehensive administration and planning of urban areas is detailed and reliable information regarding built-up areas. This data is useful for determining the types of settlements and their distribution, as well as for planning existing and future resources. The result shows that the extent of built-up areas has increased drastically from 1990 to 2017 in the study area. It is evident from the results that major growth of built-up area occurred between the period 1994–2000 with an expansion of 44.74 km^2, which represents 47.3% growth in Region 1; these figures can be attributed to post-apartheid developments and population growth.

The study successfully mapped built-up areas using SPOT2, SPOT4, SPOT5 and SPOT6, However, in comparing the results for 2005 versus 2010, and 2010 versus 2015 it seems there was a decrease in built-up areas and an increase in non-built-up areas. The decrease in area from 2005 to 2010 and then again to 2015 can be attributed to the increase in resolution from 10 m to 2.5 m and 1.5 m, respectively. Increased spatial/contextual information increases the ability to differentiate fine differences between image objects (e.g., houses and roads or house and bare soil); therefore there is an increase in the accuracy of the classification.

The results show an abrupt increase in built-up areas over the southern, eastern and north-eastern regions of the study area from the year 1990 to 2017. The results correspond with the findings of Ngcofe et al. (2017), Mahdianpari et al. (2020) and Sreekesh et al. (2020) who found that mapping of settlements from high-resolution imagery using the OBIA method is effective.

According to the CoT Region 1 Spatial Development Framework report (2018), the southern part of Region 1 is where the majority of the community works, while the northern part is where the majority of subsidized houses and informal settlements are located. This is demonstrated by the change detection results, which demonstrate a high increase of built-up areas on the northern and southern sides. Change detection analysis was achieved using the overlay tool to identify built-up area growth, and change was defined as built-up features that did not overlap. Settlement growth was determined by assessing changes in built-up areas from 1990, 1994, 2000, 2005, 2010, 2015 and 2017. The rise in built-up area in these locations is related to the growing population and the availability of jobs (CoT, 2018).

Onodugo and Ezeadichie (2019) stated that informal settlements are one of the most widespread forms of urbanization in cities and towns across the Global South. The CoT has seen the establishment of informal settlements resulting from the high demand for homes generated by population and economic growth, lack of affordable housing and housing backlogs.

The results show that classification using assign thematic layer algorithm was effective in classifying formal and informal settlements in this study. The results show the spatial distribution of formal and informal settlements for the years 2005 and 2017. The results also demonstrate that extent of formal settlements increased between the years 2005 and 2017, while the extent of informal settlements decreased. Distinguishing informal from formal settlements was achieved with an overall accuracy of 81% for 2015 and 88% for 2005; this can be attributed to the upgrading of informal settlements into low-cost housing in the area by the municipality (Ren, 2018; Mudau and Mhangara.,2022). Fallatah et al. (2019) conducted a similar study monitoring changes in settlements, with their findings corroborating those of this study.

Literature reviewed in this study outlined how the availability of high-resolution satellite datasets helps in making urban growth models more realistic. It is evident from this study that the CA-ANN was able to simulate settlement growth from high-resolution imagery. The predicted built-up area for 2025 shows that built-up areas will expand predominantly in the southern and north-eastern parts. The increase in the built-up area is likely based on the rising population in Region 1, which has been estimated will be above one million by 2025 (CoT, 2018).

CHAPTER 6: CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

6.1 Conclusions

An accurate temporal and spatial change analysis of urban regions is important for planning and decision-making. Remote sensing offers reliable data for mapping built-up areas and modelling settlement growth. The study aimed to model and monitor settlement growth using SPOT satellite images in Pretoria North (South Africa) from 1990 to 2017. This was achieved by using remote sensing OBIA classification technique, change detection method, and MOLUSCE model, thereby achieving all research objectives for the study. SPOT satellite imageries were utilized for built-up detection in the study area. The study illustrated the use of high-resolution imagery in detecting urban settlements. The results demonstrated the potential of utilising rule-based object-based image classification to monitor changes in built-up areas in 1990, 1994, 2000, 2005, 2010, 2015, and 2017. Using the post-classification change detection technique, the study showed that there was a tremendous increase in built-up areas in Pretoria North Region 1 (Soshanguve, Mabopane, and Winterveld) area over the years covered by the study. GLCM dissimilarity was effective in delineating built-up and non-built-up areas using SPOT6 imagery; however, GLCM was only used on SPOT6 because it was more effective on high-resolution SPOT6 images.

The results of this research demonstrated that MOLUSCE CA model can be used to model settlement growth. Muhammad et al. (2022) also integrated the CA-ANN model in the QGIS MOLUSCE plugin to simulate LULC changes for 2020 and 2050. In this study, a rule-based object-based classification method and SPOT datasets techniques accurately classified built-up areas of urban settlements. The results show that high spatial resolution enables a more precise classification of built-up compared to lower and medium resolution sensors. In terms of sensor performance, SPOT6 outperformed SPOT5, SPOT4, and SPOT2 in detecting built-up areas, owing to its finer spatial resolution. It is evident from this research that remote sensing can be utilized for planning and monitoring building infrastructure. The derived maps can be used by the CoT Metropolitan Municipality and the Department of Human Settlement in settlement monitoring of Pretoria North, CoT.

6.2 Limitations

Two main limitations were identified for this study which are data and computational capacity. In terms of data, there were a lot of discrepancies in the SPOT images; consequently, pre-processing of the images was time-consuming. Owing to the lack of cloud-free SPOT imagery for 1995, SPOT imagery for the year 1994 was selected which affected the intervals between the data for the study. Regarding computational capacity, the processing of high-resolution imagery using eCognition requires a high-performance computer.

6.3 Recommendations

- The mapping and monitoring of settlement growth using OBIA has not been extensively studied in South Africa. It is recommended that more studies be performed using very high-resolution data and other supervised classification methods as the results show that this delineates classes more accurately.
- The use of digital surfavce model will be very useful in distinguishing built-up from other land covers and also for classifying settlement types.
- An automated rule-based set processing chain from the ruleset can be developed to aid in monitoring and modelling of settlement growth.
- A study using morphological features can be used in classifying structural information for informal versus formal settlements which can assist in analysis.
- A study assessing the correlation between settlement growth and population growth using remote sensing-based technology can be done to understand the factors driving the growth.
- The results obtained from this study can be used by local authorities for planning purposes such as monitoring how the area has changed over time, informing budgeting for the region, identifying areas that may be prone to disasters, and identifying areas that will require upgrading from informal to formal settlement.

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