University of the Witwatersrand

Faculty of Science

School of Geography, Archaeology and Environmental Studies

MAPPING AND ASSESSMENT OF INFORMAL SETTLEMENTS USING OBJECT-BASED IMAGE ANALYSIS, A CASE STUDY OF MAMELODI, TSHWANE, SOUTH AFRICA

By

Naledzani Mudau
(1569579)

A thesis submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Doctor of Philosophy

Supervisor: Professor Paida Mhangara (Wits University)

12 February 2024

DECLARATION

I declare that this thesis is my own, unaided work. It is being submitted for the Degree of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

____

(Signature of candidate)

12 day February 2024

at Pretoria

LIST OF OUTPUTS OF THE THESIS

These outputs (stand-alone original peer-reviewed manuscripts or conference proceedings) bear the following status: (1) **Submitted** – has been submitted to a journal and the editor is yet to send it for review, (2) **Under-Review** – a manuscript has been submitted to a journal and the editor has deemed it relevant and worthy of consideration to be published and is now being reviewed by experts in the field, (3) **Accepted** – a manuscript has gone through a rigorous journal-specific peer-review process and various iterations of revisions, but not yet published pending production by the publisher, and (4) **Published** - a manuscript is now published in the journal issue and has a DOI.

Mudau N., Mhangara P., (2023), "Mapping and assessment of housing informality using Object-Based Image Analysis": a review; Urban Science; **https://doi.org/10.3390/urbansci7030098**

Mudau N., Mhangara P., (2021), Investigation of Informal Settlement Indicators in a Densely Populated Area Using Very High Spatial Resolution Satellite Imagery; Sustainability; **https://doi.org/10.3390/su13094735**

Mudau N., Mhangara P., (2022), Towards understanding informal settlement growth patterns: Contribution to SDG reporting and spatial planning; Remote Sensing Applications: Society and Environment; **https://doi.org/10.1016/j.rsase.2022.100801**

Mudau N., Mhangara P., (2023), Understanding spatial patterns of backyard shacks using landscape metrics using unmanned aerial vehicle image products; Drones; **https://doi.org/10.3390/drones7090561**

Mudau N., Mhangara P., (2023), Understanding the ecological condition of informal settlements using Settlement Surface Ecological Index; Land; **https://doi.org/10.3390/land12081622.**

Mudau N., Mhangara P., (**In preparation**), Understanding the location characteristics of informal settlements.

I declare that I had a maximum contribution (i.e., >80%) in each of the abovementioned research outputs.

____

(Signature of candidate)

____12____day____February____20 24____

at Pretoria

ABSTRACT

The social and environmental challenges faced by people living in informal settlements or slums are widely recognized by development agendas including United Nations Sustainable Development Goals, Agenda 2063 and National Development Plans. The study aims to investigate informal settlement dynamics and spatial characteristics to generate an understanding of housing informality and environmental conditions for designing innovative sustainable solutions.

The study assessed the use of 12 spectral indices and textural measures, and object-based image analysis (OBIA) technique to detect informal settlements from WorldView 2 images. A growth indicator that uses informal settlement extent and impervious surface was developed and used to assess informal settlement growth patterns between 2005 to 2020. Unmanned aerial vehicle image products, and landscape metrics were used to assess the spatial characteristics and patterns of backyard shacks and free-standing informal settlement structures. In addition, a settlement surface ecological index was developed and used to assess the ecological conditions of informal settlements. Lastly, the assessment of the location characteristics of informal settlements was done using ancillary data.

The results show that the use of built-up index, coastal blue index and first-order statistics mean textural measures and OBIA technique detected informal settlements with producer and user accuracies of 95% and 82% respectively. The developed informal settlement growth assessment indicator shows that informal settlement in 2020 had a slightly lower density of impervious surfaces than in 2005. The Euclidean Nearest-Neighbour Distance, Aggregation Index and Cohesion Index show that backyard shacks are less connected, less dense, and more isolated than freestanding informal settlement structures. Some informal settlements have better surface ecological conditions than some of the formal settlements. A higher extent of informal settlements continued to develop closer to formal settlements, rivers and railway lines between 2015 and 2020. The information demonstrated in this study can be used by local authorities to better understand and manage informal settlement developments, prioritize settlement upgrade projects and improve the environmental conditions and resilience of informal settlements.

Keywords; OBIA, housing informality, informal settlements, ecological condition, UAV

DEDICATION

I dedicate this work to my sons, Vhutali and Vhusani

ACKNOWLEDGEMENT

I would like to express profound gratitude to Professor Mhangara for the invaluable guidance, mentorship, and steadfast support I received during my research.

I wish to extend my gratitude to the South African National Space Agency for partial funding of my studies and for providing access to WorldView and SPOT images, which were instrumental in this research. Additionally, I'd like to acknowledge the University of Witwatersrand for co-sponsoring my studies and for their generous support in acquiring UAV image products.

My heartfelt appreciation goes out to my family and friends, whose unwavering encouragement and emotional support have been my steadfast companions throughout my academic journey.

ABBREVIATIONS

OBIA: Object-Based Image Analysis

GEOBIA: Geographic Object-Based image analysis

MLA: Maximum Likelihood Algorithm

SDGs: Sustainable Development Goals

UAV: Unmanned Aerial Vehicles

GLCM: gray-level co-occurrence matrix

NDVI: Normalized Differential Vegetation Index

NUA: New Urban Agenda

FOS: First Order Statistics

SAVI: Soil Adjusted Vegetation Index

IS_LCRIGR: Informal Settlement Land Consumption Rate to Imperviousness Growth Rate

BAI: Built-up Area Index

SVM: Support Vector Machine

SAR: Synthetic-Aperture Radar

CNN: convolutional neural network

GIS: Geographic Information System

LCH: low-cost houses

ExG: excess green vegetation

RF: Random Forest

NIR: Near-infrared

SWIR: Short-wave infrared

DSM: Digital Surface Model

DEM: Digital Elevation Model

REI: Road Extract Index

STEP: Shape, Theme, Edge and Position

SRTM: Shuttle Radar Topography Model

SHAPE: Shape index

FRAC: Fractal Dimension Index

CONTIG: Continuity Index

SIDI: Simpson's diversity index

SEI: Shannon’s Evenness Index

ED: Euclidean Nearest-Neighbour Distance

AI: Aggregation Index

GSO: Generic Slum Ontology

CI: Cohesion Index

SSEI: settlement surface ecological index

LST: Land Surface Temperature

SPOT: Satellite Pour L’Observation de la Terre

NDMI: Normalized Difference Moisture Index

V-I-S: Vegetation-Impervious Surface-Soil

FSO: Feature Space Optimization

MDG: Millennium Development Goal

Table of Contents

DECLARATION..i
LIST OF OUTPUTS OF THE THESIS..ii
ABSTRACT..iv
DEDICATION..vi
ACKNOWLEDGEMENT..vii
Chapter 1 INTRODUCTION..1
1.1 Background..2
1.2 Problem statement..3
1.3 Informal settlements detection using remote sensing..5
1.4 Research questions..6
1.5 Aims and objectives of the study..6
1.6 Study area..7
1.7 Significance of the study..9
1.8 Outline of the thesis..10
Chapter 2 MAPPING AND ASSESSMENT OF HOUSING INFORMALITY USING OBJECT-BASED IMAGE ANALYSIS: A REVIEW..12
Abstract..13
2.1 Introduction..14
2.2 Origin and characteristics of informal housing..15
2.3 OBIA processing steps..21
2.4 Detection of informal settlements using object level indicators..22
2.5 Detection of informal settlement using settlement level indicators 23
2.6 Detection of informal settlement using environ-level indicators. 25
2.7 Temporal analysis of informal settlement extent..26
2.8 Informal settlement mapping using UAVs..26
2.9 Studying morphology of informal settlement using landscape metrics..27
2.10 Mapping of informal settlement land use features..27
2.11 Summary and recommendations..28
2.12 Conclusions..29
Chapter 3 INVESTIGATION OF INFORMAL SETTLEMENT INDICATORS IN A DENSELY POPULATED AREA USING VERY HIGH SPATIAL RESOLUTION SATELLITE IMAGERY..31
Abstract..32

3.1 Introduction........33
3.2 Study Area........35
3.3 Data........36
3.4 Method........39
3.5 Image Segmentation........39
3.5.1 Assessment of informal settlement indicators........40
3.5.2 Detection of informal settlements........42
3.5.3 Accuracy assessment........43
3.6 Results........43
3.6.1 Image segmentation........43
3.6.2 Performance of selected image features in separating informal and formal settlements........44
3.6.3 Informal and formal settlements classification results........46
3.7 Conclusions........48
Chapter 4 TOWARDS UNDERSTANDING INFORMAL SETTLEMENTS GROWTH PATTERNS: CONTRIBUTION TO SDG REPORTING AND SPATIAL PLANNING........50
Abstract........51
4.1 Introduction........52
4.2 Study area........54
4.3 Data........55
4.4 Methodology........56
4.4.1 Data preparation........56
4.4.2 Investigation of segmentation parameters for informal and formal settlements........56
4.4.3 Classification of formal and informal settlements........56
4.4.4 Classification of impervious surface in informal settlements........57
4.4.5 The ratio of IS_LCRIGR........57
4.4.6 Accuracy assessment........58
4.5 Results........58
4.5.1 Investigation of segmentation parameters for informal and formal settlements........58
4.5.2 Segmentation of building and other land use structures........61
4.5.3 Investigation of features to classify formal and informal settlements 63
4.5.4 Classification of informal settlements........64

4.5.5 Informal settlement growth rate 66
4.5.6 Impervious surface growth rates 67
4.5.7 The ratio of Informal Settlement Land Consumption Rate to Imperviousness Growth Rate (IS_LCRIGR) 68
4.5.8 Quality assurance 69
4.6 Discussions 70
4.7 Conclusions 72
Chapter 5 UNDERSTANDING SPATIAL PATTERNS OF BACKYARD SHACKS USING LANDSCAPE METRICS 73
Abstract 74
5.1 Introduction 75
5.2 Study area 77
5.3 Data 77
5.4 Methodology 80
5.4.1 Classification of Formal and Informal Building Structures 80
5.4.2 Random Forest Classifier 81
5.4.3 Rule-based classifier 82
5.4.4 Classification of backyard shacks 83
5.4.5 Accuracy Assessment 83
5.4.6 Spatial pattern analysis 83
5.5 Results and discussions 85
5.5.1 Image segmentation 85
5.5.2 Classification results 86
5.5.3 Accuracy assessment 89
5.5.4 Spatial pattern analysis 91
5.5.4.1 Shape metrics 91
5.5.4.2 Aggregation metrics 92
5.5.4.3 Landscape metrics 93
5.6 Conclusions 94
Chapter 6 UNDERSTANDING THE ECOLOGICAL CONDITION OF INFORMAL SETTLEMENTS USING THE SETTLEMENT SURFACE ECOLOGICAL INDEX. 96
Abstract 97
6.1 Introduction 98
6.2 Study area 100
6.3 Data 101

6.4 Methodology........102
6.4.1 Classification of Urban Land-Use Classes........102
6.4.2 Mapping of LST........104
6.4.3 Mapping of vegetation moisture........104
6.4.4 The assessment of settlement surface ecological index........104
6.4.5 Quality assurance........105
6.5 Results........105
6.5.1 Image segmentation........105
6.5.2 Classification results........106
6.5.3 Assessment of Biophysical Characteristics........108
6.5.4 Assessment of Settlement Surface Ecological Index (SSEI)........111
6.6 Discussions........114
6.7 Conclusions........115
Chapter 7 ASSESSMENT OF LOCATION INFORMAL SETTLEMENT GROWTH AND LOCATION CHARACTERISTICS OF INFORMAL SETTLEMENTS........122
Abstract........123
7.1 Introduction........124
7.2 Study area........126
7.3 Data and methodology........127
7.3.1 Data........127
7.3.2 Method........128
7.3.2.1 Image classification........129
7.3.2.2 Quality assessment........130
7.3.2.3 Assessment of the location characteristics of informal settlements........130
7.4 Results........131
7.4.1 Classification of informal settlements........131
7.4.2 Location characteristics assessment results........132
7.4.3 Accuracy assessment........135
7.5 Discussions........135
7.6 Conclusions........136
Chapter 8 SYNTHESIS........137
Reflections........140
Conclusion........143

REFERENCES 145

List of Figures

Figure 1-1: Location of the study area, Mamelodi Township, Gauteng Province, South Africa. 8
Figure 2-1: Number of publications on informal settlement mapping using remote sensing technology per year based on the Scopus database. 17
Figure 2-2: Proportion of publications on informal settlement mapping from remote sensing technology per country. 18
Figure 2-3: Top funders of research on informal settlement mapping 18
Figure 3-1: Location of the study area, Mamelodi Township, City of Tshwane, Gauteng Province, South Africa 36
Figure 3-2: One of the informal settlements in the study area over a Worldview 2 image. 38
Figure 3-3: Methodology followed to detect informal settlements 39
Figure 3-4: Chessboard segmentation results over WorldView 2 multispectral image 44
Figure 3-5: Detected informal settlement layer over Worldview 2 image. 47
Figure 4-1: Location of the study area 55
Figure 4-2: Segmentation parameters assessment results 59
Figure 4-3: Segmentation results over 2005 WorldView 2 image 60
Figure 4-4: Segmentation results: buildings and other land-use image objects 62
Figure 4-5 : Divergence assessment results 63
Figure 4-6: Informal settlement classification results for 2005, 2010, 2015 and 2020 over a 2020 image 65
Figure 4-7: Zoom-in pictures of the detected informal settlement for 2005 (A), 2010 (B), 2015 (C) and 2020 (D) over a 2020 image 65
Figure 4-8: Impervious surface for 2005, 2010, 2015 and 2020 67
Figure 5-1**.** An RGB orthophoto of the study area, showing formal settlement with backyard shacks and informal settlements. 78
Figure 5-2**.** A DSM of the study area, generated using data collected during the flyover. 79
Figure 5-3: DTM of the study area, generated using data collected during the flyover. 79
Figure 5-4: Flowchart illustrating the methodology followed to extract backyard shacks and assess the spatial patterns of backyard shacks and informal settlement dwelling structure. 80
Figure 5-5: Zoom-in image of the spectral different segmentation results, threshold scale: 4. 86
Figure 5-6: Classification results achieved using RF classifier, after applying proximity analysis to classify backyard shacks. 87
Figure 5-7: OBIA classification results achieved using rule-based classification techniques, after applying proximity analysis to classify backyard shacks. 88
Figure 6-1**.** Location of the study area and different human settlement types assessed in the study 100
Figure 6-2: Level 1 multiresolution segmentation results over SPOT 7 images (**a**) and Level 2 multiresolution segmentation results over SPOT 7 images (**b**) 106

Figure 6-3: Classification results and the location of assessed settlements........... 107
Figure 6-4: Spatial distribution of the different settlement types over the LST layer 108
Figure 6-5: Spatial distribution of assessed settlement types over vegetation moisture layer 109
Figure 6-6: SSEI values of different settlement types 113
Figure 7-1: Location of the study area 127
Figure 7-2: Workflow followed to assess the location characteristics of informal settlements. 129
Figure 7-3: Zoom picture of Level 1 segmentation results over a 2020 panchromatic image.. 131
Figure 7-4: 2015 and 2020 informal settlement classification results, location of features and resources assessed.. 132
Figure 7-5: Location of informal settlements in 2015 and 2020 with corresponding slope values 134

List of Tables

Table 2.1: Description of informal settlement detection methods 20
Table 3.1: List of spectral and textural features investigated in the detection of classification of informal from formal settlements. 40
Table 3.2: Image features and values used to detect formal and informal settlements......... 43
Table 3.3. Performance of selected image features in classifying informal from formal settlements 45
Table 4.1: Band properties of Quickbird 2 and WorldView 2 sensors 55
Table 4.2: Informal settlement extent and impervious surface classification result in 2005, 2010,2015 and 2020. 66
Table 4.3: Informal settlement extent growth rates of 2005-2010, 2010-2015 and 2015-2022 time intervals 66
Table 4.4: Imperviousness growth rate of 2005-2010, 2010-2015 and 2015-2020 time intervals 67
Table 4.5: Ratio of Informal Settlement land Consumption Rate to Imperviousness Growth Rate results 68
Table 4.6: Informal settlement and buildings accuracy assessment..................................... 69
Table 5.1. The drone specifications and the flight plan parameters. 78
Table 5.2: List of shape, aggregation and landscape metrics assessed 84
Table 5.3: STEP accuracy assessment results of land use classes derived using RF classifier.. 90
Table 5.4: The STEP metrics assessment results of land use classes derived using rule-based classification method. 90
Table 5.5. The overall producer and user accuracy assessment results are based on the theme similarity metric of the land use classes.. 91
Table 5.6: Class aggregation metrics 93
Table 6.1. List of the spectral band, bandwidth, and spatial resolutions of SPOT 7 and Landsat 8 satellite images.. 102
Table 6.2: Producer and user accuracies achieved during classification 107
Table 6.3: Proportions and values of biophysical characteristics assessed during the study. 109
Table 6.4: Normalized classification and mapping results 111
Table 7.1: Spectral bands, spectral range and spatial resolution of Worldview 2 images ... 128
Table 7.2: Spatial location of informal settlements assessment results 133

Chapter 1 INTRODUCTION

1.1 Background

In 2020, one in four of the global urban population lived in informal settlements or slums (The Sustainable Development Goals Report, 2020). About 85% of global informal settlement dwellers are found in Asia and Sub-Saharan Africa with Sub-Saharan Africa having 238 million people living in informal settlements (The Sustainable Development Goals Report, 2020). Future urbanization is expected to take place around cities and towns of developing countries while at the same time, the number of people living in informal settlements is expected to double i.e., to 3 billion by 2050 unless proper action is taken (United Nations Department of Economic and Social Affairs, 2013). The developing economies that are already struggling with informality might be faced with even bigger challenges in the next few decades. Informal settlements lack access to improved water sources, improved sanitation facilities, sufficient living area, housing durability or security of tenure (UN-Habitat, 2004) and are usually home to new migrants, unemployed or unskilled (Eckstein, 1990; Oksiutycz & Azionya, 2022). Access to adequate housing is a human right (UN-Habitat, 2004), and the lack of it affects dignity, safety, security, and livelihood opportunities (Marutlulle, 2021).

In 2000, United Nations member states committed to achieve eight Millennium Development Goals (MDGs) of which one of the targets was to significantly improve the lives of at least 100 million slum dwellers by 2020 (UN-Habitat, 2003). This led to a decline in the proportion of people living in informal settlements or slums from 39% in 2000 to 29% in 2014 (UN-Habitat, 2015). While significant progress was made toward improving the livelihood of people living in informal settlements during the implementation of the MDGs, the number of people living in informal settlements continued to rise during the same period (United Nations, 2015). In 2015, the United Nations member state renewed their interest in improving informal settlements or slums and committed to Sustainable Development Goal (SDG) 11, with Target 11.1 aimed at providing access for all to adequate, safe, affordable housing and basic service and upgrade slums (UN-Habitat, 2016).

The development of informal settlements continues to be a challenge for developing countries like South Africa with one in five of the urban population living in informal settlements in 2021 (South African Cities Network, 2022). Even though significant progress has been made towards the upgrading of informal settlements in South Africa in the past two decades, the number of people living in informal settlements continues to rise (Statistics South Africa, 2016). In addition to informal settlements, South Africa also battles with the development of shacks in the backyard of formal dwelling structures, known as backyard shacks which have been on the rise in the past two decades (Statistics South Africa, 2016). The backyard dwellers may not afford or are not willing to pay for formal rentals or may be on the waiting list to receive government-subsidized houses (South African Local Government Agency, 2014).

Backyard shacks are mostly found in townships around cities, home to medium-to-low-income populations (Shapurjee et al., 2014) and have become the most prevalent and fast-growing way of informal rental housing (Turok & Borel-Saladin, 2016). Backyard shacks have been experiencing higher growth rates than informal settlements in recent years (Shapurjee et al., 2014). Backyard shacks are built using poor materials like those in informal settlements and do not have direct access to basic services, but generally have access to services from the existing formal property (Mahlakanya & Willemse, 2022). Information on the informality of settlements is required to support the development of policies and programs to ensure adequate housing and the upgrade of informal settlements (UN-Habitat, 2018c). The success of national initiatives such as the Informal Settlement Upgrading Programme (ISUP) which are aimed at providing basic services or adequate houses, and international agendas such as SDGs require access to up-to-date information on informality.

1.2 Problem statement

Data on the location and extent of informal settlements is usually non-existent (Patel & Baptist, 2012). Data on the population of informal settlements is usually collected in many countries through ground surveys such as census, leading to gaps in data as many countries conduct census every ten years (Kohli et al., 2016). In addition, information collected during the census contains mainly headcount information and lacks the spatial dimension of the informal settlement (Kohli et al., 2012). Informal settlements are arguably the most likely settlement type to be under-sampled during the census, resulting in an undercount of the number of households who live in an informal settlement (Housing Development Agency, 2012). In countries like South Africa, information on informal settlements and backyard shacks is also collected during general household surveys (Statistics South Africa, 2022). Even though these surveys are conducted regularly, around a percentage of the total households are assessed (Statistics South Africa, 2022).

Traditional methods of deriving information on informal settlements using remote sensing technologies include counting informal settlement structures from high spatial resolution satellite imagery or aerial photography (Kit & Lüdeke, 2013). Even though visual image interpretation is time-consuming and resource intensive, it is still being used as it produces higher accurate results when performed by experienced image interpretation skills (Kuffer et al.,2016a). The increase in the availability of high spatial resolution imagery provides access to data to support planning and policy making by urban authorities (Patino & Duque, 2013). Several studies have investigated the use of high spatial resolution imagery to detect informal settlement areas within specific areas of interest with mixed settlement types and other urban land use features (Hofmann et al., 2001; Jain, 2007; Kohli, Sliuzas, et al., 2016). Other studies have investigated the spatial growth patterns of informal settlements (Hao et al., 2013; Pellikka et al., 2004). Some studies focused on the mapping of informal settlement land use features such as roads (Nobrega et al., 2006) while other studies focused on population estimation in informal settlements (Galeon, 2008; Veljanovski et al., 2013).

Even though several studies have investigated the methodologies to detect informal settlements from other land uses using remotely sensed data, robust methods that can be adapted to any region still do not exist. This can be attributed to the varying physical characteristics of informal settlements in different regions, countries and to a certain extent within cities. The lack of robust methodologies to detect informality can contribute to a lack of understanding of the evolution of informality in areas around the cities. In addition, studies to automatically detect backyard shacks in formal areas using remotely sensed data do not exist. Lastly, little is known about the environmental condition of informal settlements and the landscape where these settlements develop. A lack of understanding of the environmental condition of informal settlements may increase the health risk and disaster vulnerability of informal settlement dwellers.

Mamelodi is one of the biggest townships in City of Tshwane Metropolitan Municipality (Statistics South Africa, 2012). According to Statistics South Africa (2013), about 50%

of dwellings in Mamelodi were informal in 2011. Due to this high number of informal dwellings, the authorities are struggling to meet the demands of housing and provision of basic services. Additionally, Mamelodi is faced with a number of social and environmental challenges including high crime rates, water pollution and solid waste management. Concerning the impact of informal settlements on the environment, Darkey, et al. (2000) showed that the stream that flows through an informal settlement in Mamelodi is odorous and contaminated, yet it was still used for household chores, putting the health of the people at risks.

Despite several informal settlement upgrade projects taking place in Mamelodi, the expansion of informal settlements continues. Understanding the characteristics and dynamics of informal settlements is vital to ensure that local authorities and policy makers implement necessary measures and allocate resources aimed at upgrading informal settlements and managing their development (Gevaert et al., 2017).

1.3 Informal settlements detection using remote sensing

Understanding informal settlement dynamics and characteristics is crucial for the development of sustainable urban cities and human settlements. The success of initiatives to improve informal settlements is highly dependent on the data and information used during the planning of such solutions. Remote sensing provides the capability to map and monitor informal settlements, offering information to support planning and the development of necessary policies for better city management. Traditional methods of mapping informal settlements include counting informal settlement structures using high spatial resolution satellite imagery or aerial photography (Kit & Lüdeke, 2013).

The complexity of informal settlement roofing materials makes it difficult to extract informal settlements from high spatial resolution imagery using spectral information alone. Object-Based Image Analysis (OBIA) techniques analyze and classify image objects based on spectral, spatial, and contextual information (Castilla & Hay, 2008). This results in higher classification accuracy in urban environments when using high-resolution imagery compared to traditional pixel-based classification techniques (Desheng & Fan, 2010; Novack & Kux, 2010). A number of studies have tested and used OBIA technique to detect informal settlements with varying accuracies. Kuffer et al., 2016a, Owen & Wong, 2013; Kohli, et al., 2013, Fallatah et al., 2015; Kohli et al., 2012; Hofmann et al., 2001; Hofmann et al., 2008; Kohli et al., 2016; Kuffer et al., 2016a). The use of machine learning techniques and OBIA offers an opportunity to increase the accuracy of informal settlement detection from high spatial resolution imagery (Fallatah et al., 2020). Deep learning techniques have been investigated to detect informal settlement (Gadiraju et al., 2019; Mboga et al., 2017). Random Forest (RF), Support Vector Machines (SVM) and Linear Regression have also been investigated (Gadiraju et al., 2019; Leonita et al., 2018).

1.4 Research questions

The following research questions were addressed in this study:

1. Which settlement-based indicators can be applied on high spatial resolution images to detect informal settlements from formal settlements using OBIA?
2. What are informal settlement growth patterns in the study area?
3. Can we classify backyard shacks from free standing shacks and formal building structures using UAV?
4. What are the spatial patterns of backyard and free standing shacks in the study area?
5. What are ecological conditions of informal settlements compared to other settlement types?
6. What are the spatial characteristics of informal settlements in the study area?

1.5 Aims and objectives of the study

The aim of the study is to investigate informal settlement dynamics and spatial characteristics to generate an understanding of housing informality and environmental conditions for designing innovative sustainable solutions. The following objectives were set to achieve the aim of the study:

1. To investigate settlement-based indicators to detect informal settlements from formal settlements using very high spatial resolution imagery
2. To assess informal settlement growth patterns using very high spatial resolution imagery
3. To investigate the spatial patterns of backyard shacks and free-standing shacks using UAV image products and landscape metrics

4. To investigate an ecological index to assess the surface ecological condition of informal settlements and other settlement types
5. To assess location characteristics of informal settlements between 2015 and 2020.

1.6 Study area

The study area is in Mamelodi Township, which is located in the City of Tshwane Metropolitan Municipality, Gauteng Province, South Africa, Figure 1-1. The population of Mamelodi Township was 334,577 in 2011 (Statistics South Africa, 2012). Consequently, this township is densely populated with large areas of informal settlements. About 50% of dwellings in Mamelodi were informal in 2011 (Statistics South Africa, 2011). A total of 83 378 households in the City of Tshwane lived in backyard shacks in 2013 (City of Tshwane, 2017). The number of backyard shacks in the City of Tshwane increased by almost 400% between 2001 and 2011 (Gauteng City-Region Observatory, 2018).

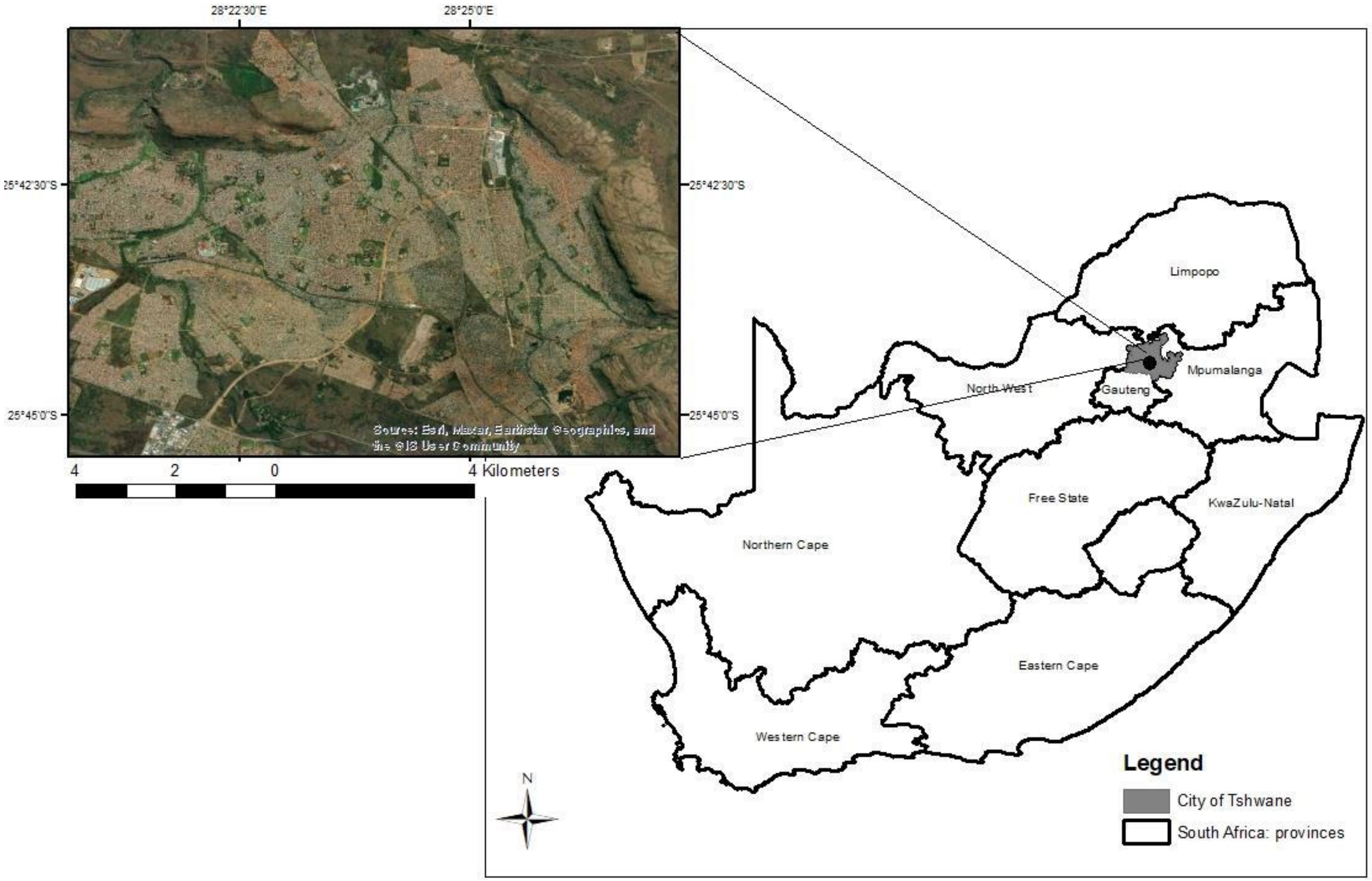


Figure 1-1: Location of the study area, Mamelodi Township, Gauteng Province, South Africa.

1.7 Significance of the study

The dynamics of informal settlements and their characteristics using remote sensing data including UAV, has not been adequately explored in South Africa from the research perspective. In addition, housing informality and the physical environment of informal settlements has not been explored using remote sensing data. The proliferation of informal settlements and increased development number of backyard shacks do not only threaten sustainable urban development efforts, but also jeopardize urban environmental sustainability, putting the lives of people at health and environmental risk.

The study is anticipated to contribute to an increased understanding of informal settlements by offering deep insights into their spatio-temporal growth patterns. These insights are required to formulate effective strategies to address the challenges posed by the development of informal settlements. Spatial information on the growth patterns of informal settlements can also help evaluate the effectiveness of upgrade projects and provide insights for improving future initiatives. Understanding the physical and environmental characteristics of informal settlements and other settlement types is crucial during planning interventions to meet the diverse needs of the different settlements in the study area. This understanding can also help mitigate health and disaster risks associated with the physical locations of informal settlements.

The investigation of new settlement indicators derived from high spatial resolution images and OBIA technique is expected to add new knowledge to informal settlement detection research. The mapping and assessment of spatial patterns of backyard shacks using UAVs showcases an innovative method to derive up-to-date and accurate information on backyard shacks, setting a precedent for future research to understand housing informality. Overall, the study is anticipated to contribute to the broader context of local and regional development planning by providing data-driven insights into the characteristics and dynamics of informal settlements.

1.8 Outline of the thesis

This is a paper-based approach thesis. The thesis comprised eight chapters, with six chapters describing how the set objectives were realized:

Chapter 1 provides the background, problem statement, objectives, and outline of the research.

Chapter 2 provides a review of the use of OBIA and remote sensing technologies to detect informal settlements and informal settlement land use information.

Chapter 3 developed a methodology to detect informal settlements from other land uses in a densely populated settlement. The study assessed the effectiveness of twelve spectral indices, first and second-order statistical measurements in the detection of informal settlements from formal settlements.

Chapter 4 assessed the spatial growth patterns of informal settlements in the study area using very high spatial resolution imagery. The study assessed changes in the extent and impervious surface within informal settlements and proposed an index to assess informal settlement growth patterns based on the extent and impervious surface.

Chapter 5 investigated the use of height information derived from UAV products in the mapping of backyard shacks and free-standing shacks. The study used landscape metrics to measure and analyze the object-level and settlement-level properties of the backyard and free-standing shacks.

Chapter 6 assessed the surface ecological conditions of informal settlements, formal settlements with backyard shacks and other human settlement types. The study proposes a SSEI that uses soil, tree, grass and impervious surface covers, LST and soil moisture to assess surface ecological conditions of human settlements.

Chapter 7 analyzed the location characteristics of informal settlements over a five-year period using ancillary data. The study assesses informal settlement growth and identifies the top three location characteristics of informal settlements.

Chapter 8 concludes the thesis by highlighting the main findings achieved on each objective, the contribution of research to the remote sensing field and recommendations for future studies.

Chapter 2 MAPPING AND ASSESSMENT OF HOUSING INFORMALITY USING OBJECT-BASED IMAGE ANALYSIS: A REVIEW

This chapter is based on the following manuscript:

Mudau N., Mhangara P., (2023), "Mapping and assessment of housing informality using Object-Based Image Analysis": a review; Urban Science; **https://doi.org/10.3390/urbansci7030098**

Abstract

Research on the detection of informal settlements has increased in the past three decades owing to the availability of high- to very-high-spatial-resolution satellite imagery. The achievement of development goals, such as the Sustainable Development Goals, requires access to up-to-date information on informal settlements. The review shows the number of publications has significantly increased between 2018 and 2019. Even through there has been an increased interest in the past few years, the review shows that limited studies were conducted in regions that are home to 80% of the informal settlements or slums, i.e. Africa and Asia, with South Africa and China being the only two countries conducting research in informal settlements and remote sensing in these two regions. In addition, the research on informal settlements and remote sensing is mostly funded by Europeans institutions with only one African institution in the top ten funders. In terms of object-based image analysis (OBIA), the review shows that there is increased focus on the use of OBIA and settlement level indicators to detect informal settlements than object level indicators. The review shows that the success of OBIA in detecting informal settlements depends on the understanding and selection of informal settlement indicators and image-based proxies used during image classification suitable for a particular city. The machine learning OBIA techniques are have a potential of increasing the accuracy of the informal settlements over a larger geographic area.

Keywords: OBIA, informal settlements, high spatial resolution images

2.1 Introduction

The world is experiencing alarming urbanization growth. In 1900, only 15% of the world's population lived in urban areas (Satterthwaite, 2005). This picture changed drastically during the 20th century. During the sixty years from 1950 to 2010, the world experienced rapid urbanization, leading to more than 50% of the world's population living in urban areas (Spence et al., 2009). Eight years later, more than 58% of the world's population were living in urban areas (United Nations Department of Economic and Social Affairs, 2019). The current projections indicate that approximately 75% of the world's population will live in urban areas by 2050 (United Nations Department of Economic and Social Affairs, 2019), with most urban development expected to occur in the towns and cities of developing countries (United Nations Department of Economic and Social Affairs (DESA), 2013). Unfortunately, urbanization in these countries is not always linked to economic development (Kessides, 2007), and population influx often surpasses the formal housing supply. This is already evident from the development of informal settlements or slums and informal dwelling structures, including backyard shacks around the cities and towns of developing countries. Many countries and international bodies have initiated policies and strategies that set targets to provide adequate housing and improve the living conditions of people living in informal dwellings.

Informal settlements are illegal and lack access to improved water sources, sanitation facilities, good living areas, housing durability or security of tenure (UN-Habitat, 2004) and are usually homes for new migrants and unemployed or unskilled people (Eckstein, 1990, Oksiutycz &Azionya 2022). In addition to the increased health, social and environmental vulnerability of people living in informal structures, the development of such dwellings can lead to environmental degradation. Even though the development of other forms of informal housing takes place on surveyed traditional land, the development of such structures is illegal, and the people living in such dwelling structures may lack security of tenure and direct access to basic services, leading to settlement informality. Effective urban planning requires access to consistent, reliable and up-to-date information on informal settlements and settlement informality.

In many countries, data on informal settlements are traditionally collected during ground surveys, including censuses. Censuses are usually conducted every ten years owing to the substantial financial resources required to conduct these surveys (United Nations: DESA, 2019). In addition, such censuses primarily capture headcount information rather than the spatial dimensions of informal settlements (United Nations: DESA, 2019). Even though the population census is the most comprehensive source of demographic data, information on informal settlements is usually underestimated compared to other settlement geographies (Maluleke, 2013). The temporal gap of census data poses many challenges in planning services, as the fiscal transfer of services is based on headcounts. In addition, development agendas such as the Sustainable Development Goals (SDGs) use headcounts to assess progress toward the achievement of sustainable cities. Understanding the spatial-temporal dynamics of informality in terms of demographic information, areal extent, morphology and environmental conditions can assist in the development of sustainable solutions to better manage urbanization. This paper reviews the published research on object-based image analysis (OBIA) methods for detecting informal settlements using remote sensing data, focusing on the indicators used to detect informal settlements. The paper also reviews the published research on the extraction of informal settlement land use features. The paper concludes by providing a summary and recommendations for potential future studies applying remote sensing in informal settlement mapping.

2.2 Origin and characteristics of informal housing

Informal settlements existed in the 16th century in Europe, Australia and North America, serving to provide housing solutions in now-developed countries for those with little or no income (UN-Habitat, 2004). Rapid urbanization during the Industrial Revolution led to the rapid increase in the number of slums during the last two decades of the 19th century (UN-Habitat, 2004). These settlements were usually located within the cities in old buildings. They lacked access to essential services and were not included in the planning of the cities, leading to these areas having poor living standards and being sources of social ills such as crime and drug abuse (UN-Habitat, 2004). Sub-Saharan African and South American urban areas were limited in number and extent during the pre-colonial era (UN-Habitat, 2004). Examples include Jenne-

Jeno in Mali and Aksum in Ethiopia. The urban settlements and towns were not formally planned but rather had settlements patterns, structures and land use systems dictated by their traditional and religious leaders. The dwelling structures in informal settlements differed from country to country and sometimes varied per ethnic group. Nevertheless, there was recognition of what constituted an acceptable settlement pattern, specifically one that provided for all necessary land uses, such as transportation, education and shops. During the last few decades of the 19th century and early 20th century in sub-Saharan Africa, the European colonizers established and settled in new settlements and generally changed or expanded the existing urban areas so as to be situated closer to natural resources, leading to more people moving from rural areas to urban areas in search of employment with the established industries (Okpala, 2009). The colonizers also established coastal cities such as Cape Town, Lagos and Accra to facilitate the transportation and trading of resources (Okpala, 2009). The spatial plans of colonial cities were created using racial segregation policies resulting in underserviced or unserviced black areas, mostly informal settlements, located far from the commercial and desirable residential areas separated with buffers such as railway lines (Strauss, 2019). To this day, most informal settlements in developing countries are home to unskilled or semi-skilled workers who have become the labor pool for industries particularly affected by economic instabilities. Hence, most of these workers are laid off during recessions, making it difficult for them to change or improve their living conditions (Frankenhoff, 1967).

Nowadays, informal housing can be found in informal settlements where free-standing informal structures are built on illegal land (UN-Habitat, 2004). The second scenario of informality in countries like South Africa takes place through the building of informal structures on formal surveyed land (Statistics South Africa, 2016). The third scenario is where people live in old buildings that lack city services. These settlements are mostly found within cities, such as the urban villages in some cities in China that were rural villages but are now rented out to create income (since agricultural land has been consumed by urbanization) (Pryce et al., 2021). The mapping of informal settlements or informal housing using remote sensing data requires a context-/countryspecific understanding and definition of informality. The terms informal settlement and slum are currently used interchangeably in United Nations documents (United Nations Department of Economic and Social Affairs., 2013). Other terms are used to describe informal settlements in different countries, including fevals (Brazil), bidovilles (Francophone), villa miseria (Argentina) and kampungs (Indonesia and Malaysia) (UN-Habitat, 2004).

Remote sensing technologies provide the capabilities to map and monitor informal settlement developments. The analysis of publications performed using the Scopus database in May 2023 shows that the number of studies using satellite imagery to map and monitor informal settlements or slums has increased since 2015, with fewer studies recorded between 1996 and 2008. Approximately 50% of the publications were published between 2019 and 2022, with the highest number of publications in 2019 (Figure 2-1).

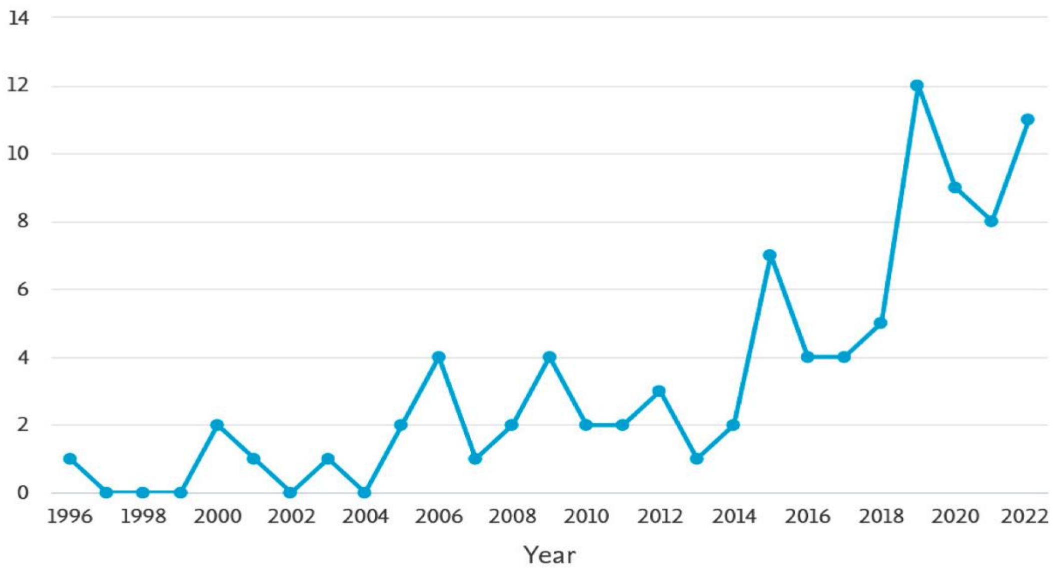


Figure 2-1: Number of publications on informal settlement mapping using remote sensing technology per year based on the Scopus database.

The increased interest in the studies on informal settlements in 2015 may be related to increased interest in informal settlements during and after the establishment of the SDGs. Even though informal settlements are mainly prevalent in Africa and Asia (where 80% of people live in informal settlements), most studies on formal settlements or slums have been conducted by researchers in Europe and the United States (see Figure 2-3).

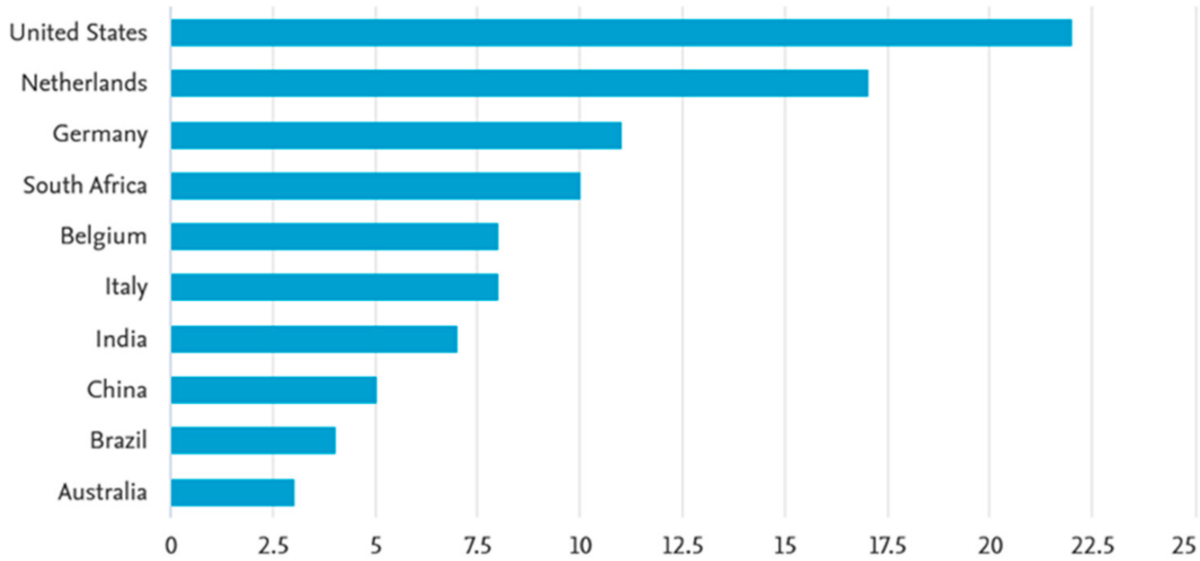


Figure 2-2: Proportion of publications on informal settlement mapping from remote sensing technology per country.

South Africa is the only country in Africa that is among the top ten countries conducting research on informal settlements. Other African countries whose research has been published in the Scopus database include Kenya, Ghana, Zambia and Nigeria. India and China are the only countries researching informal settlements in Asia. The proportion of studies in the different regions may be influenced by the funding opportunities to support research on informal settlements. Europe is the leading funder of research on informal settlement mapping (see Figure 2-3).

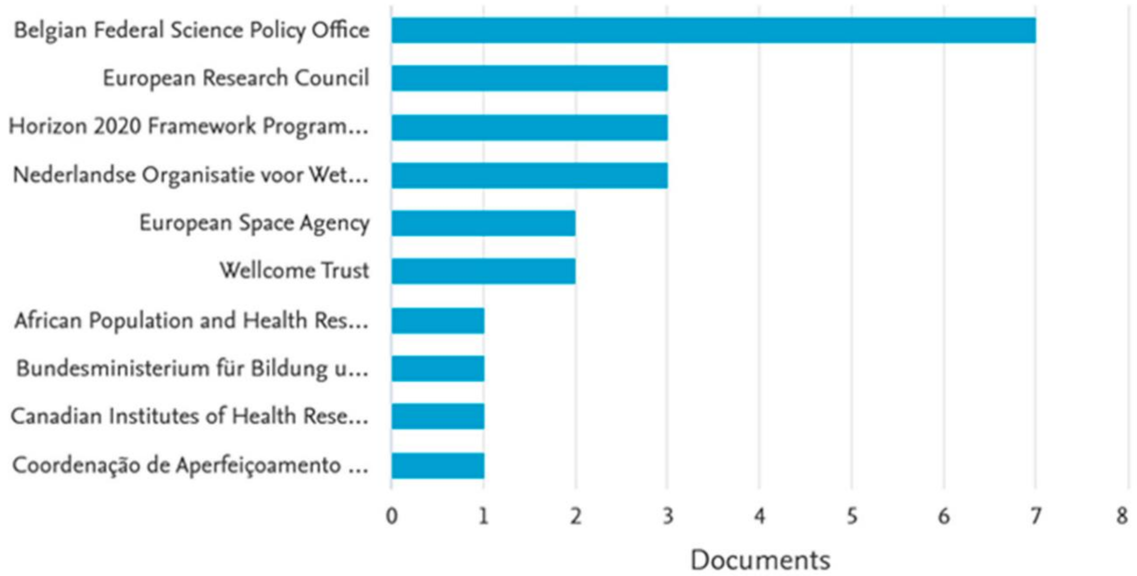


Figure 2-3: Top funders of research on informal settlement mapping

In addition, most of the published research on informal settlements is conducted by European academic institutions, as compared to research institutions or governments.

The methodologies used to detect informal settlements include manual digitization, pixel-based classification, OBIA, machine learning, and texture-based and statistical-based techniques. Even though visual image interpretation is time-consuming and resource intensive, it is still used today, as it produces more accurate results when performed by people with skills and experience in image interpretation (Kuffer et al., 2016a).

The complexity of the roof materials of structures and the heterogeneity of land use in urban areas make it challenging to distinguish informal settlements from other land use types using spectral information based on high-spatial-resolution imagery alone (Graesser et al., 2012). The use of machine learning techniques for informal settlement mapping has been slowly increasing in recent years. Machine learning techniques have proven to perform better than survey-based mapping methods. These techniques depend on the settlements' spectral, morphological or structural properties (Duque et al., 2017). This leads to confusion between informal settlements versus formal settlements with small buildings (Leonita et al., 2018). The methodologies that have been tested in the detection of informal settlements include Random Forest (RF), Support Vector Machines (SVM) and Linear Regression. The SVM provides more accurate results with fewer errors of commission and omission (Gadiraju et al., 2019; Leonita et al., 2018). Deep learning techniques such as Convolutional Neural Network (CNN) can potentially improve the accuracy of informal settlement classification (Gadiraju et al., 2019; Mboga et al., 2017). Unlike pixel-based machine learning techniques, deep learning techniques use image patches during model training (Mboga et al., 2017).

Additionally, known as Geographic Object-Based Image Analysis (GEOBIA), OBIA techniques have received increased attention in the past two decades as solutions for informal settlement detection (Castilla & Hay, 2008; Hofmann et al., 2001; Kohli et al., 2016a). Unlike pixel-based classification techniques, OBIA classification techniques use the spectral, spatial and contextual characteristics of image objects for classification (Castilla & Hay, 2008).

Table 2-1 summarizes the differences between the mapping methodologies used to detect informal settlements.

Table 2-1: Description of informal settlement detection methods

Method	**Description**
Manual digitization	This method is time-consuming and resource intensive; however, it yields more accurate results compared to other informal settlement detection methodologies (Kuffer et al., 2016a).
Pixel-based classification	The method results in high confusion between informal settlements and features with similar spectral signatures (Myint et al., 2011).
Machine learning	The method can be used with other image classification techniques, such as OBIA, and texture (Duque et al., 2017; Leonita et al., 2018).

The OBIA technique has been the most common method for informal settlement detection in the past two decades, as compared to other image-processing methods (Kuffer et al., 2016a). Compared to pixel-based classification, OBIA is beneficial for the classification of slums because the segmentation process generates segments that have additional spectral, geometric and textural information that is essential for differentiating slums (Kit & Lüdeke, 2013; Kuffer et al.,2016a). The image segments contain descriptive statistics such as mean, median, minimum and maximum values per band and the mean ratios and variances of the images' spectral, spatial and textural characteristics (Baatz, 2000; Esch et al., 2008; Hofmann et al., 2008; Kit & Lüdeke, 2013; Kuffer et al.,2016a). Multiresolution segmentation has been implemented successfully in GEOBIA to delineate buildings and uses scale, shape and compactness to segment objects (Drăguţ et al., 2010).

The use of machine learning techniques and OBIA techniques to detect informal settlements is attracting interest from researchers. The settlement-based indicators and RF classifier successfully detected informal settlements with increased accuracy (Fallatah et al., 2020). The use of the OBIA technique and RF classifier in the detection of informal settlements applying optical sensors and Synthetic Aperture Radar (SAR) images has the potential to produce more accurate results (Naorem et al., 2016). The

OBIA technique (which uses settlement-level image features derived from high-spatial-resolution imagery) and RF (derived from high-spatial-resolution satellite imagery) have been used to detect informal settlement growth from Landsat temporal images with high accuracy (Fallatah et al., 2020).

2.3 OBIA processing steps

The first step in OBIA is image segmentation. This process partitions the image into meaningful image objects which are used during image classification or interpretation. OBIA was introduced around 2000 and implemented in software like Trimble eCognition. The most common image segmentation technique used in informal settlement detection is the multiresolution segmentation process (Kuffer et al., 2016a). One of the time-consuming tasks in image segmentation is to determine the scale parameters that will produce image objects that represent the desired classes (Esch et al., 2008). The scale parameter is an important variable in image segmentation as it determines the heterogeneity and size of segmented objects (Baatz, 2000). The higher the scale parameter the higher degree of heterogeneity in the object, resulting in bigger image objects. Most studies have used a trial and error process to determine the scale parameter that will provide the required objects (Mudau & Mhangara, 2021; Fallatah et al., 2019; Kuffer et al., 2016b; Hofmann et al. 2001). This is a supervised segmentation method that requires a user to inspect the segmentation results using reference data or local knowledge and fine-tune the parameters until desired image objects are achieved.

Scale parameter remains a problem noteworthy in the transferability of OBIA classification techniques. The transfer of image segmentation parameters from one sensor to the other requires fine-tuning of the parameters (Hofmann et al., 2008). Reference data such as roads or rail have been used during the segmentation process to improve the boundaries of the resulting image object (Kuffer et al.,2016a). The Estimation of the Scale Parameter tool developed by Drăguţ et al., 2010, has been employed by some researchers to determine the scale parameter to be used during the segmentation of informal settlement objects (Pratomo et al., 2018; Naorem et al., 2016). Several studies have used two segmentation levels to detect informal settlements (Mudau & Mhangara, 2021; Fallatah et al., 2019; Hofmann et al., 2001). This usually involves the segmentation of larger image objects that represent non built-up and built-up areas, whereas the second level is created using higher scale values to create informal and formal land use objects used as sub-objects to distinguish informal settlements from formal settlements. The use of one segmentation level is observed where only spectral-based features are used during the classification of informal settlements (Kuffer et al.,2016a).

The availability of image processing platforms such as Google Earth Engine provides opportunities to implement other segmentation methods such as Simple Non-Iterative Clustering which have been successful in segmenting informal settlement image objects from medium spatial resolution optical images and SAR (Matarira et al., 2022). Grid-based segmentation approaches have also between used in informal settlement detection OBIA (Mudau & Mhangara, 2022; Zhao et al., 2020).

Image classification in OBIA is usually done using rulesets. Expert knowledge is required to generate the rulesets. The most challenging task during mapping informal settlements using OBIA is translating the characteristics of informal settlements into robust indicators that can be used across the globe during classification (Fallatah, et al., 2015; Kohli et al, 2012; Hofmann et al., 2001) developed. A GSO was developed to define generic indicators of informal settlements that can be used to detect informal settlements from remotely sensed data across the globe (Kohli et al., 2012). The GSO is based on the built morphology of informal settlements at three spatial levels i.e. environs, settlement and object.

2.4 Detection of informal settlements using object level indicators

Several studies have investigated using OBIA techniques to detect informal settlements (Hofmann et al., 2008; Kohli et al., 2016; Kuffer et al., 2016a). The rulesets used for detecting informal settlements vary in terms of complexity from one area to another, depending on the ontology of the informal settlements. The object-level indicators tested or used to detect informal settlements include the tone and shape characteristics of dwelling structures (Hofmann et al., 2001; Pratomo et al., 2018). The shape characteristics that are used serve to detect informal settlements’ size and the simplicity of their roof structures. The dwelling structures in informal settlements are usually smaller (Fallatah et al., 2019a; Kohli, 2015a; Pratomo et al., 2018) and more irregular in shape (Pratomo et al., 2018) than formal structures.

The roofs of the dwelling structures in informal settlements vary from iron sheets, asbestos (Pratomo et al., 2018) and a combination of clothes, woods and straw (Nassar & Elsayed, 2018; Sliuzas, 2008). Image features that have been investigated to distinguish tone of dwelling structures in formal and informal settlement brightness, which measures the intensity of the bands of the image used or is done using the intensity of the individual bands. The use of measurements derived from the tone of the roof of the dwelling structures in informal settlements derived from high spatial resolution imagery alone is not sufficient in the detection of informal settlements (Myint et al., 2011). This is due to spectral confusion of dwelling roofs and surrounding surfaces (Myint et al., 2011). The producer accuracy of studies that have investigated the use of shape characteristics of the dwelling structures and achieved poor accuracy of around 2% - 65% (Fallatah et al., 2019; Pratomo et al., 2018; Hofmann et al., 2001).

2.5 Detection of informal settlement using settlement level indicators

Settlement-level indicators are physical characteristics of informal settlements that describe the overall shape, form or density of the respective settlement (Kohli et al., 2012). These indicators include the relative density of building structures and the absence of regular road networks and vegetation. Further indicators are the lacunarity and orientation of built structures (Kohli et al., 2012). The density of structures in unformal settlements can vary from one settlement to another. In addition, the density of the structures can vary depending on the developmental stage of the informal settlement, i.e., in infancy, consolidation or maturity (Sliuzas, 2008). Several studies in the literature have been conducted on medium- to high-density informal settlements (Fallatah et al., 2019a; Hofmann et al., 2008; Hofmann et al., 2001; Kohli et al., 2016). At the time of the writing of this paper, no studies had yet been published that focused on the use of remote sensing to detect informal settlements with low-density building structures. The image proxies used in the detection of informal settlements using settlement indicators include the grey-level co-occurrence matrix (GLCM), lacunarity of building structures to open spaces, and built-up and vegetation indices.

The measurement of the GLCM is used to analyze the occurrence of pairs of pixels with specific values and a specific spatial relationship (Haralick et al., 1973). The GLCM textural measurements are the image features commonly explored, investigated or used for informal settlement detection in areas with medium- to high-density building structures, from high- to very-high-spatial-resolution imagery (Kuffer et al.,2016a; Mudau & Mhangara, 2021a; Prabhu & Parvathavarthini, 2022; Zhao et al., 2020). The window size used during the texture analysis and the spatial relationship analysis can affect the detection of informal settlements (Kuffer et al.,2016a; Mudau & Mhangara, 2021b). The success of these GLCM features in detecting settlements varies from one area to another depending on the morphology of the settlement, the surrounding land use features and the developmental stage of the settlements (Fallatah et al., 2019a; Mudau & Mhangara, 2021a). The integration of GLCM and other features, such as vegetation indices, has been proven to increase the quality of the results (Kuffer et al.,2016a).

Several studies have attempted to detect informal settlements by analyzing the presence or morphology of land use features. A lack of vegetation is one of the characteristics of informal settlements that have been investigated (Kuffer et al., 2016a). This indicator is assessed using vegetation indices such as the Normalized Differential Vegetation Index (NDVI). The NDVI quantifies vegetation cover and has been used to classify land use and land cover features (Jeevalakshmi et al., 2016). Informal settlements typically have lower vegetation cover than formal settlements (Hofmann et al., 2015; Kuffer et al.,2016a; Owen & Wong, 2013). This indicator is mainly used with other indicators, such as high building density, to detect informal settlements. Even though lack of vegetation could be used as an indicator during informal settlement detection, studies that assess vegetation cover and the biophysical characteristics of informal settlements have not been conducted. Understanding the biophysical characteristics and environmental conditions could help to manage the development of a measure aiming to improve the resilience and health of people living in informal settlements.

The use of lacunarity to detect informal settlements has been investigated in several studies (Gefen et al., 1983; Kit et al., 2012; Owen & Wong, 2013). Lacunarity is a measure of the deviation of geometric objects which quantifies the spatial heterogeneity of an object (Jeevalakshmi et al., 2016). Formal settlements are expected to have higher lacunarity values, whereas informal settlements have lower values (Kit et al., 2012). The lacunarity values of informal settlements depend on the developmental stage and density of the settlements (Owen & Wong, 2013).

Line detection algorithms such as Canny edge have been used to measure lacunarity in the detection of informal settlements (Kit & Lüdeke, 2013; Owen & Wong, 2013; Wasisa et al., 2016). In OBIA, lacunarity is also calculated by assessing the relative distance of building structures from vacant land (Fallatah et al., 2019a). The effectiveness of lacunarity in detecting informal settlements requires highly accurate informal settlement land use features. The integration of ancillary data available from platforms such as OpenStreetMap can potentially improve the detection of informal settlements.

Informal settlements are characterized by organic and irregular road networks or paths (Wurm et al., 2017). Only a limited number of studies have integrated the detection of road networks in distinguishing informal from formal settlements (Kuffer et al.,2016a; Najmi et al., 2022; Salem et al., 2020). The geometric characteristics of informal settlement land use features have been investigated using the asymmetry of sub-objects (Hofmann et al., 2001; Mudau & Mhangara, 2022). Informal settlements tend to have a lower asymmetry of sub-object values owing to the complex nature of land use features in informal settlements. The asymmetry of sub-objects performs better in detecting informal settlements than the use of the area or density of sub-objects (Mudau & Mhangara, 2022). This may be attributed to the fact that the assessment of the area and density of sub-objects depends on the accuracy of the segmentation results of building structures and land use features in informal settlements (Norman et al., 2021).

2.6 Detection of informal settlement using environ-level indicators.

The detection of informal settlements using environment level characteristics has not been thoroughly investigated. Informal settlements are mostly developed in vacant land in an undesirable location closer to rivers or services, in very low or steep slopes areas or areas prone to environmental disasters (Kohli et al., 2012; (Pratomo et al., 2018). Some studies have investigated the location characteristics of informal settlements using ancillary data (Dovey et al., 2020; Abebe et al., 2019; Githira, 2016; Sirueri, 2015; Dubovyk et al., 2010). The integration of location characteristics such as proximity to rivers, roads or railway lines in OBIA classification process has proven to increase the detection of informal settlements (Pratomo et al., 2018; Shekhar, 2012).

2.7 Temporal analysis of informal settlement extent

Understanding informal settlements can help authorities to better manage the development of informal settlements and urbanization in general. Even though several studies have investigated the detection of informal settlements using satellite images, limited studies have focused on analyzing informal settlement growth (Dubovyk et al., 2010; Fallatah et al., 2019a; Liu et al., 2019; Maiya & Babu, 2018; Mudau & Mhangara, 2022; Pratomo et al., 2018). The accuracy of post-classification-based change detection greatly depends on the accuracy of the classification results. In OBIA, the detection process's or ruleset's transferability remains challenging (Pratomo et al., 2018). Machine-learning-based change detection offers a better solution for informal settlement detection (Maiya & Babu, 2018). The information assessed in change detection studies has mainly focused on the extent of settlements. The availability of Unmanned Aerial Vehicles (UAV) provides an opportunity to assess building structure growth or changes in informal settlements (Gevaert et al., 2020).

2.8 Informal settlement mapping using UAVs

The use of 3D information for detecting building structures in informal settlements using UAVs, unmanned aerial systems or drones has been an area of interest among researchers in recent years. UAV technology can acquire ultra-high-spatial-resolution images, 3D point clouds, detailed Digital Surface Models and Digital Elevation Models (Gevaert et al., 2016). This technology also provides flexibility in the selection of spatial and revisit times based on the information requirements of the project (Nex & Remondino, 2014). The integration of 2D and 3D information heights generated from UAV products has been proven to provide more accurate results than pixel-based classification (Gevaert et al., 2017). The mapping of land use features in informal settlements (including building structures through integrating 2D and 3D information provided by UAV technology) produces the detailed information required to support many applications, including planning for the upgrading of slums (Gevaert et al., 2017).

UAV products have also been used to classify roofs according to the roof materials and building heights, providing valuable information that can be used during spatial planning and as an indicator for classifying informal versus formal settlements (Ashilah et al., 2021). The assessment of land use features in informal settlements using UAV image products is limited to smaller geographic areas (Pérez et al., 2013); for city-wide informal settlement mapping, high-spatial-resolution images are required. In contrast, UAV technology is suitable for the localized assessment of features in informal settlements to support specific projects, such as upgrade projects (Sliuzas et al., 2017).

The capacity of UAVs to assess the morphology of building structures for determining fire disaster risk in informal settlements has been demonstrated (Gibson et al., 2021). Point cloud data used to create a 3D model of the building structure have been investigated to support several applications, including informal settlement upgrades (Khawte et al., 2022). Furthermore, multitemporal UAV products have successfully identified upgraded dwelling structures in informal settlements (Gevaert et al., 2020). It has been shown that using UAV products to detect features in informal settlements provides classification accuracies of 90% or higher (Gevaert et al., 2020).

2.9 Studying morphology of informal settlement using landscape metrics

The research aiming to distinguish informal settlements from formal settlements using landscape metrics is new. A recent study in China successfully distinguished urban villages from formal areas with higher accuracy in two cities using patch and landscape metrics (Liu et al., 2017). The study of the spatial patterns of informal settlement structures using landscape patterns has also received limited attention (Gibson et al., 2021; Sirueri, 2015). Studying the spatial patterns of informal settlements can provide information with which to better understand the configurations of settlements and, hence, aid in planning services. Furthermore, integrating spatial patterns with other information types, such as disaster occurrence, can help to identify areas at risk of such events (Gibson et al., 2021).

2.10 Mapping of informal settlement land use features

Understanding the built environments of informal settlements is essential for providing primary and emergency services. Research on the high- to very-high-spatial-resolution extraction of building structures in informal settlements has been an area of interest for many scholars and researchers in the past two decades (Dahiya et al., 2020; Mayunga et al., 2010). This was made possible by the launch of satellites such as IKONOS, QuickBird and Worldview. The quantification of building structures provides information required to estimate population size and facilitates the provision of health and other essential services, such as emergency response services (including fire and disaster management). The extraction of building structures from high-spatial-resolution imagery is a complex process owing to the size and heterogeneity of the surrounding land use features, such as roads and open spaces.

Limited studies have investigated the extraction of roads in informal settlements, yet these are essential infrastructure, as they provide transportation and emergency service access. The detection of road features in informal settlements is challenging, as roads in informal settlements have similar physical characteristics compared to other land use features when using high-spatial-resolution satellite imagery (Nobrega et al., 2006).

2.11 Summary and recommendations

This study shows that remote sensing has been widely used to detect informality where free-standing shacks or dwelling structures were built on land that was not approved for habitation. The literature search indicates that there are no studies using remote sensing to detect informality in formal areas. Even though some studies have investigated the use of remote sensing in informal detection, the adaption of the investigated methodologies in different areas remains a challenge. While the use of OBIA techniques to detect informal settlements has been thoroughly investigated, for the detection methodologies to be transferable to more than one city, fine-tuning of the segmentation parameters and the thresholds used during the classification process will be required.

This review shows that settlement-level indicators have been thoroughly investigated and have been more successful in detecting informal settlements than object-level and environment-level indicators have. Furthermore, object- and environment-level indicators have produced lower-quality results than settlement-level indicators. As shown in this review, informal settlements are characterized by high-density structures in sparsely vegetated areas. Thus, many studies have investigated the use of GLCM and NDVI for detecting informal settlements. The success of the settlement indicators investigated in the respective studies is shown in the literature to strongly depend on the characteristics of informal settlements. Therefore, there is a need to investigate and test the robustness of methodologies that integrate different detection techniques.

To detect informal settlements, it is crucial to understand the local typology of informal settlements when developing rulesets. Studies have shown that informal settlements around cities may have different physical characteristics (specifically, density and vegetation coverage). The use of OBIA combined with machine learning techniques may yield a better accuracy in detecting informal settlements compared to the use of traditional ruleset-based OBIA techniques alone. The combination of OBIA and machine learning techniques also offers a means of detecting informal settlement land use features such as roads and vegetation. The studies reviewed in the literature have demonstrated that the use of UAVs provides researchers with height information that can be used to improve the outlining of object-level features and assess other forms of informality. This is especially the case in areas with both formal and informal settlements. The use of different sensors, e.g., SAR and optical sensors, for detecting informal settlements increases image proxies that can improve classification accuracy. In addition to informal settlements' extent, other research has focused on parameters such as the height of building structures and roads. The availability of UAVs provides the opportunity to extract and analyze informal settlements on a larger scale, which is necessary for the effective planning of infrastructure and services. Limited studies have mapped and assessed land use features in informal settlements. Little is known about the environmental conditions of informal settlements.

Future studies should develop local ontologies of informal settlements and develop robust methodologies to detect informal settlements over a larger geographic area. Secondly, there is a need to investigate the use of image proxies with optical and active sensors over a larger area or different cities. When mapping other forms of informality, such as backyard shacks, OBIA techniques should be prioritized. Furthermore, studies should examine the spatial patterns of formal and informal settlements based on very-high-spatial-resolution data provided by UAVs and aerial photography. The use of more object-level information to detect informal settlements and use of UAVs to assess the environmental conditions of informal settlements will provide crucial insights into the mapping of informal settlements.

2.12 Conclusions

In this study, we identified technological advancements in mapping and detecting informal settlements using high spatial resolution data and OBIA approach. The review reveals that, despite an increase in studies focusing on informal settlements mapping and monitoring in the past two decades, the quantity of published papers remains low. Even though a high percentage of people live in informal settlements in Africa and Asia, South Africa and China are the only countries in the top ten publishing studies in these regions. The study further reveals that only one funding institutions from these regions is in the top 10 funders of informal settlement studies, potentially contributing to the lower number of published papers in these regions. Therefore, there is a need to increase the focus of research in regions that are mostly affected by the development of informal settlements or slums.

The review indicates that many studies have used optical satellite images rather than SAR and UAV to detect informal settlements. Among these studies, the majority have investigated the use of settlement-level image proxies to detect informal settlements using OBIA techniques, rather than object-level image proxies. The use of environmental image proxies in the detection of informal settlements has not been explored. The transferability of rulesets derived using image proxies remains a challenge due to the varying morphology of informal settlements across the world, regions and in some cases across the city. There is a need to explore city-level image proxies that can be used to develop OBIA approaches suitable for the city, contributing to increased understanding of the dynamics of informal settlements and providing opportunities for more analyses, including vulnerability to health and environmental risks.

Chapter 3 INVESTIGATION OF INFORMAL SETTLEMENT INDICATORS IN A DENSELY POPULATED AREA USING VERY HIGH SPATIAL RESOLUTION SATELLITE IMAGERY

This chapter is based on the following manuscript:

Mudau N., Mhangara P., (2021), Investigation of Informal Settlement Indicators in a Densely Populated Area Using Very High Spatial Resolution Satellite Imagery; Sustainability; https://doi.org/10.3390/su13094735

Abstract

Automation of informal settlement detection using satellite imagery remains a challenging task in urban remote sensing. This is because informal settlements vary in shape, size and spatial arrangement from one region to the other in some cases within a city. This paper investigated the methodology to detect informal settlements in a densely populated township using informal settlement indicators observed from very high spatial resolution satellite imagery. In addition to commonly used informal settlement indicators, we assessed the effectiveness of built-up and iron cover. The Gray-Level Co-occurrence Matrix (GLCM) textural measures performed poorly in the separation of formal and informal settlements compared to First Order Statistics (FOS) measurements and radiometric indices. The Built-up Area Index, Coastal Blue Index and the FOS Mean measurements achieved higher separability distance between formal and informal settlements. The Iron Index performed better in the separation of the two settlement types than the common GLCM measure and Normalized Differential Vegetation Index (NDVI). The proposed classification tree that uses the three features with the highest separability distance achieved producer and user accuracies of informal settlements of 95% and 82% respectively. The results of this study will contribute to the development of methodologies to automatically detect informal settlements.

Keywords; OBIA, coastal blue index, informal settlements, built-up area index

3.1 Introduction

More than 58% of the world population lived in urban areas in 2018, and the number is expected to increase to 75% in 2050 (United Nations Department of Economic and Social Affairs, 2019). Unfortunately, urbanization in developing countries is not always linked to economic development (Kessides, 2007) and may lead to an increase in the number of people without access to basic infrastructure and the proliferation of informal settlements or slums. Informal settlements usually lack access to basic services and are not included during the planning of the cities, leading to these areas having poor living standards and being a source of social ills, such as crime and drug abuse (UN-Habitat, 2004). With future urbanization expected to take place in towns and cities of developing countries, the number of people living in slums is expected to double, i.e., more than 3 billion by 2050 (UN-Habitat, 2020). While most developing countries are already struggling with the effects of rapid urbanization, future urbanization may result in increased development of informal settlements, poverty and inequality. Information on the extent, population or condition of the informal settlement of informal settlements is not always available, which results in these areas not included in the government plans and policies (Patel & Baptist, 2012). This calls for a need to develop new methodologies to generate data and information to support the management of informal settlements.

The common source of information on informal settlements in many countries is census data. Census is usually done every five to ten years period, leading to data gap challenges (Kakembo & van Niekerk, 2014; Kohli et al., 2016). In addition, information collected during the census contains mainly headcount information and lacks the spatial dimension on the informal settlement (Kohli et al., 2012). Information on the population and condition of informal settlements is also collected through surveys to support specific projects. These projects may vary from informal upgrade programs to the provision of services by non-governmental institutions. This leads to spatial and temporal gaps in informal settlement data as the procedures used to survey informal settlements are not always published (Housing Development Agency, 2012). In addition, data collection using field surveys is a time-consuming and resource-intensive exercise. Consequently, governments are struggling to maintain informal settlement database due to prohibitive costs associated with field surveys (United Nations Population Fund, 2002).

Remote sensing provides an opportunity to map and characterize human settlements based on their morphology, allowing for the cost-effective data collection on informal settlements (Patino & Duque, 2013). The use of remote sensing data can independently map a countrywide to a city-wide location and condition of informal settlements. Remote sensing technologies that have been investigated in the literature for informal settlements mapping include aerial photography (Li et al., 2005; Williams, 2016), unmanned aerial vehicles (Gevaert et al., 2016) and satellite imagery (Ribeiro, 2015; Hofmann et al., 2008; Hofmann et al., 2001; Jain, 2007; Kohli et al., 2016; Kuffer & Barros, 2011).

Methodologies used in mapping informal settlements from remote sensing data include visual image interpretation, traditional pixel-based classification, Object-based image analysis (OBIA) and machine learning techniques. The visual image interpretation method is usually applied to very high spatial resolution satellite imagery. Even though this methodology is time-consuming and resource-intensive, it is still commonly used as it produces higher accurate results when performed by experienced technicians than automated methodology (Kuffer et al., 2016a). however, it leads to outdated data over larger geographic areas.

The detection of settlement types using spectral characteristics alone is not possible. This is due to varying physical characteristics of informal settlements (Hofmann et al., 2001; Kohli et al., 2013), roof materials of the dwelling structures within informal settlements (Hofmann et al., 2001; Martino & Daniele, 2009) and development stages (Hofmann et al., 2008; Sliuzas, 2008). Many studies in the literature used object and settlement characteristics to detect informal settlements from satellite imagery with varying accuracy based on the informal settlement indicator and geographic area. To solve the problem associated with the detection of informal settlements using only spectral characteristics, generic slum ontology (GSO) was developed to assist with the detection and mapping of informal settlements from remotely sensed data across the globe. The GSO is based on the built morphology of informal settlements at three spatial levels, i.e., environment, settlement and object (Kohli et al., 2012). Building density remains the most explored settlement indicator that produces high accuracy compared to other indicators (Fallatah et al., 2019a; Hofmann et al., 2008; Kohli et al., 2012; Kuffer et al.,2016a; Kuffer & Barros, 2011; Prabhu & Parvathavarthini, 2022). The use of gray-level co-occurrence matrix (GLCM) textural statistics has been investigated with varying accuracies depending on the morphology of the informal settlements and surrounding settlements (Kuffer et al.,2016a). In some cases, GLCM textural analysis fails to detect informal settlements from the built-up area (Fallatah et al., 2019; Hofmann et al., 2001).

Even though several studies have focused on mapping informal settlements in different geographic areas, an automated methodology for informal settlement mapping from remotely sensed data still does not exist. In addition, varying accuracies are achieved using the same indicators for informal settlement detection in different geographical areas. This study investigates the performance of twelve image-based indicators on the detection of informal from formal settlements in Mamelodi, in South Africa, using WorldView 2 satellite imagery. In addition to commonly used informal settlement indicators, the study investigates two informal settlement indicators that can be derived from high-resolution satellite imagery.

3.2 Study Area

Mamelodi is one of the biggest townships in the city of Tshwane, South Africa, located 20 km east of the city, see Figure 3-1. The total area of Mamelodi Township is around 32 km^2. Mamelodi was established in 1953 as an urban housing scheme designed exclusively for occupation by black African residents. In line with Apartheid planning, Mamelodi was intended to provide a cheap labor pool for industries in Pretoria and the wider Gauteng region (Statistics South Africa, 2011).

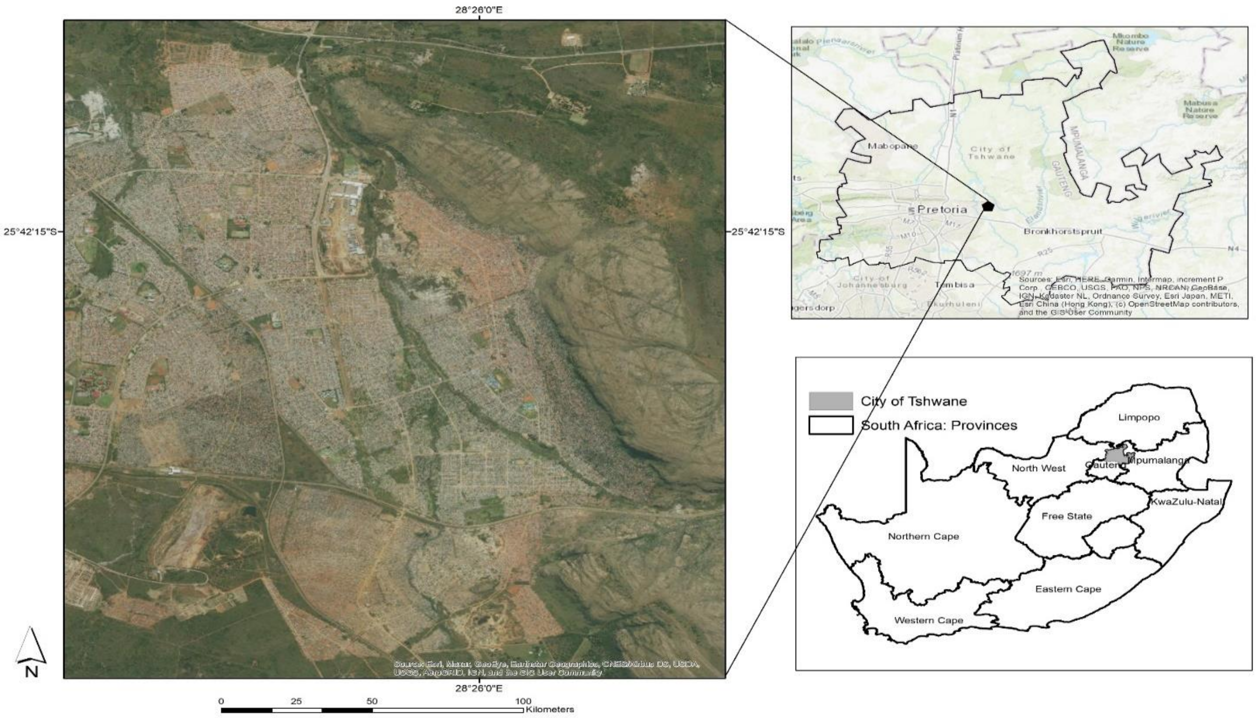


Figure 3-1: Location of the study area, Mamelodi Township, City of Tshwane, Gauteng Province, South Africa

Mamelodi Township has a population of 334,577 (Statistics South Africa, 2011). The township is densely populated with large areas of informal settlements. About 50% of dwellings in Mamelodi were informal in 2011 (Statistics South Africa, 2011). Due to this high number of informal dwellings, the authorities are struggling to meet the housing demands and the provision of basic services. Additionally, Mamelodi is faced with many social and environmental challenges, including high crime rates, water pollution and solid waste management. In terms of the impact of informal settlements on the environment, the stream that flows through one informal settlement in Mamelodi is odorous and contaminated but still used for household chores putting the health of the people at risk (Darkey & Donaldson, 2000). Despite several informal settlement upgrade projects taking place in Mamelodi, the expansion of informal settlement is still on the rise. Spatial information on informal settlements is vital to ensure that local authorities and policymakers put necessary measures and resources aimed at upgrading informal settlements and managing their development.

3.3 Data

We used WorldView 2 8-band multispectral and panchromatic images acquired on 28 July 2015, sourced from Maxar Technologies. The multispectral bands and panchromatic bands have a spatial resolution of 2.4 m and 46 cm, respectively. The 8 bands multispectral image contains coastal, blue, green, yellow, red, red edge near-infrared and near-infrared 2. The images were received georeferenced to the geographic coordinate system and WGS 84 data. The images covered Mamelodi East area, with the coordinates 25°41′–25°45′ S and 28°23′–28°27′ E. Figure 3-2 shows an informal settlement in Mamelodi Township over WorldView 2 image.

Figure 3-2: One of the informal settlements in the study area over a Worldview 2 image

3.4 Method

In this study, we used object-based image analysis (OBIA) to detect informal from formal settlements. The methodology followed involves segmentation of an image into smaller image tiles, selection of samples, assessment of informal settlement indicators, built-up and non-built-up classification, detection of informal settlements and accuracy assessment.

Figure 3-3. The processing was done using Trimble eCognition Developer 9 software. The processing steps followed are explain the processes in the next sub sections.

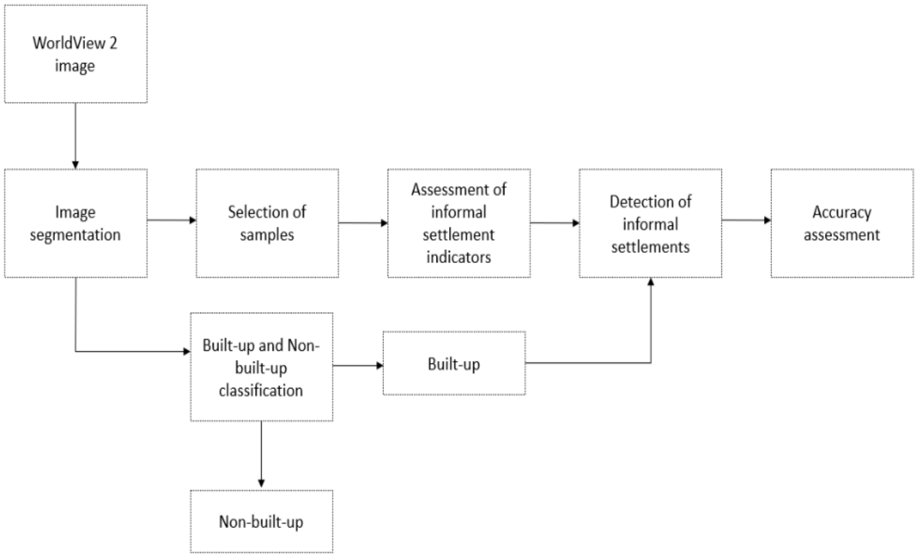


Figure 3-4: Methodology followed to detect informal settlements

3.5 Image Segmentation

The most important step in OBIA classification is image segmentation, which partitions an image into desired objects, which are used during image classification or image interpretation. In this study, a grid-based segmentation was chosen to allow for the assessment and classification of formal and informal settlements based on the characteristics and patterns of the land-use features within a grid. We used chessboard segmentation techniques to segment the image into 150 by 150 pixels tiles or grids. Chessboard image segmentation algorithm partitions an image into smaller square objects (Jinli et al., 2019). This segmentation algorithm uses only the scale parameter and does not consider the spectral or shape features of the objects (Xue & Lin, 2020). The selection of the tile size was done using an interactive approach based on expert knowledge of the study area.

3.5.1 Assessment of informal settlement indicators

Table 3-1 lists the informal settlement indicators that were assessed and image features investigated and the image features that best separate informal settlements from formal settlements.

Table 3-1: List of spectral and textural features investigated in the detection of classification of informal from formal settlements.

Informal indicator	Image feature	Formula
Vegetation extent	NDVI	NIR - R/NIR+ R
Built-up area extent	BAI	B- NIR/ B + NIR
Iron cover	Iron Index	R/B
Asphalt cover	REI	NIR2-B/NIR2+B*NIR2
Built-up extent	CB Index	CB - NIR/ CB + NIR
Texture	GLCM Mean	$\sum_{i,j=0}^{n-1} i(p_{i,j})$
	GLCM Variance	$\sum_{i,j=0}^{n} p_{i,j} (\mathrm{i}-\mathrm{j})^2$
	GLCM Homogeneity	$\sum_{i,j=0}^{n} \sum_{i,j=0}^{n} \frac{p_{i,j}}{1+(\mathrm{i}-\mathrm{j})^2}$
	GLCM Contrast	$\sum_{i,j=0}^{n-1} p_{i,j} (\mathrm{i}-\mathrm{j})^2$
	FOS Mean (u)	$\frac{1}{n} \sum_{i,=0}^{n-1} (P_i)$
	FOS Variance	$\frac{1}{n} \sum_{i,=0}^{n-1} P(\mathrm{i})(\mathrm{i}-u)^2$
	FOS Skewness	$\frac{1}{n} \sum_{i,=0}^{n-1} P(i)(\mathrm{i}-u)^3$

Where NIR, R, B, G and C are Near-infrared, Red, Blue, Green and Coastal Blue bands respectively, n is the total number of gray levels in the image; The matrix element P (i,j) is the set of second-order statistical probability values for changes between gray level i and j at a particular displacement distance and P_i is the probability of each pixel.

The indicators assessed included the commonly investigated informal settlement indicators, which are vegetation cover, asphalt cover and texture (Kohli et al., 2012). In addition, we assessed the performance of the built-up and iron cover in distinguishing between informal and formal settlements.

The density of building structures in the informal settlements varies across the study area from 5 to more than 15 building structures per 100 m^2. Lack of vegetation or limited vegetation has been used as an indication of informal settlements (Owen & Wong, 2013). Several studies have concluded that vegetation cover in informal settlements is lower than in low-density formal settlements (Fallatah et al., 2019a; Hofmann et al., 2001; Owen & Wong, 2013). We used vegetation cover derived using normalized difference vegetation index (NDVI) to investigate its performance in the detection of informal settlements.

Built-up area indices have been used to highlight built-up areas from other land cover features from satellite imagery (Bhatti & Tripathi, 2014; He et al., 2010; Zhang et al., 2014). Areas with high built-up density have higher built-up index values compared to areas with lower density built-up areas. We used the built-up area index (BAI) (Mhangara et al., 2011) to assess the separation of formal and informal settlements. In addition to BAI, we developed a new built-up index, which is based on the coastal band, i.e., coastal blue index and assessed the separability of the two settlement types.

Absence or irregular roads have been identified as an indicator of informal settlements (Kohli et al., 2012). We used the road extraction index (REI) (Shahi et al., 2015) to investigate the separation of informal and formal settlements. The REI highlights asphalt surfaces from other land-use features. The road surfaces or paths in informal settlements in the study area are not paved.

In addition to the commonly used spectral indicators, we investigated the effectiveness of the iron index in separating informal from formal settlements. The roofs of building structures in informal settlements in the study area contain various materials, such as corrugated iron, woods, stones, and/or cloth sheets. The formal settlements contain roofs with iron oxide roof tiles or iron sheets and are, therefore, expected to have higher values of the iron index.

Texture is one of the most important spatial characteristics used in identifying the object of regions of interest (Haralick et al., 1973). Gray level co-occurrence matrix (GLCM) is a second-order statistic measure and one of the commonly used methods in urban mapping. GLCM measures the spatial relations of neighboring pixels and is one of the investigated texture analysis methods in informal settlements detection. The GLCM textural measures have been used towards slum or informal settlements detection with varying accuracy from one area to the other due to the morphology of informal settlements (Ansari & Buddhiraju, 2019; Fallatah et al., 2019a; Kuffer et al.,2016; Prabhu & Parvathavarthini, 2022). We have assessed the performance of GLCM mean, variance, contrast and homogeneity textural features in separating informal from formal settlements.

Lastly, we assessed the performance of first order statistics (FOS) measurement, mean, variance and skewness in distinguishing informal from formal settlements. These measurements calculate statistics based on the individual pixels and do not take into account the relationship to the neighboring pixels (Aggarwal & Agrawal, 2012; Kumar & Gupta, 2012). The informal settlements are illegal in nature, leading to an organic pattern of dwelling pattern and irregular or lack of road networks and other land use activities. Consequently, the texture measures between formal and informal settlements vary (Haralick et al., 1973). We used feature space optimization (FSO) to determine the separability of 72 and 78 informal and formal sample objects against all the twelve image-based indicators listed in Table 3-1. The samples were selected using visual image interpretation and contained settlements with varying dwelling structure density and vegetation cover. Image tiles created during the segmentation process, which contained formal or informal settlements, were selected as samples. The FSO is an eCognition software tool that evaluates the Euclidean distance in feature space between sample objects to determine the best separation distance (Ho & Rao, 2016).

3.5.2 Detection of informal settlements

The first step in the detection of informal settlements was to separate built-up from non-built-up areas. We used GLCM dissimilarity textural analysis to classify built-up from non-built-up objects. The GLCM dissimilarity textural analysis separates built-up from non-built-up areas with higher accuracy than other GLCM textural features and spectral indices (Zhang et al., 2014).

The classification of informal from formal settlements was applied on the built-up class using indicators and image-based indicators that produced high informal settlement class separation. The ruleset to detect informal settlement was developed using FOS mean, BAI and coastal blue index and thresholding technique. The thresholds were determined by visually inspecting informal and formal objects. Table lists the values of the image-based indicators used in the detection of informal settlements.

Table 3-2: Image features and values used to detect formal and informal settlements

Image feature	**Class** **Threshold**
GLCM Dissimilarity	Non built-up < 0.8 Built-up > 0.8
FOS mean	Formal settlements > 550 Informal settlements <550
BAI	Formal settlements > 550 Informal settlements < 550
Coastal Blue	Formal settlement >500 Informal settlements >500

3.5.3 Accuracy assessment

Accuracy assessment was done by comparing informal and formal sample image objects mapped in section 5.3.1 and the classified informal settlements objects using a confusion matrix (Definiens, 2007).

3.6 Results

3.6.1 Image segmentation

The chessboard segmentation method was able to create formal settlements, informal settlements and non-built-up objects. Open spaces, such as sports fields and parks within the built-up area, were separated from other land-use features, Figure 3-5.

There were, however, tiles that contained parts of open areas and a small portion of settlements. In addition, there were few areas where both formal and informal settlements formed part of one tile. This was observed mostly in the edges of informal and formal settlements.

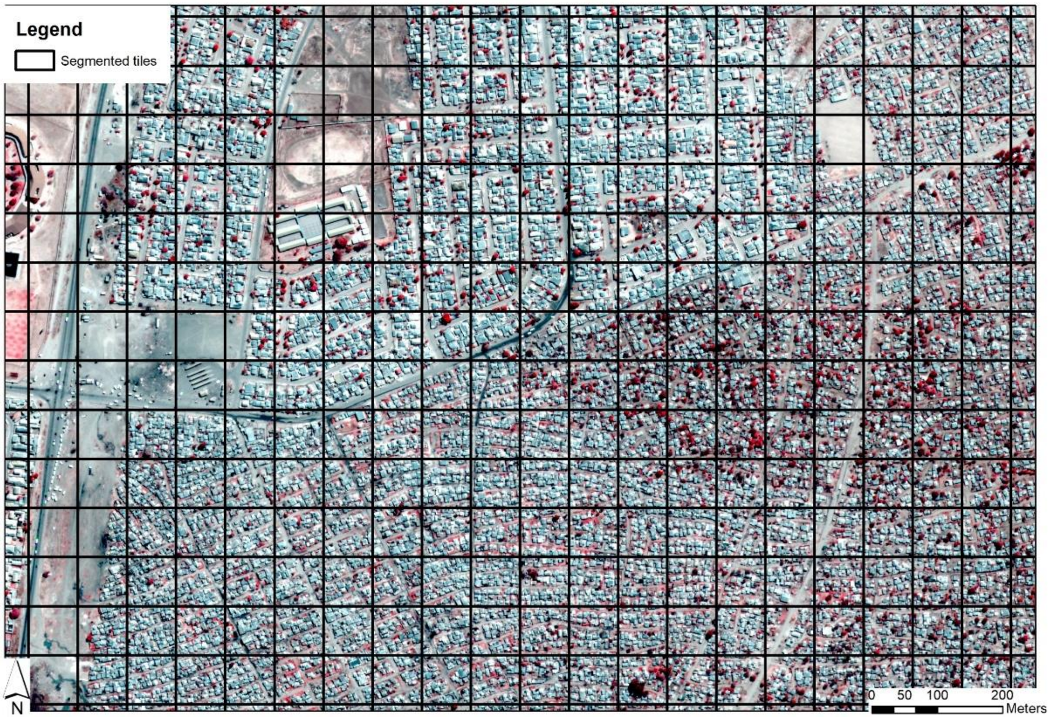


Figure 3-5: Chessboard segmentation results over WorldView 2 multispectral image

3.6.2 Performance of selected image features in separating informal and formal settlements

The FSO class separability results are shown in Table 3-3. The results show that the GLCM mean, variance, homogeneity and contrast, produced the lowest class separation distance of informal and formal settlements compared to spectral indices and FOS measurements. The GLCM variance, homogeneity and contrast had the best separating distance of the two classes of less than 0.02, with GLCM contrast having the least separation distance of 0.001. The results indicate that the selected GLCM textural measures are not effective in distinguishing informal from formal settlements in a densely populated area. This can be attributed to the varying densities of building structures and other land-use features in informal settlements resulting in varying co-occurrence values within the informal settlements class.

Table 3-3**.** Performance of selected image features in classifying informal from formal settlements

Image feature	**Separability**
NDVI	0.075
BAI	0.201
Iron Index	0.191
REI	0.036
Coastal Blue Band	0.219
GLCM Mean	0.100
GLCM Variance	0.019
GLCM Homogeneity	0.001
GLCM Contrast	0.011
FOS Mean	0.235
FOS Variance	0.019
FOS Skewness	0.027

The separation of informal and formal classes using NDVI and REI yielded the least separability distances of 0.075 and 0.036, respectively, compared to other spectral indices. The poor performance of NDVI can be attributed to the fact that the informal settlements in the study area vary in vegetation cover and density. Low vegetation cover was observed in high-density informal settlements, whereas some of the lower-density informal settlements had higher vegetation cover than some of the formal settlements. The lower separation distance of the two classes using REI can be attributed to similar spectral properties of road and building structures in the study area. In addition, unpaved roads can be observed in both formal and formal settlements adding the confusion between the two classes.

The coastal blue index and BAI resulted in a better separability between informal and formal settlements with the best separation distances of 0.219 and 0.201, respectively, compared to other spectral indices. Most of the informal settlement tiles have lower built-up index values compared to formal areas. The use of the coastal blue index slightly increased the separability of the two classes compared to BAI. The coastal blue index was able to separate some of the dense informal settlements from formal areas that have similar values when using BAI.

The iron index performed better than NDVI and REI, with the best separation distance of 0.191 between the two classes. The informal settlements have lower values of the iron index compared to formal areas. This is due to the diversity of roof material found in informal settlements, whereas the roofs in formal settlements contain a mixture of iron sheets or iron oxide tiles, resulting in higher iron index values. The iron index failed to detect high-density informal settlements and resulted in an increased confusion between low-density informal and formal areas.

The FOS mean produced the highest separability distance of 0.235 compared to all image-based indicators investigated, whereas FOS skewness and FOS variance performed slightly better than the GLCM variance, homogeneity and contrast. The FOS mean was effective in detecting low-density informal settlements with lower spectral values but failed to detect high-density informal settlements.

3.6.3 Informal and formal settlements classification results

This section presents the classification results of built-up and non-built-up classes, informal and formal settlements, and accuracy assessment results achieved on the classification of informal settlements using the top three image-based indicators, which, i.e., FOS mean, coastal blue index and BAI.

The GLCM dissimilarity was successful in classifying built-up and non-built-up areas. Some of the image tiles with more than 50% non-built-up were classified as non-built-up. These areas were found mostly on the edges of the settlements.

The use of the FOS, coastal blue index and BAI were successful in classifying informal from formal settlements, Figure 3-6. Most of the informal settlements in the study have lower values of the built-up index than formal settlements. This is due to a lower amount of impervious surface in informal settlements in the study area. Hence, they were detectable using BAI and the coastal blue index. Some of the lower-density informal settlements also have lower values of FOS mean compared to formal settlements.

The FOS mean and BAI are unable to separate high-density informal settlements from formal areas. These areas have a higher amount of impervious surface and high mean values compared to low-density informal settlements. The detection of high-density informal settlements was slightly improved by the coastal blue index though at the same time introducing commission errors in some of the high-density formal settlement's tiles. Some of the tiles representing formal settlements that are on the edges of settlements were also misclassified due to the contribution of spectral properties of open spaces, which are similar to some of the informal settlement tiles.

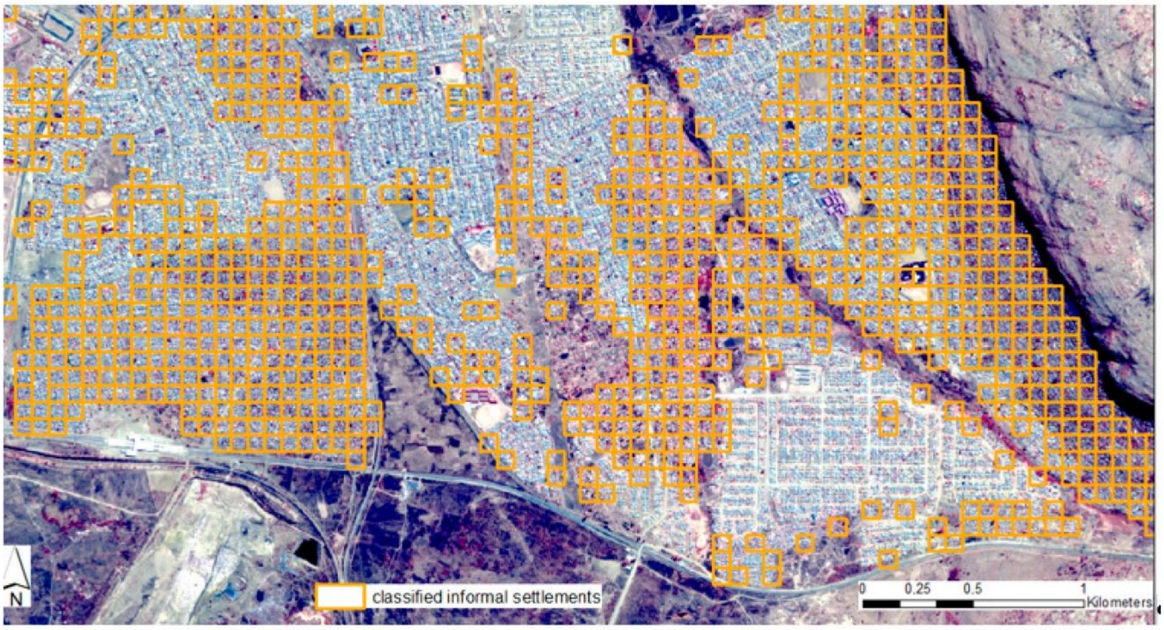


Figure 3-6: Detected informal settlement layer over Worldview 2 image.

Assessment top three image-based indicators used separately show that BAI produced the highest overall accuracy of 90%, followed by coastal blue index with 88%. The coastal blue index produced the highest producer accuracy of informal settlements of 94%, followed by BAI with 84%, while the FOS mean yielded producer accuracy of 80%. The use of FOS mean and BAI resulted in an overall accuracy of 90% and a producer accuracy of informal settlements of 87%. The use of BAI and coastal blue index in the ruleset produced an overall accuracy of 88% and producer accuracy of informal settlements of 95%. The inclusion of the coastal blue index with BAI and FOS in the ruleset increased the overall accuracy by 1% and the producer accuracy of informal settlements by 6%. In addition, the use of coastal blue index with FOS mean and BAI in the detection of informal settlements increased the kappa index Agreement of informal settlements from 75% to 87% but reduced the kappa index Agreement of formal settlements from 88% and 69%. This shows that the coastal blue index increased the amount of correctly classified informal settlement tiles but also increased the confusion between informal and formal settlements.

The areas detected by FOS mean overlap with the areas detected by BAI and coastal blue index, whereas the built-up indices can detect additional informal settlements with higher FSO mean values. This shows that the proposed methodology depends highly on the built-up indices. BAI may be applied on very high spatial resolution images that do not have a coastal blue band, whereas the coastal blue index can be applied in images with the coastal blue band.

3.7 Conclusions

Our study showed the importance of studying the characteristics of informal settlements in different geographic areas to develop methodologies to automatically detect informal settlements. In this study, we investigated the performance of twelve informal settlement indicators in classifying informal from formal settlements. Using the FSO class separation assessment tool, only three out of twelve indicators had the best separation distance of informal and formal settlements of more than 0.2. These indicators are the FOS mean and built-up indices, i.e., BAI and coastal blue index. The study successfully identified and demonstrated a built-up area as an informal settlement indicator and a built-up index derived using the coastal band. The study also identified iron cover as an informal settlement indicator that can improve the detection of informal settlements. The study showed that the GLCM measurements performed poorly in distinguishing informal and formal settlements in the study area. The FOS variance and skewness were not successful in distinguishing between informal and formal settlements. The study also showed that vegetation cover was not effective in detecting informal settlements. This contradicts many studies that suggested that informal settlements have lower vegetation cover than formal areas. Asphalt cover derived using REI was also not effective in detecting informal settlements in the study area.

The study results contributed additional informal settlement indicators and image-based indicators that can be tested in certain areas and contribute to developing tools to detect informal settlements. Even though higher accurate results were achieved in the study, the proposed methodology needs to be tested in other areas with informal settlements of similar characteristics. In addition, there is a need to performs a thorough assessment of the twelve indicators using class separability tools with higher accuracy, such as Jeffries Matusita distance, to assess the limitation and opportunities of the indicators investigated. The performance of these indicators can also be tested using the multiresolution segmentation method. Lastly, there is a need to investigate the informal settlement indicators that distinguish high-density informal settlements from high-density formal settlements with backyard shacks using very high spatial resolution imagery acquired by drone or aerial photography.

Chapter 4 TOWARDS UNDERSTANDING INFORMAL SETTLEMENTS GROWTH PATTERNS: CONTRIBUTION TO SDG REPORTING AND SPATIAL PLANNING

This chapter is based on the following manuscript:

Mudau N., Mhangara P., (2022), Towards understanding informal settlement growth patterns: Contribution to SDG reporting and spatial planning; Remote Sensing Applications: Society and Environment; https://doi.org/10.1016/j.rsase.2022.100801

Abstract

The study proposes a ratio of informal settlement land consumption rate to impervious surface growth rate to understand informal settlement growth patterns. To compute this ratio, information on the informal settlement extent and impervious surface within informal settlements over at least two time periods is required. This ratio can be used to understand the density of building structures within informal settlements. We investigated this ratio in a densely populated township in Tshwane Metropolitan Municipality over a five-year interval between 2005 and 2020. Informal settlement extent was generated using the OBIA technique, which uses asymmetry of image objects to classify informal settlements. The impervious surface was mapped using a ruleset that uses soil adjusted vegetation index (SAVI), border index and reflectance of the blue band. The results show that the ratio of land consumption rate of informal settlement to the impervious surface growth rate was 0.70 during the 2005-2010 interval, decreased substantially to -11.25 during the 2010-2015 interval and increased to 0.85 during the 2015-2020 interval. This shows the impervious expansion rate of informal settlements was higher than the densification rate between 2005 and 2010, similarly between 2015 and 2020. However, the expansion rate was significantly slower that the densification rate between 2010 and 2015. The results can be used to support the management and planning of informal settlement upgrade projects and to monitor progress made toward achieving SDGs.

Keywords: SDGs, informal settlement, growth patterns, impervious surface

4.1 Introduction

Despite significant progress made toward upgrading informal settlements in the past few decades, the number of people living in informal settlements continues to rise (United Nations, 2015). The development of informal settlements results in unplanned and unmanaged conversion of undeveloped land into settlements (Nassa and Elsayed, 2018), contributing to the unmanaged and unplanned increase in land consumption in urban areas which threatens sustainable development. According to United Nations, sustainable development is achieved when the development meets the needs of the present without compromising the ability of the future generation to generate their own. The New Urban Agenda (NUA) adopted in 2016 recognizes sustainable urban development as a key to achieving sustainable development (United Nations, 2016b). In addition, NUA promotes the upgrading of slums or informal settlements while containing urban sprawl (United Nations, 2016b). This is well-aligned with the United Nations, Sustainable Development Goal (SDG) 11, which is aimed at developing inclusive, safe, resilient, and sustainable cities and settlements (United Nations, 2016a). Timely and high-quality data is required to accelerate the implementation of these development agendas (United Nations, 2021). Aggregation of some of the SDG indicators by social powers and settlement types gives insights to redress inequalities (Kruk et al., 2018).

To track progress made towards achieving sustainable urbanization, countries or cities are required to report on several indicators including SDG indicators 11.3.1 and 11.1.1. Indicator 11.3.1 measures the ratio of land consumption rate to the population growth rate (ratio of LCRPGR) whereas indicator 11.1.1 measures the proportion of people living in informal settlements (UN-Habitat, 2018b). These indicators do not assess the spatial extent or land consumption of informal settlements, creating a gap in the information required to develop policies to better manage human settlement developments and the land use efficiency of cities. In addition, these indicators use population information which limits the ability for temporal analysis.

Remote sensing technology provides data to map and monitor urban land use activities. Several studies have used satellite images to assess the urban growth of cities in developing countries (Al-Bilbisi, 2019; Belal & Moghanm, 2011; Boori et al., 2015; Hegazy & Kaloop, 2015; Mudau et al., 2014). There has been a renewed interest in the assessment of urban growth or land consumption influenced by the need for cities or countries to report progress made towards achieving SDG 11 (Nicolau et al., 2018; Mudau et al., 2020; Sharma et al., 2012; Rienow et al., 2022; Wang et al., 2020).Advances in data extraction from satellite imagery have led to the development of global data sets such as Global Human Settlement Layer (GHSL) (Pesaresi et al., 2016) and World Settlement Footprint (WSF), (Marconcini and Gemeda, 2020) which map and assess built-up growth patterns over the past few decades. These data sets provide information to assess progress made in achieving sustainable urbanization. Even though there has been an increase in the number of studies focusing on urban growth or land consumption, limited studies focused on assessing informal settlement growth (Abebe et al., 2019; Dubovyk et al., 2010; Maiya & Babu, 2018). This may be attributed to the lack of automated tools to detect informal settlements.

Land consumption rate is measured by assessing the conversion of one urban land use to another within an area of interest during a specified time interval (UN-Habitat, 2018b). Information on informal settlement growth is usually captured using data collected during surveys such as censuses and household surveys. However, the information on informal settlements is usually underestimated due to the fluidity of informal settlements (Socio-Economic Rights Institute of South Africa, 2018; UN-Habitat, 2004). The use of available gridded population information such as Gridded Population of the World (GPW) (CIESIN, 2018) or Global Human Settlement-Population (GHS-Pop) (European Commission Joint Research Centre, 2018) has proven to underestimate the population in informal settlements (Thomson et al., 2021).

To address the gap in information relating to informal settlements, several studies have attempted to develop methodologies to detect informal settlements from other land use classes using high to very high spatial resolution images. Many studies investigated the use of object-based image analysis (OBIA) techniques which use textural or morphological features to classify informal settlements (Hofmann et al. 2001; Hofmann et al. 2008; Jain, 2007; Kohli et al., 2012). The results achieved using these techniques vary from one geographic area, in some cases within a city due to varying physical characteristics of informal settlements. Recent studies on informal settlement detection have tested deep machine learning techniques such as convolutional neural network (CNN) and very high spatial resolution imagery to detect informal settlements (Ajayakumar et al., 2021; Maiya & Babu, 2018). These techniques have the potential of improving the accuracy of informal settlement detection compared to other machine learning techniques such as Support Vector Machine (Gram-Hansen et al., 2019; Maiya & Babu, 2018). The use of polymetric SAR data has the potential of detecting informal settlements with acceptable accuracy (Wurm et al., 2017). The use of the Geographic Informal System (GIS) and crowdsourced data to assess informal settlements on a global scale is gaining some momentum recently (Samper et al., 2020; Soman et al., 2020). Even though a lot of progress has been made toward detecting informal settlements, a fully automated methodology for informal settlement detection from satellite imagery still does not exist.

To address the knowledge gap in the land consumption of informal settlements, this study develops a ratio of informal settlement land consumption rate to the imperviousness growth rate. This ratio measures the rate of expansion and densification of informal settlements which contributes critical information required for the planning of informal settlements upgrade projects. The study is aimed at assessing this indicator in Mamelodi, Pretoria, South Africa, over the 2005-2010, 2010-2015 and 2015-2020 intervals using very high spatial resolution satellite imagery.

4.2 Study area

The study area is in Mamelodi township, located in the City of Tshwane Metropolitan Municipality, South Africa (Figure 4-1). The township is located about 23 km from the city and is one of the ten biggest townships in South Africa with a population of almost 350 000 in 2011 (Statistics South Africa, 2011). According to Statistics South Africa, about 18.8% of households in Mamelodi township were informal (excluding backyard shacks) in 2011 (Statistics South Africa, 2016). Mamelodi township was established in 1953 in Vlakfontein farm as a labor reservoir of Pretoria (Hund & Kotu-Rammopo, 1983). The first informal settlement was developed in the eastern part of the township where informal settlements continue to develop. The study area covered the eastern part of Mamelodi township.

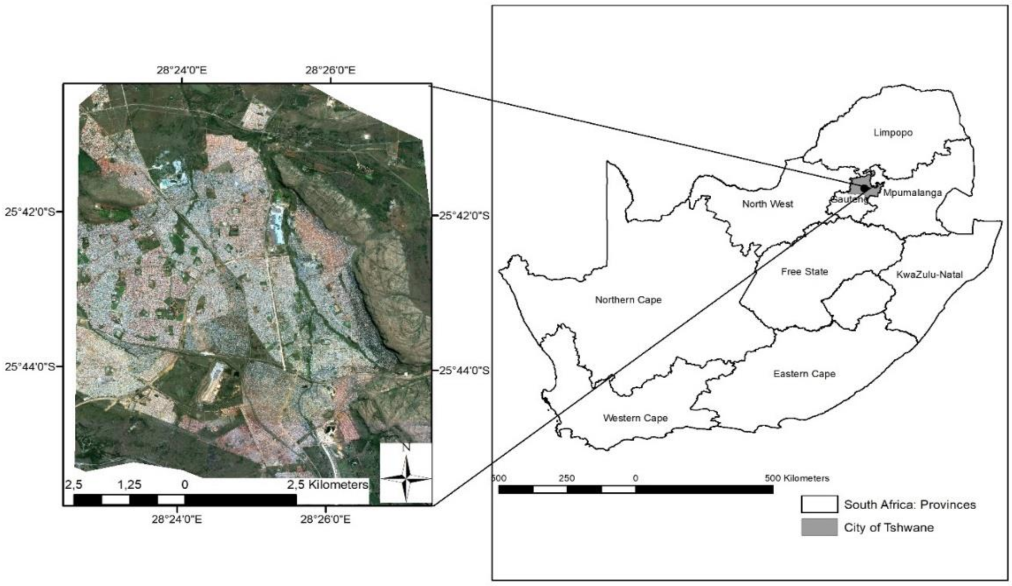


Figure 4-1: Location of the study area

4.3 Data

We used Quickbird 2 and WorldView 2 images captured on 27 May 2005, 16 June 2010, 29 July 2015 and 06 May 2020. Table 4-1 describes the bands and spatial resolution of Quickbird 2 and WorldView 2. The images were sourced from the South African National Space Agency. The images were received georeferenced to a geographic coordinate system, WGS 84 Datum and WGS 84 Spheroid.

Table 4-1: Band properties of Quickbird 2 and WorldView 2 sensors

Band name	**Bandwidth (nm)**	**Spatial resolution(m)**
Quickbird 2		
Blue	450- 520	2.4
Green	520-600	2.4
Red	630-690	2.4
Near Infrared	760-900	2.4
Panchromatic	450-900	0.61
WorldView 2		
Blue	450-510	1.8
Green	510-580	1.8
Red	630-690	1.8
Near Infrared	770-895	1.8
Panchromatic	450-800	0.46

4.4 Methodology

4.4.1 Data preparation

The first step conducted before the image classification process was the pansharpening of the multispectral images. The pansharpening process is a pixel-level fusion technique that enhances the spatial resolution of a multispectral image using a high spatial resolution panchromatic image. In this study, we used the Gram-Schmidt image fusion technique. The Gram-Schmidt technique has been widely used for pansharpening WorldView images as it improves the spatial resolution and preserves the spectral information of the input images compared to other image fusion techniques (Panigrahi et al., 2021; Snehmani et al., 2017; Yilmaz et al., 2020). The pansharpening process was done using ArcMap 10.3 software, ESRI.

4.4.2 Investigation of segmentation parameters for informal and formal settlements

The classification of informal from formal settlements was done to derive the informal settlement extent for the four years. The classification was done using Trimble eCognition software. The OBIA classification method was used to classify informal from formal settlements. The most important step followed in the OBIA classification technique is image segmentation. Image segmentation partitions an image into meaningful image objects required for classification or image interpretation (Baatz, 2000). To determine the best segmentation parameters to generate formal and informal settlement image objects, we evaluated the use of the multiresolution segmentation method with scale parameters of 100, 150 and 200, shape values of 0.5 and 0.7 and compactness values of 0.5 and 0.7. The quality assessment of segmented image objects was done using area fit index (Lucieer, 2004). Twenty reference polygons were created and assessed against segmented image objects.

4.4.3 Classification of formal and informal settlements

The classification of informal from formal settlements was done to derive the informal settlement extent for the four years. The classification was done using Trimble eCognition software. The object-based image analysis classification method was used to classify informal from formal settlements. The most important step followed in the OBIA classification technique is image segmentation. Image segmentation partitions an image into meaningful image objects required for classification or image interpretation (Baatz, 2000). To determine the best segmentation parameters to generate formal and informal settlement image objects, we evaluated the use of the multiresolution segmentation method with scale parameters of 100, 150 and 200, shape values of 0.5 and 0.7 and compactness values of 0.5 and 0.7. The quality assessment of segmented image objects was done using Area Fit Index (Lucieer, 2004). Twenty reference polygons were created and assessed against segmented image objects.

4.4.4 Classification of impervious surface in informal settlements

We used the area covered by building structures to measure impervious surfaces in informal settlements. The main anthropogenic features in the informal settlements in the study area are building structures. The image objects created using multiresolution segmentation technique with a scale parameter of 15, shape and compactness values of 0.5 created in 4.2, were used to classify buildings and other land-use features. A ruleset that uses the soil-adjusted vegetation index (SAVI), border index and radiometric values of the blue band was used during the classification. The SAVI measures live green vegetation with a reduced impact of soil properties (Xue & Su, 2017). Impervious surfaces are expected to have lower values of SAVI than other land use features in informal settlements. The shadows and darker land use features also exhibit lower SAVI values causing confusion between building structures and other land use features. The shadows and other dark objects reflect lower in the blue band compared to the roofs of building structures. The border index was used to remove the confusion between some open spaces and building structures. Building structures have a lower border index compared to big open spaces.

4.4.5 The ratio of IS_LCRIGR

The computation of the ratio of LCRPGR, SDG indicator 1.3.1 requires information on urban extent and population. Population information of informal settlements is usually non-existent or outdated, limiting the information that can be generated on the population density in informal settlements. We, therefore, propose a ratio to estimate the density of dwelling structures in informal settlements using satellite imagery. This ratio quantifies the rate at which the informal settlement expansion is taking place against the rate of impervious surface development in an informal settlement. We assessed IS_LCRIGR for 2005-2010, 2010-2015 and 2015-2020 intervals. To calculate the Ratio of IS_LCRIGR, we propose the following formula:

$$IS\_LCRIGR = LCR / IGR \tag{4- 1}$$

Where LCR is the land consumption rate of informal settlement and is calculated as follows:

$$IS\_LCR= \ln (IS_{t+1}/ IS_t)/y \tag{4- 2}$$

Where IS_t is the extent of the informal settlement at the initial period, IS_{t+n} is the extent of informal settlements at the current year and y is the number of years between two intervals. The IGR is the imperviousness growth rate and is calculated as follows:

$$IGR=\ln (Im_{t+1} / Im_t)/y \tag{4- 3}$$

Where Im_t is the impervious surface at the initial year, Imt_{+1} is the impervious surface at the current year and y is the number of years between two intervals.

The higher value of the ratio of IS_LCRIGR means that the expansion growth rate of informal settlement is higher than the impervious surface growth rate whereas the lower ratio value means that the imperviousness growth rate is higher than the informal settlement land consumption rate. The latter means that higher structure densification was observed during the period of assessment. The analysis of the ratio of IS_LCRIGR can help identify areas with higher informal expansion rates compared to settlements that are densifying in terms of building structures.

4.4.6 Accuracy assessment

The accuracy assessment of informal settlements and the impervious surface was done by assessing manually mapped informal settlements and dwelling structures with the classification results. We assessed the overall, producer and user accuracies using Trimble eCognition software (Definiens, 2007).

4.5 Results

4.5.1 Investigation of segmentation parameters for informal and formal settlements

The multiresolution segmentation with scale parameter of 100, 150 or 200, shape values of 0.5 or 0.7 and compactness values of 0.5 or 0.7 resulted in over-segmentation of informal settlement image objects, leading to negative area fit index values, Figure 4-2. The use of scale parameters of 100 and 150, shape and compactness values of 0.5 resulted in area fit index values of -0.21 and -0.23 respectively whereas the use of scale parameter of 200 resulted in an area fit index of -0.44. We, therefore, used a multiresolution segmentation algorithm with the scale parameter of 100 and shape and compactness values of 0.5 to segment the image into land use objects.

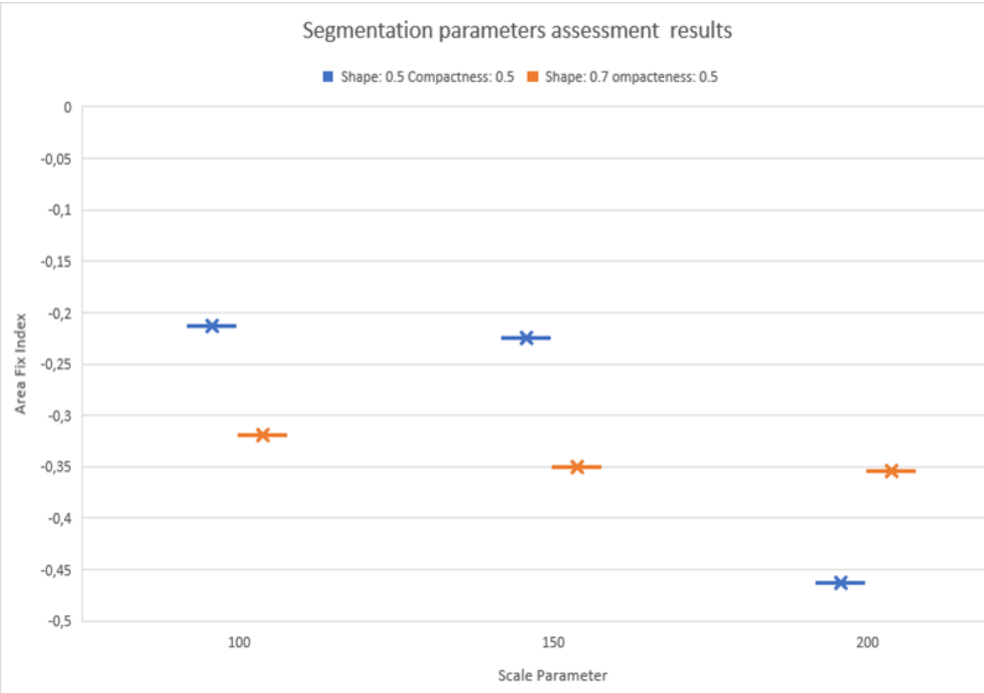


Figure 4-2: Segmentation parameters assessment results

Over-segmentation of informal settlements in the study area may be due to the lower density of some of the patches of informal settlements, Figure 4-3, whereas under-segmentation was also observed in a few cases where informal settlement objects were merged with formal settlements and larger open spaces. In other cases, the informal settlement objects were merged with formal areas or large open spaces.

Figure 4-3: Segmentation results over 2005 WorldView 2 image

4.5.2 Segmentation of building and other land use structures

The multiresolution segmentation process using scale parameter of 15, shape value of 0.5 and compactness value of 0.5, was able to create land use objects which represent buildings and other land-use features. The image objects created were sufficient to generate shape texture to classify informal from formal settlements and to classify impervious surfaces within informal settlements, Figure 4-4. Most of the building structures in informal areas have gable roofs, resulting in over-segmentation of the building structures.

Figure 4-4: Segmentation results: buildings and other land-use image objects

The building structure image objects in informal settlements mostly represented individual structures. There were, however, areas in both formal and informal settlements where more than one dwelling structure formed part of one image object. There were also areas where building structure objects contained other land use features such as road objects. That was observed mainly in formal areas.

4.5.3 Investigation of features to classify formal and informal settlements

The results of the class divergence assessment show that the shape texture based on asymmetry of land use sub-objects created in section 4.5.2 was able to distinguish formal and informal settlements better than shape texture based on direction, density and area of sub-objects as confirmed by lower overlapping area of the two classes. This may be attributed to the fact that the formal areas contain regular road network whereas informal settlements have unpaved and irregular road network. The shape texture based on area, direction and density of sub-objects resulted in higher divergence of the two classes of 80 - 100%, Figure 4-5.

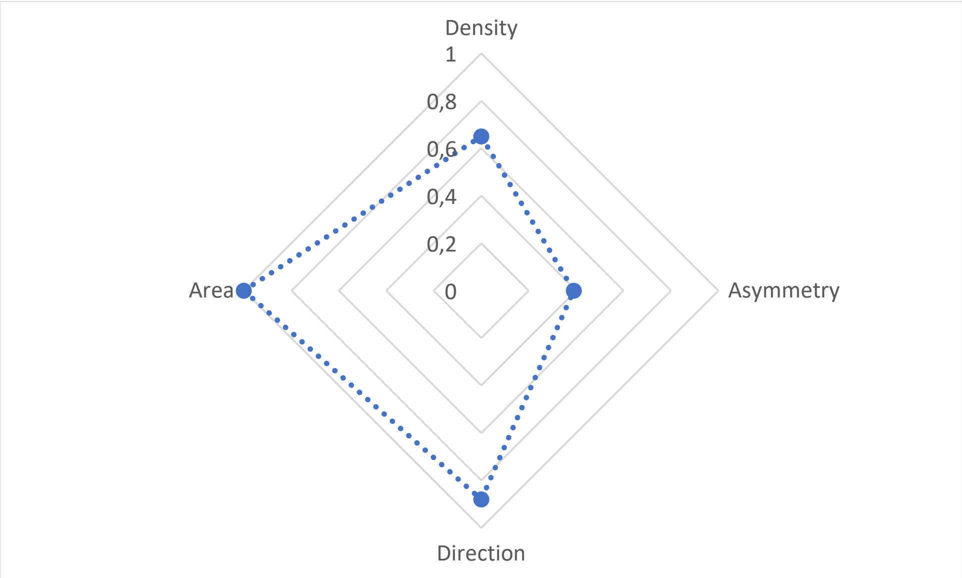


Figure 4-5 : Divergence assessment results

The divergence values resulting from the use of area texture may be influenced by over-segmentation of formal building structures which resulted in formal structures having two or more image objects. The same effect may be attributing to the poor performance of direction texture. The poor performance of shape texture of density may be attributed to the fact that the formal settlements contain a high density of building structures due to smaller sizes of yards in the study area. Some of the formal areas also contain backyard shacks which may lead to similar values of structure density and direction in both formal and informal settlements. We used shape texture based on the asymmetry of land-use image objects to classify formal and informal settlements.

4.5.4 Classification of informal settlements

The shape texture based on the asymmetry of land use objects was successful in separating informal and formal settlements, Figure 4-6 and Figure 4-7. The success of shape texture based on asymmetry in separating the formal and informal settlements is influenced by the lack of elongated structures such as roads or buildings with long roofs in informal settlements. Informal settlements in the study area have lower values of shape texture based on asymmetry of land use objects compared to formal areas. Formal settlements in the study area have regular road networks which resulted in the creation of longer linear objects during segmentation. There were, however, few areas where the formal areas were misclassified as informal settlements. This can be attributed to the fact that some formal areas contain smaller building structures, mostly shacks, which are found in informal settlements. Errors of omission were observed in areas where some of the informal settlement objects contained bigger open spaces or road segments.

Figure 4-6: Informal settlement classification results for 2005, 2010, 2015 and 2020 over a 2020 image

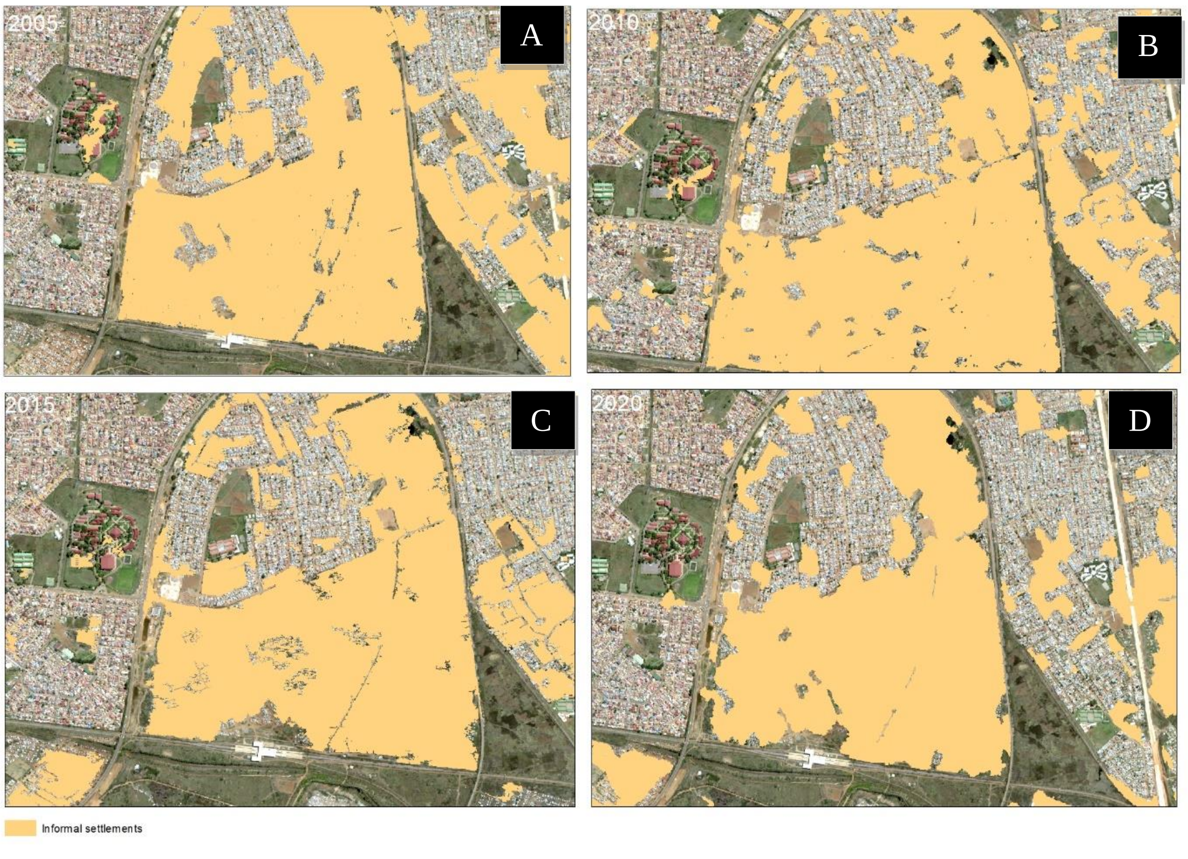


Figure 4-7: Zoom-in pictures of the detected informal settlement for 2005 (A), 2010 (B), 2015 (C) and 2020 (D) over a 2020 image

4.5.5 Informal settlement growth rate

The area covered by informal settlements more than doubled during the 15 years of assessment, Table 4-2. The analysis of the results shows that the informal settlements were mainly found in the northern and the eastern part of the study area in 2005 and have been continuing to grow mostly in the eastern and the southern parts of the study area during the period of assessment. The results show that there was an increase of 1.07 km^2 in the extent of informal settlements between 2005 and 2010.

Table 4-2: Informal settlement extent and impervious surface classification result in 2005, 2010,2015 and 2020.

Year	Informal settlement extent (km^2)	Impervious surface (km^2)
2005	6.47	1.07
2010	7.54	2.57
2015	7.98	2.53
2020	15.16	4.22

The expansion of informal settlements was observed in the eastern part of the study area between 2005 and 2010. The informal settlement extent remained nearly the same between 2010 and 2015, with an increase of only 0.44 km^2. The 2015-2020 period saw the highest increase in the extent of 7.18 km^2, almost double the extent of informal settlements in 2015. The growth between 2015 and 2020 was mainly in the south-eastern part of the study area.

Informal settlement growth rate decreased from 0.21 to 0.09 over the 2005-2010 and 2010-2015 intervals. The 2015-2020 period saw a rise in the informal settlement growth rate of 1.44 from 0.9 experienced during the 2010-2015 period, Table 4-3.

Table 4-3: Informal settlement extent growth rates of 2005-2010, 2010-2015 and 2015-2022 time intervals

Period	Informal settlement growth rate
2005-2010	0.21
2010-2015	0.09
2015-2020	1.44

4.5.6 Impervious surface growth rates

The amount of impervious surface within informal settlements more than doubled in size between 2005 and 2010, from 1.07 km^2 to 2.57 km^2, Table 4-4. The impervious surface almost doubled between 2015 and 2020. The growth may be attributed to the high rate of informal settlement growth during the same period. The proportion of impervious surfaces within informal settlements increased by more than 100% between 2005 and 2010, from 16.54% to 34.08% and slightly decreased from 31.70% in 2015 and 27.84% in 2020, Table 4-4. The decline in impervious surface could be attributed to moving of people from flood risk areas to other areas.

Table 4-4: Imperviousness growth rate of 2005-2010, 2010-2015 and 2015-2020 time intervals

Period	Imperviousness growth rate
2005-2010	0.175
2010-2015	-0.003
2015-2020	0.128

The imperviousness growth rate slightly decreased during the period of assessment from 0.175 to 0.128, Figure 4-8. This can imply that the informal settlements developed between 2015 and 2020 had a slightly lower density of impervious surfaces compared to those developed between 2005 and 2010.

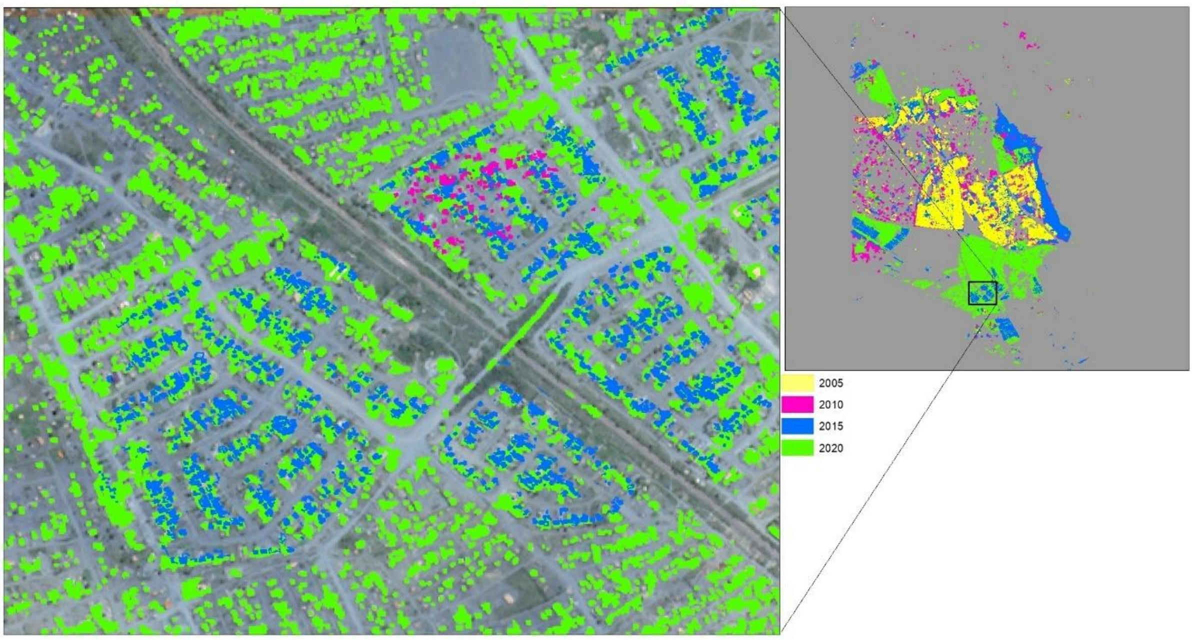


Figure 4-8: Impervious surface for 2005, 2010, 2015 and 2020

The results show that informal settlements developed between 2010 and 2020 contained a lower density of impervious surface compared to those that existed in 2005.

4.5.7 The ratio of Informal Settlement Land Consumption Rate to Imperviousness Growth Rate (IS_LCRIGR)

The Ratio of IS_LCRIGR in the study area decreased significantly from 0.70 to -11.25 over the 2005-2010 to 2010-2015 period Table 4-5 . The 2010-2015 period saw the lowest ratio of informal settlement growth rate and imperviousness growth rate. The negative value of the ratio between 2010 and 2015 is influenced by the decline in impervious surface area in the study area. Overall, the results show that there was a slight increase in the expansion of informal settlement with the lower density of impervious surface over the periods of assessment.

Table 4-5: Ratio of Informal Settlement land Consumption Rate to Imperviousness Growth Rate results

Period	**Ratio of IS_LCRIGR**
2005-2010	0.70
2010-2015	-11.25
2015-2020	0.85

The lower ratio of IS_LCRIGR between 2005 and 2010 means that the imperviousness growth rate was higher than the informal extent growth rate during the period. This may mean that the informal settlements were densifying at a higher rate than the expansion of informal settlements. The 2015-2020 period saw the highest value of the ratio of IS_LCRPGR of more than one compared to the other two-time intervals. This means that the rate of expansion during the period assessed was higher than the rate of development of impervious surfaces. The results can imply that informal settlements developed during this period were not densifying at a faster rate compared to informal settlement expansion and to those developed between 2005 and 2010. Overall, the results show that there was a significant increase in the expansion of informal settlements with a lower density of impervious surfaces over the period under review.

4.5.8 Quality assurance

Table 4-6 shows accuracy assessment results achieved in the classification of informal settlements and impervious surfaces within the informal settlements. The overall accuracy of 84.8%-96.4% was achieved in the classification of informal from formal settlements. The success of asymmetry in the detection of informal from formal settlements can be attributed to the lack of road infrastructure in most informal settlements within the study area. Another factor that may have influenced the effectiveness of asymmetry is that most of the roofs of the dwelling structures within informal settlements contain various materials such as stones, wood and clothes which results in a non-linear roof outline, hence, lower asymmetry values in informal settlements. The lower user accuracy in 2005 may be attributed to the fact that some of the formal settlements with regular road networks had shacks as dwelling structures that produced fewer elongated shapes resulting in lower asymmetry values.

An overall accuracy of between 80.1% and 96.4% was achieved during the classification of impervious surfaces in informal settlements. The lower producer accuracies of the impervious surface may be influenced by the diversity of materials found in the roofs of some dwelling structures in informal settlements which resulted in higher SAVI values compared to other dwelling structures.

Table 4-6: Informal settlement and buildings accuracy assessment

Year	(%) Producer Accuracy	(%) User Accuracy	(%) Overall accuracy
2005			
Informal settlements	94.7	75.0	84.8
Impervious surface	85.0	95.3	86.5
2010			
Informal settlements	90.7	95.4	90.6
Impervious surface	96.0	96.8	96.4
2015			
Informal settlements	98.8	87.5	92.3
Impervious surface	75.3	96.2	80.5
2020			
Informal settlements	98.0	96.2	96.4

Impervious surface	88.1	96.6	89.1

4.6 Discussions

The success of sustainable development goals is highly dependent on the availability of accurate and consistent data used during the planning and monitoring of development solutions. The advent of very high spatial resolution sensors provides the base data required to understand informal settlement growth patterns. The computation of the proposed development indicator, the ratio of (IS_LCRIGR), requires information on the extent of informal settlements.

The study used shape texture based on sub-objects to distinguish informal from formal settlements. Several studies have investigated the use of spectral-based textures such as grey level co-occurrence matrix (GLCM) (Haralick et al., 1973), to detect informal settlements (Fallatah et al., 2019b; Girija & Nikhila, 2018; Kuffer et al.,2016; Mudau & Mhangara, 2021b). The performance of the pixel-based textural analysis in informal settlements depends on the land use and roof material of informal settlement structures. The study demonstrated that the use of object-based asymmetry has the potential of detecting informal settlements from formal settlements using very high spatial resolution satellite images as demonstrated by higher producer accuracy overall the years investigated, providing essential information required to compute the proposed ratio.

The study shows that the extent of the informal settlements in the study area more than doubled between 2005 and 2020 whereas imperviousness in informal settlements almost quadrupled during the same period. Even though there has been an increase in the number of government-subsidized houses, the number of households living in informal settlements continues to rise (Statistics South Africa, 2020). Unfortunately, the GHS information is not published at a settlement scale to allow comparison between household surveys and the results achieved in this study.

The assessment of the ratio of IS_LCRIGR shows that the growth rate of informal settlement expansion was slightly lower than the growth rate of imperviousness in informal settlements. However, the higher increase of the IS_LCRIGR between 2015 and 2020 indicates that the area is experiencing increased informal settlements expansion with a lower density of imperviousness. Since this analysis only focused on informal settlements, the results suggest that the informal settlements developed during the period of assessment may be suitable for insitu upgrade or temporal services depending on the environmental conditions. This can also mean that the informal settlements have a lower risk of being affected by shack fire compared to informal settlements with a higher density of shacks.

Sustainable Development Goal 11 suggests that formal densification is a sign of sustainability of a city while informal settlements with a lower density of dwelling structures may be preferred to ensure safety and provision of services. Health pandemics such as Coronavirus disease 19 require reasonable spaces between structures in informal settlements. The area assessed forms part of the City of Tshwane, one of the cities that are experiencing higher urban expansion rates than population growth rates (Mudau, et al., 2020). Even though the study did not assess all the informal settlements in the city, the results show that higher values of LCRPGR may be desirable in certain settlement types. Hence, a decision that can be made based on the ratio of LCRPGR of a city may have a negative effect on other settlement types. Even though the proposed indicator does not consider the population growth rates, it provides additional information on the spatial distribution of building strictures in informal settlements and the extent of informal settlements that can be used to support decision-making. The derived information can also complement the reporting of SDG 11.1.1 which does not consider the spatial extent of informal settlements.

Cities are experiencing urban extent and population growth due to several social, environmental and political factors. Previous studies have shown that land use efficiency and the ratio of LCRPGR differ from one city to another even when assessing cities within the same population category (Mudau, et al., 2020) (Laituri, et al., 2021). The information provided in these studies provides useful information on the relationship between urban expansion and population, however, more information on the type of development, e.g. informal, formal or rural needs to be assessed to better understand urbanization and to provide local authorities with the information required during the implementation of sustainable development solutions. Since population information in informal settlements is usually underestimated, the proposed indicator can be a sub-indicator of SDG indicators 11.3.1 and 11.1.1 which can be generated in the absence of population information, providing valuable information to support SDG reporting and management of informal settlements.

4.7 Conclusions

The study investigated and proposed a new land use efficiency indicator that uses very high spatial resolution imagery to generate the information required to understand informal settlement growth patterns. Understanding informal settlement growth patterns in terms of the extent and imperviousness of informal settlements can help in the management of informal settlements and planning of informal settlement upgrade projects. The proposed indicator can be used as a sub-indicator of SDG indicator 11.3.1 to generate more information about land use consumption and patterns in the cities. The ratio of informal settlement land consumption rate to imperviousness growth rate can also be used to support tracking progress made towards achieving SDG target 11.1. The proposed ratio does not require the use of demographic data and therefore could be computed regularly to support decision-making and monitoring of progress made towards the upgrading of informal settlements.

Chapter 5 UNDERSTANDING SPATIAL PATTERNS OF BACKYARD SHACKS USING LANDSCAPE METRICS

This chapter is based on the following manuscript:

Mudau N., Mhangara P., (2023), Understanding spatial patterns of backyard shacks using landscape metrics using unmanned aerial vehicle image products; Drones; **https://doi.org/10.3390/drones709**

Abstract
Urban informality in developing economies like South Africa takes two forms: freestanding shacks are built in informal settlements, and backyard shacks are built in the yard of a formal house. The latter is evident in established townships around South African cities. In contrast to freestanding shacks, the number of backyard shacks has increased significantly in recent years. The study assessed the spatial patterns of backyard shacks in a formal settlement containing low-cost government houses (LCHs) using Unmanned Aerial Vehicle (UAV) products and landscape metrics. The backyard shacks were mapped using Object-Based Image Analysis (OBIA), which uses height information, vegetation index, and radiometric values. We assessed the effectiveness of rule-based and Random Forest (RF) OBIA techniques in detecting formal and informal structures. Informal structures were further classified as backyard shacks using spatial analysis. The spatial patterns of backyard shacks were assessed using eight shapes, aggregation, and landscape metrics. The analysis of the shape metrics shows that the backyard shacks are primarily square, as confirmed by a higher shape index value and a lower fractional dimension index value. The contiguity index of backyard shack patches is 0.6. The values of the shape metrics of backyard shacks were almost the same as those of formal and informal dwelling structures. The values of the assessed aggregation metrics of backyard shacks were more distinct from formal and informal structures compared with the shape metrics. The aggregation metrics show that the backyard shacks are less connected, less dense, and more isolated from each other compared with formal and freestanding shacks. The Shannon’s Diversity Index and Simpson’s Evenness Index values of informal settlements and formal areas with backyard shacks are almost the same. This means that the relative representation of these structures in the study area is almost the same. The results achieved in this study can be used to understand and manage informality in formal settlements.

Keywords: Backyard shacks, informal settlements, UAVs

5.1 Introduction

The proportion of people living in urban areas is expected to increase to 70% in 2030 (UN-Habitat, 2022). Most of this growth is expected to occur in developing countries already struggling with the increased expansion of informal settlements or slums and overburdened infrastructure (UN-Habitat, 2022). There is an increasing demand for accurate and timely information regarding the extent, environmental, and socioeconomic characteristics of urban areas and settlements to support the planning and development of evidence-based policies (Jing et al., 2023).

Countries like South Africa, which struggle with rapid informal settlement developments, also battle with the development of shacks in the backyard of formal dwelling structures known as backyard shacks (Turok & Borel-Saladin, 2016). Backyard shacks are primarily found in townships around cities, home to medium-to-low-income populations (Shapurjee et al., 2014), and have become the most prevalent and fast-growing form of informal rental housing (Turok & Borel-Saladin, 2016). The growth of backyard shacks can be attributed to urban-rural migration, the lack of affordable rental opportunities in the cities, and the slower rate of house provisions for people experiencing poverty. Backyard shacks do not have direct access to essential services but generally have access to services from the existing formal property (Mahlakanya & Willemse, 2022).

Most occupants have more formal jobs than those living in informal settlements (de Kadt et al., 2021). Accessing services from a formal property attracts more people to move or rent backyard shacks than to stay in informal settlements (South African Local Government Agency, 2014). The development of backyard shacks is also observed in newly developed government-subsidized low-cost houses, as many beneficiaries of the houses are unemployed and end up renting out their backyards to generate income, creating informality in formal area (Bank, 2007). Information on backyard shacks is usually captured during censuses (Statistics South Africa, 2016), resulting in temporal gaps.

Unmanned Aerial Vehicles (UAV) or drone technology provide more evidence-based decision-making and accurate spatial information than conventional remote sensing techniques (Chaudhry et al., 2020; Gevaert et al., 2016; Preethi et al., 2019). The UAV mapping technology provides products such as 2D orthophotos, digital surface terrain models (DTM), digital surface models (DSM), and 3D point cloud data. The use of these products in geospatial applications has been on the rise in recent years. This may be attributed to reduced costs relating to drone operations compared with ground surveys (Koeva et al., 2018). Drone technology provides imagery with very high spatial resolution at sub-decimeters compared with satellite and aerial observations (Gevaert et al., 2016; Ruwaimana et al., 2018). In addition, drone technology can provide high-temporal-resolution imagery required for accurate and on-demand spatial data to support urban planning and infrastructure monitoring (Noor et al., 2018). Another advantage of drones is their flexibility to define spatial and temporal resolutions of images depending on the applications (Shapurjee et al., 2014).

Integrating 3D information in urban land use mapping increases classification accuracy by reducing some of the challenges posed by 2D images, such as spectral signature confusion (Mugiraneza et al., 2019; Myint et al., 2011). Several studies have investigated building morphology using 3D information from LiDAR or orthophotos (Huang et al., 2017; Lu et al., 2014; Mitra & Aithal, 2020). Other studies have extracted or assessed topographic information using UAV product (Sibaruddin et al., 2018; Teng et al., 2022). The high spatial resolution data and height information provided by drone images provide detailed information to classify and assess land-use changes in informal settlements compared with aerial photography or satellite imagery (Ashilah et al., 2021; Gevaert et al., 2020). Methodologies for the classification of urban land use features using very high spatial resolution images and 3D information include spatial pattern analysis (Lu et al., 2014), Object-Based Image Analysis (OBIA) (Lu et al., 2014; Peeroo et al., 2017; Sibaruddin et al., 2018), and machine learning techniques (Shih et al., 2022; Touzani et al., 2023; Wu et al., 2019).

Spatial information on housing informality, i.e., free-standing informal structures and backyard shacks, is crucial for effective planning, decision-making, and interventions toward improving the lives of people living in informal settlements (Housing Development Agency, 2012). Even though several studies have focused on developing tools to map and monitor informal settlements (Fallatah et al., 2020; Kohli, 2015b; Kuffer & Barros, 2011; Leonita et al., 2018; Mudau & Mhangara, 2021a), limited studies have focused on mapping backyard shacks (Shapurjee et al., 2014). Understanding the spatial patterns of informal settlement structures can help develop the required emergency responses during health, natural, and man-made disasters (Abunyewah et al., 2018).

The objectives of this paper are threefold: firstly, to investigate a methodology to map land-use features in an area that has both informal and formal settlements with backyard shacks using 2D and 3D information acquired by UAV, and secondly, to assess the spatial pattern of backyard shacks using landscape metrics. Lastly, the study assesses the degree of association between selected shape and aggregation metrics.

5.2 Study area

The study area is in Mamelodi Township, in the City of Tshwane Metropolitan Municipality. The rapid growth of informal settlements and backyard shacks is a problem in South Africa’s big cities, including the City of Tshwane (City of Tshwane, 2020). In 2013, about 83,378 households in the City of Tshwane lived in backyard shack (Department of Cooperative Governance and the Department of Traditional Affairs, 2020b). The number of backyard shacks in the City of Tshwane increased by almost 400% between 2001 and 2011 (GCRO, 2018). The backyard shacks contain similar physical characteristics to informal settlement dwelling structures (Statistics South Africa, 2016). The study area contains single-story government-subsidized houses, low-cost houses, backyard shacks, and freestanding shacks. The formal area also contains “backrooms” houses.

5.3 Data

Drone Solutions International flew the drone images on 11 December 2020.
Table 5-1 contains information about the drone used and the parameters of the flight plan.

Table 5-1. The drone specifications and the flight plan parameters.

Characteristic	Specification
Camera	Sony A6000, 20 mm lens
Altitude	120 m
Side lap	80%
Forward lap	80%
Spatial resolution	3 cm
Ground control points	29
Imagery bands	Red (R), Green (G), Blue (B)

The images were received as orthophotos. The images, DSM, and DTM were processed and projected to the Transverse Mercator, Lo 29°, and Hartebeeshoek Datum. Figure 5-1, Figure 5-2 and Figure 5-3 show the orthophoto, DSM, and DTM used in this study.

Figure 5-1. An RGB orthophoto of the study area, showing formal settlement with backyard shacks and informal settlements.

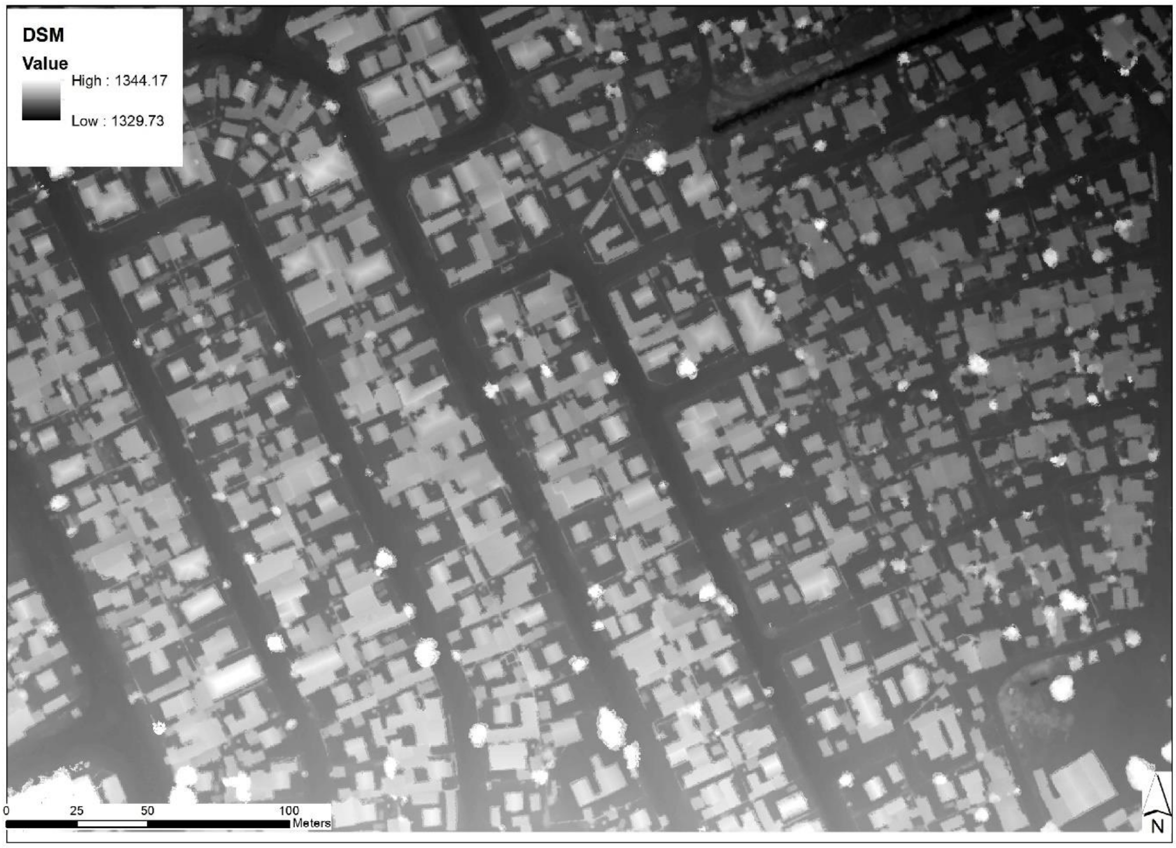


Figure 5-2. A DSM of the study area, generated using data collected during the flyover.

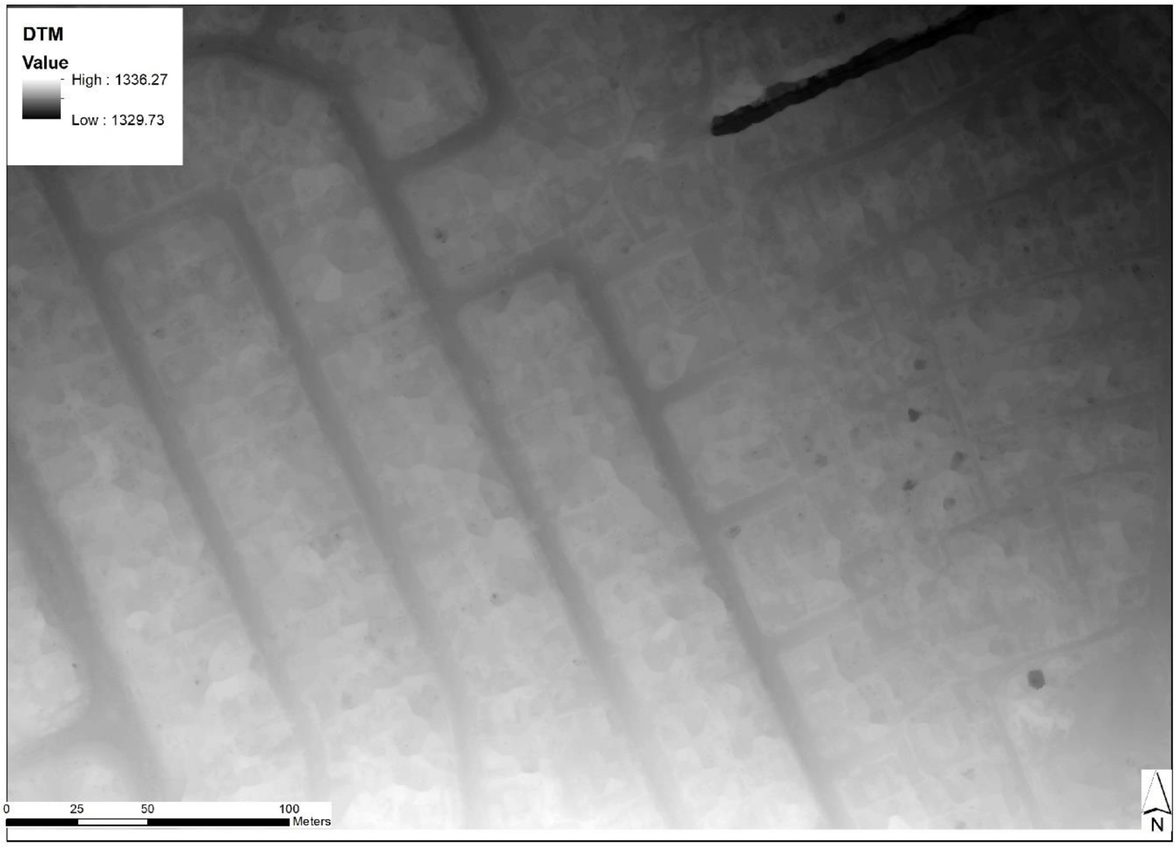


Figure 5-3: DTM of the study area, generated using data collected during the flyover.

5.4 Methodology

The methodology followed in this study is shown in Figure 5-4. The workflow contains four main steps: estimation of height values, classification of informal and formal structures, classification of backyard shacks, and assessment of spatial patterns of informal, backyard shacks, and formal settlements.

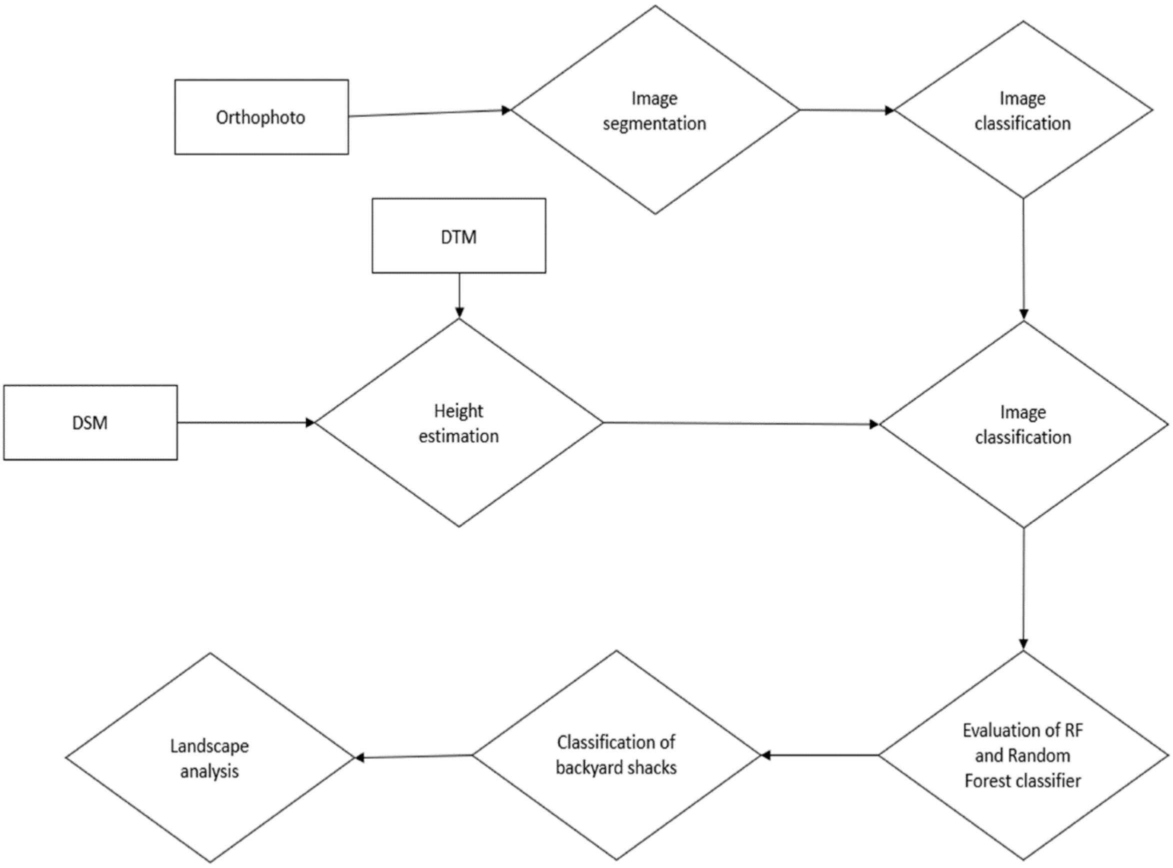


Figure 5-4: Flowchart illustrating the methodology followed to extract backyard shacks and assess the spatial patterns of backyard shacks and informal settlement dwelling structure.

5.4.1 Classification of Formal and Informal Building Structures

Image classification was completed using Trimble eCognition Software 10.2. We used the OBIA technique to classify land use features in the study area. Unlike pixel based classification, OBIA techniques use spectral, spatial, topographical, and contextual information to classify land cover and land use objects. These techniques have been used in urban land use mapping and provide better results than pixel-based classification methods.

The first step in OBIA classification is the segmentation of an image into image objects that represent the objects of interest. The multiresolution segmentation algorithm created image objects representing land use features in the study area. Multiresolution segmentation is a bottom-up, region-merging technique that segments an image into image objects of homogeneous regions at any given resolution (Baatz, 2000). In the eCognition environment, the size of image objects resulting from the multiresolution segmentation algorithm is determined by scale parameters, shape, and compactness values. The ortho photo's spectral bands, i.e., R, G, and B, were used with equal weight during segmentation. We used a supervised segmentation process to determine the parameters that best separate informal and formal dwelling structures. A supervised segmentation approach is a trial and error approach that allows the user to test the segmentation parameters and compare the results with expected objects via visual image recognition (Mitra & Aithal, 2020). Scale parameter, shape, and compactness values of 60, 0.3, and 0.5, respectively, were used during segmentation. To improve the quality of the image objects, the spectral difference segmentation technique was applied to multiresolution segmentation results to allow for the merging of spectrally similar image objects, resulting in larger image objects representing the objects of interest. The spectral difference threshold of 4 was selected using the supervised segmentation method used during the multiresolution segmentation. We tested and evaluated the effectiveness of the Random Forest (RF) Classifier and rule-based classification technique that uses height information and OBIA to detect formal and informal building structures.

5.4.2 Random Forest Classifier

Object-based machine learning algorithms are becoming an area of interest in feature extraction (Fan et al., 2021; Jovanović et al., 2021; Norman et al., 2021). The RF classification algorithm is an ensemble of decision trees trained using a combination of learning models (Breiman, 2001). An RF classifier is defined as a classifier made up of several tree-structured classifiers $\{h(x, \Theta_k); k = 1,\ldots\}$ where x is the input vector and $\{\Theta_k\}$ are the independent and identically distributed random vectors (Breiman, 2001).

The classification was completed using the eCognition built-in RF classifier. We used radiometric values, excess green vegetation (ExG) (Woebbecke, 1995), and estimated height information during classification. We used 16 maximum categories, 50 maximum trees, and 0.01 forest accuracy during the training of the RF classifier. The height information was estimated by subtracting the DTM from the DSM. The ExG index was suitable for the classification since the UAV imagery lacked the Near Infrared (NIR) band. ExG is calculated as follows:

$$ExG = 2G - R - B \tag{5- 1}$$

Training samples representing informal, formal, tree, and grass classes were created using visual image interpretation. 25 formal and 46 informal structures, 10 grass, and 19 tree samples were created and used as samples. The classification used the RGB layers, height information, and ExG index. Maximum categories, maximum trees, and forest accuracy of 16, 50, and 0.01 were used during the classification.

5.4.3 Rule-based classifier

A rule-based classifier makes a class decision based on “if-else” rules and is one of the most commonly used object-based classification techniques. The rule-based classification relies on expert knowledge of the classes under investigation. The rules and facts about the objects under investigation are converted into a sequence of logical statements (Kurfess, 2003). We developed a rule set that uses ExG and height information to classify formal, informal, grass, and tree classes through visual assessment. The classification was completed using a thresholding technique. The first step performed was to classify vegetated and non-vegetated areas using ExG. Vegetated areas have higher ExG values of 20 or higher than non-vegetated areas.

The vegetated areas were further classified into grass and trees using the estimated height values. Vegetated areas with less than 1 m of height were classified as grass, while those taller than 1 m were classified as trees. Building structures were separated from non-vegetated areas by thresholding the height values. Non-vegetated areas with less than 1 m height values were classified as open. Building structures taller than 2.3 m were classified as formal dwelling structures, whereas those shorter than 2.3 m were classified as informal dwelling structures. Formal and informal dwelling structures were classified using estimated height information. Formal structures are expected to be taller than informal settlement dwelling structures.

5.4.4 Classification of backyard shacks

Backyard shacks are informal dwelling structures in the yards of formal properties and have the same properties as informal settlement dwelling structures. The classification of backyard shacks was done using the classification results achieved from a methodology that achieved higher accuracy. We developed a rule set that uses contextual information to classify backyard shacks as informal settlement dwelling structures. We used proximity to formal structures to classify backyard shacks as freestanding, informal structures. The distance between formal structures and backyard shacks was assessed visually and used to classify backyard shacks as freestanding informal settlement structures. Backyard shacks are situated within 5 m of the formal dwelling structures.

5.4.5 Accuracy Assessment

The accuracy assessment of the classification results was done using the similarity metrics of STEP (Shape, Theme, Edge and Position) (Lizarazo, 2014). The STEP measures the accuracy of the boundaries of the classified objects compared with reference shapes. The overall accuracy assessment was done by evaluating the weighted theme error matrices. Reference objects were digitized using visual image interpretation of the images due to a lack of ancillary data mapped at similar spatial resolution and during the date of acquisition. A quality assessment was done in an area that covers about 10% of the study area.

5.4.6 Spatial pattern analysis

We used landscape metrics to assess the characteristics and spatial patterns of backyard shacks and formal and informal dwelling structures in the study area. Landscape metrics have been widely used in landscape ecology to understand the relationship between landscape patterns and ecological processes (Street et al., 2016; Y. Zhang et al., 2021). Understanding the spatial patterns of land use activities in a settlement or city can help manage a city or settlement and develop policies to manage development in a city or settlement (Anderson & Bell, 2009; Zambrano et al., 2021). In addition, understanding the spatial pattern of dwelling structures in informal settlements can help improve decision-making when planning informal settlement upgrade projects. Understanding the spatial patterns of land use can also help manage biodiversity in cities or settlements, which is crucial for achieving sustainable development goals (Norton et al., 2016).

In this study, we assessed eight shape, aggregation, and landscape metrics to analyze the shape and spatial patterns of the backyard shacks and informal and formal structures. The metrics assessed are listed in Table 5-2.

Table 5-2: List of shape, aggregation and landscape metrics assessed

Landscape Metric type	**Landscape Metrics assessed**
Shape	Shape index (SHAPE) Fractal Dimension Index (FRAC) Continuity Index (CONTIG)
Landscape	Simpson's diversity index (SIDI) Shannon's Evenness Index (SEI) Euclidean Nearest-Neighbour Distance
Aggregation	Aggregation Index (AI) Cohesion Index

We used Fragstats software (McGarigal & Marks, 1995) to derive and assess the spatial metrics of backyard shacks. The shape and aggregation metrics were assessed at the patch and class levels. The diversity analysis was done at the settlement level, i.e., informal settlement and formal settlement with backyard shacks. In addition, we used the Pearson correlation coefficient to assess the degree of association between the shape and aggregation metrics of backyard shacks and formal and informal dwelling structures. The Pearson correlation coefficient is a statistical method that assesses the strength of a linear association between two quantitative variables. The results of this analysis vary from +1 to −1, where +1 represents a strong positive association, whereas −1 represents a strong negative association.

5.5 Results and discussions

5.5.1 Image segmentation

The multiresolution segmentation with scale, shape, and compactness values of 60, 0.3, and 0.5, respectively, created images representing formal and informal building structures and other land use features. Most of the building structures in informal were over-segmented. The formal building structures were also over-segmented but with bigger segments than the informal settlement structures. Some of the backrooms were also over-segmented. The spectral difference segmentation technique reduced the over-segmentation of some of the building structures (Figure 5-5). Most informal settlement building structures continued to experience over-segmentation even after applying the spectral difference segmentation algorithm. This may be attributed to the heterogeneity of the roofing material of informal building structures. Some of the roofs in informal settlements contained old, corrugated iron sheets, resulting in different grayscale levels on one roof (Figure 5-5). The same results were observed in some parts of the backrooms in the formal area. After applying spectral difference segmentation, most formal structures were covered by one or two image objects.

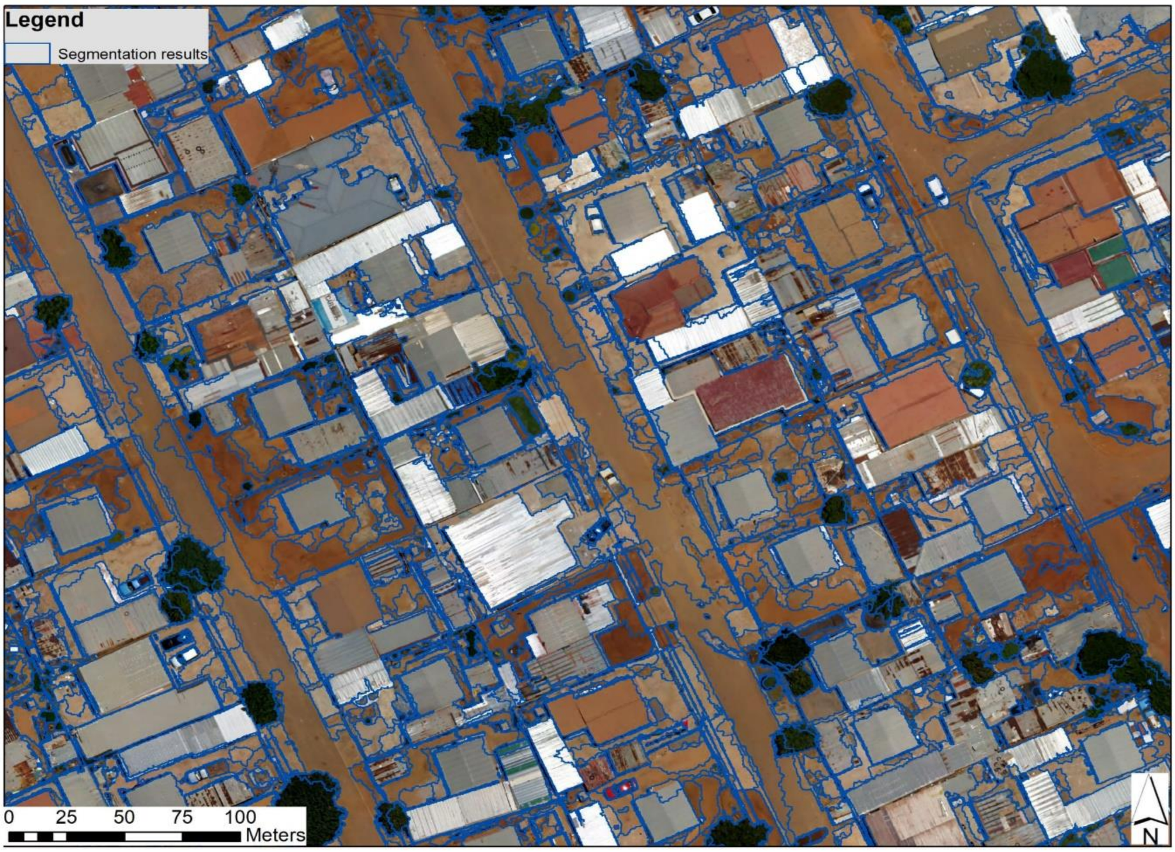


Figure 5-5: Zoom-in image of the spectral different segmentation results, threshold scale: 4.

5.5.2 Classification results

In this section, we compare the results achieved using RF and rule-based classification techniques. The classification results of the RF classifier are shown in Figure 5-6. The results show that the study area is mostly covered by building structures compared with trees and grass classes. The backyard shacks are located closer to the formal structures. The informal structures are located at the top right corner of the study area. The assessment of the results shows that some of the formal building structures were classified as informal dwelling structures or backyard shacks. This is attributed to the misclassification of the backrooms as backyard shacks, as some of the roofs of the backrooms contain old corrugated iron sheets similar to those of informal building structures. Some of the pixels on the edges of the formal building structures were misclassified as backyard shacks or trees. Some fences around the formal areas, edges of trees, and shorter trees were misclassified as grass. There were also a few cases where the edges of the trees were misclassified as grass. In addition, some of the formal busing structures were classified as informal settlement dwelling structures. This may be influenced by using proximity measures to classify backyard shacks as informal settlement structures.

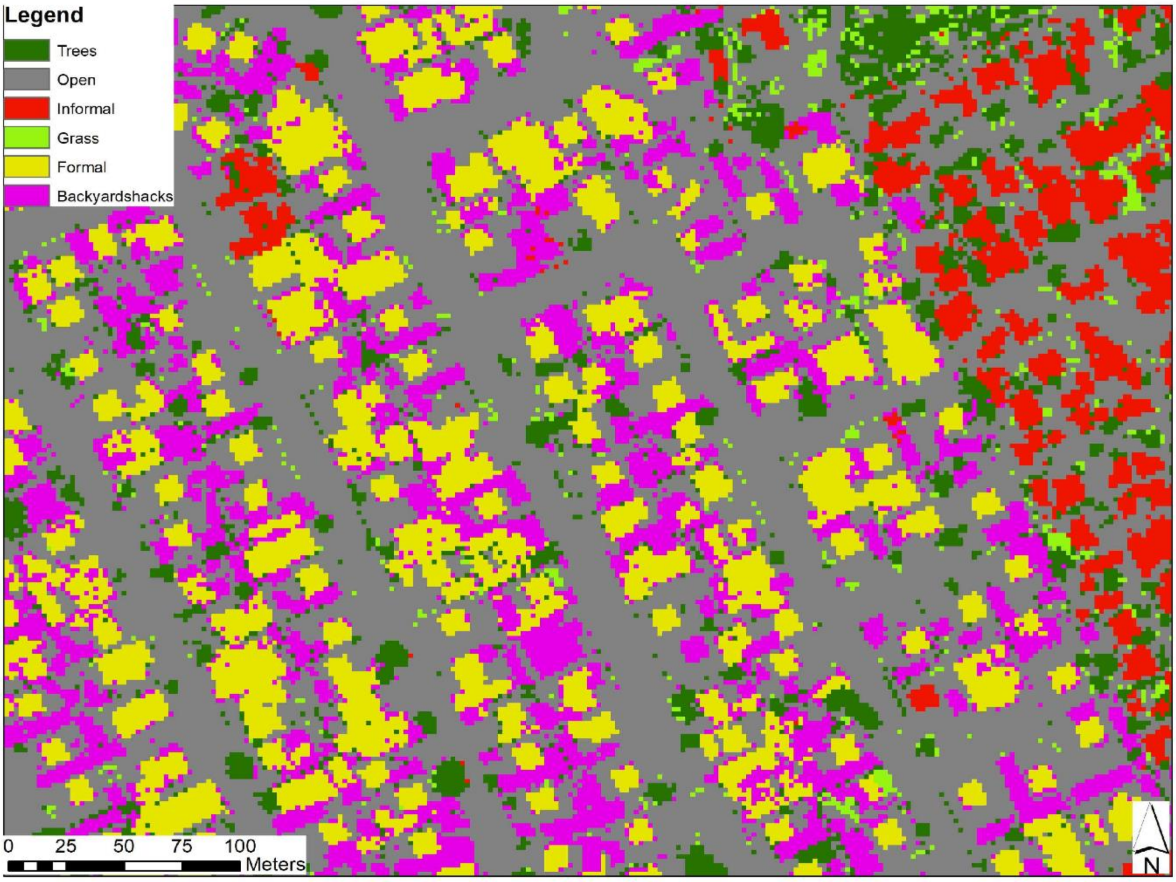


Figure 5-6: Classification results achieved using RF classifier, after applying proximity analysis to classify backyard shacks.

The rule-based classification technique was able to separate backyard shacks, formal and informal dwelling structures, grass, and tree classes with high accuracy compared with the RF classifier (Figure 5-7). Most of the edges of the formal structures were misclassified as backyard shacks compared with results achieved using the RF classifier. There were a few cases where building structures were misclassified as trees. Most informal settlement dwelling structures were correctly classified. Some of the backyard shacks were misclassified as free-standing informal settlement dwelling structures. This may be attributed to the use of proximity analysis to classify backyard shacks as free-standing informal dwelling structures, as some of the building structures in informal settlements are almost the same height as formal structures.

Figure 5-7: OBIA classification results achieved using rule-based classification techniques, after applying proximity analysis to classify backyard shacks.

The tree class is scattered around both formal and informal settlements. The big patches of trees and grasses are found on the top left, closer to informal settlement structures. The separation of the green spaces from other classes is attributed to using the ExG index used during the classification. The use of the ExG and height information was able to separate the tree class from the grass class. There were, however, areas where the shadows of the trees and fences were misclassified as grass. The number of grass patches is limited in the study area. However, more grass patches can be observed around the informal settlement. The tree class in formal areas is located mainly in the streets, while the trees in informal settlements seem more organic.

The RF classifier could not separate some informal settlement dwelling structures from backroom structures, even though the two structures have different heights (Figure 5-6). Spectral values might influence this during the RF learning process, as the two dwelling types have similar spectral values. Therefore, using spatial analysis to classify backyard shacks resulted in some backroom structures being classified as backyard shacks due to their proximity to formal dwelling structures. The rule-based classification method, however, distinguished backroom structures from informal settlement dwelling structures. The rule-based classification method also reduced the confusion between formal and informal structures, thereby reducing the confusion between backyard shacks and formal classes (Figure 5-7). There were, however, a few cases where parts of informal settlement dwelling structures were classified as formal during rule-based classification. This resulted in some informal settlement dwelling structures being classified as backyard shacks.

Some of the edges of formal structures and trees were misclassified as informal settlement structures or backyard shacks during the RF classification. This can be attributed to creating image objects that combine the edges of the structures and shadows, resulting in the average height of the structures being like that of informal structures. Some man-made structures, such as cars, were also misclassified as backyard shacks or informal settlement structures, as some of the cars have height and spectral properties like those of informal dwelling structures.

5.5.3 Accuracy assessment

The STEP metrics assessment results for the RF classifier are shown in Table 5-3. The STEP accuracy measurements range from 0 to 1, with 0 representing poor and 1 representing excellent. The similarity assessment results show that none of the assessed metrics achieved excellent accuracy, i.e., a value of 1. The theme similarity metric achieved higher accuracy than position, edges, and shape metrics, with the backyard shacks class achieving the highest accuracy of 0.86 compared with other classes. The results show that the shape similarity was poor for all the classes produced during the RF classification method compared with edges and position metrics.

Table 5-3: STEP accuracy assessment results of land use classes derived using RF classifier.

Category	Shape	Theme	Edge	Position
Backyard shacks	0.28	0.86	0.59	0.29
Formal	0.27	0.49	0.33	0.34
Grass	0.07	0.10	0.07	0.08
Informal	0.35	0.67	0.41	0.46
Trees	0.44	0.84	0.49	0.73

The similarity assessment of classification results achieved using rule-based classification techniques is shown in Table 5-4. The theme similarity assessment results range from 0.61 to 0.85, presenting the most accurate metrics compared with shape, edge, and position metrics. The shape, edges, and position similarity assessment results achieved using the rule-based classification method were slightly higher than the results achieved using the RF classifier.

Table 5-4: The STEP metrics assessment results of land use classes derived using rule-based classification method.

Category	Shape	Theme	Edge	Position
Backyard shacks	0.22	0.74	0.50	0.34
Formal	0.42	0.83	0.57	0.43
Grass	0.44	0.61	0.43	0.46
Informal	0.33	0.71	0.42	0.49
Trees	0.48	0.85	0.49	0.75

The overall accuracy assessment of RF and rule-based classification results is shown in Table 5-5. The overall quality assessment of the RF classifier was 60%, with informal settlement dwelling structures achieving the highest producer and user accuracy compared with formal and informal dwelling structures. The formal building structure and grass classes achieved the lowest user accuracy of 12% and 11%, respectively.

Table 5-5. The overall producer and user accuracy assessment results are based on the theme similarity metric of the land use classes.

Class	Random Forest Classifier		Rule-Based Classification	
	Producer Accuracy %	User Accuracy %	Producer Accuracy %	User Accuracy %
Backyard shacks	69	96	89	93
Formal	92	11	88	57
Grass	91	12	9	77
Informal	97	72	90	93
Trees	73	99	72	99
Overall accuracy %	60		82	

The overall accuracy theme similarity of the rule-based classifier was 82% (Table 5-5). These results are aligned with studies that assessed the use of UAV 2D and 3D products and rule-based classification techniques to map urban land use features (Christopher, 2019; Zahidi et al., 2015). Overall, the rule-based classification produced higher producer and user accuracies of over 70%, except for the formal class, which achieved a user accuracy of 57% compared with the RF classifier. The informal settlement class achieved the highest overall accuracy of the building structure classes.

5.5.4 Spatial pattern analysis

The spatial pattern analysis was done using the rule-based classification results. The sections below describe the results obtained in assessing the shape, aggregation, and landscape metrics.

5.5.4.1 Shape metrics

The patches of formal structures had an average shape index of 1.6, whereas the backyard shack and informal classes had an average shape index of 1.4. The slightly lower shape index value of backyard shacks and informal dwelling structures can be attributed to the heterogeneous roof material, which resulted in multiple irregular image object segments. A shape index of more than one means that the dwelling building structure classes are mostly square. The visual interpretation of the results shows that most of the backyard shacks are rectangular, especially those located on the sides of the formal structures. Formal structures are mostly square. The backrooms seemed rectangular. The shapes of informal settlement dwelling structures are mostly rectangular. The results achieved in this study show the dependency of this metric on the accuracy of the shapes of the image objects created during segmentation or used for analysis.

The average contiguity index of formal and informal class patches was 0.7, whereas the contiguity index of backyard shacks was 0.6. The slightly lower contiguity index implies that backyard shacks in the study areas share fewer edges than formal and informal structures. The visual interpretation of the results shows that the study area contained more formal structures than backyard shacks. The slightly higher value of the contiguity index of formal structures in this study may be attributed to the availability of backrooms that are classified as formal structures.

The average FRAC value of formal structures and backyard shacks was 1.2, whereas the average FRAC value of informal structures was 1.1. These values show that the dwelling structures in the study area have regular square shapes. Since the FRAC index is based on patch area and perimeter and the shape accuracy of the informal and backyard shacks was poor, the values of this index may change with improved shape accuracy.

The evaluation of the degree of association of the shape metrics shows that the CONTIG and Shape indices have an insignificant positive correlation with r, of 0.16. The CONTIG and FRAC indices have an insignificant negative correlation coefficient of −0.27. The shape and FRAC indices have a lower correlation coefficient of 0.45. Overall, the assessed shape metrics are not strongly correlated.

5.5.4.2 Aggregation metrics

The results show that formal, informal, and backyard shack classes are connected, as indicated by high cohesion index values (Table 5-6). The backyard shack class seems less connected than the formal and informal classes. This can be attributed to the lower density of shacks in the formal stand and the availability of backrooms, which increase the average distance between backyard shacks. The availability of regular roads may also increase the space between backyard shacks. The results show that informal dwelling structures are more connected than formal structures and backyard shacks. The results imply that informal settlements have smaller yards or stands than formal settlements. The narrow paths in informal settlements may also contribute to a higher cohesion index in informal settlements.

Table 5-6: Class aggregation metrics

Class	Euclidean Nearest-Neighbour Distance	Cohesion Index	Aggregation Index
Formal	142.023	83.39	80.75
Backyard shacks	147.610	73.71	57.7
Informal	116.553	89.54	80.74

The analysis of the ED shows that the backyard shacks have the highest mean ED, followed by formal class and then informal class (Table 5-6). This shows that the study area's backyard shack class is less dense than other dwelling types. This could be attributed to the fact that this class is in the yard of formal structures separated by a formal road network. The lower mean ED of the informal class means dwelling structures in informal settlement structures are closer to each other compared with the formal and backyard shack classes. This shows that the informal structure class is dense compared with the study area's formal and backyard shack classes.

The average AI value of the backyard shacks class is significantly lower than those of formal and informal structures (Table 5-6). This shows that backyard shack structures are more isolated than formal and informal structures. The higher AI values of formal and informal dwelling structures may be influenced by the availability of backrooms, which increases the adjacency of formal structures and smaller yards in informal settlements. The analysis of the degree of association shows the cohesion index and ED of formal and informal settlement dwelling structures have a strong negative correlation coefficient r of −0.88. In contrast, the cohesion index and AI have a strong positive correlation coefficient of 0.92.

5.5.4.3 Landscape metrics

The SIDI values of the formal and informal settlements are 1.24 and 1.18. The lower value of SIDI in the informal settlement may be attributed to the limited patches of backyard shack class in informal settlements. The SIEI values of formal and informal settlements are 0.79 and 0.87, respectively. The slightly higher value of SIEI in informal settlements is likely attributed to the limited patches of backyard shacks, which increased the chance of equally spreading the classes in informal settlements.

5.6 Conclusions

The study demonstrated that 2D and 3D datasets acquired by UAV were successful in capturing land use features in an area containing formal properties with backyard shacks and informal settlements. The study shows that the rule-based classification was more effective in classifying formal and informal settlement dwelling structures than the RF classifier. The results show that both methodologies failed to extract boundaries similar to reference data, as shown by poor edge, shape, and position accuracy. The proximity analysis was successful in classifying backyard shacks as free-standing informal dwelling structures. The assessment of the landscape metrics showed that there is no significant difference in shape characteristics of backyard shacks or formal and informal dwelling structures extracted. Since the shape index metrics strongly depend on the shape of the objects assessed, there is a need to investigate the methods that can improve the accuracy of the shapes produced during segmentation and the impact of accurate shapes on shape metrics analysis. The study revealed that the cohesion index, AI, and ED characteristics of backyard shacks are more district compared with the shape metrics of formal and informal structures. The results show backyard shacks are less connected than formal and informal dwelling structures. AI showed an excellent split of the aggregation of backyard shacks from other dwelling structures in the study. The degree of association between aggregation metrics was significantly high. This means that the aggregation metric may be used to classify backyard shacks as formal and informal structures in a settlement with similar characteristics as the study area.

The results achieved in this study demonstrate that drone images and landscape metrics can be used to map and derive new information on the spatial distribution of backyard shacks and other building structures. The spatial patterns of backyard shacks may vary from one settlement to the next due to several factors, including the age of the township. The information derived from this study can be used to understand the degree of informality in formal areas. This information can be used to develop plans to formalize or manage backyard rentals in low-income formal areas.

The information can also be used during the management of health pandemics such as COVID-19, where spatial information, including the density of dwelling structures and access to services, is required to support the management of the pandemic. Spatial distribution of informal settlement dwelling structures is also required during decision-making relating to fire disaster management, planning of services, and upgrading or formalizing informal settlements and backyard shacks.

Chapter 6 UNDERSTANDING THE ECOLOGICAL CONDITION OF INFORMAL SETTLEMENTS USING THE SETTLEMENT SURFACE ECOLOGICAL INDEX.

This chapter is based on the following manuscript:

Mudau N., Mhangara P., (2023), Understanding the ecological condition of informal settlements using Settlement Surface Ecological Index; Land; DOI: 10.3390/land12081622

Abstract
To manage urban ecological ecosystems adequately, understanding the urban areas' biophysical characteristics is required. This study developed a settlement surface ecological index (SSEI) using tree, soil, impervious surface and grass covers, land surface temperature (LST), and soil moisture derived from Satellite Pour L'Observation de la Terre (SPOT) 7 and Landsat 8 satellite images. The assessment of the SSEI was conducted over twelve sites of 300 m by 300 m. The selected sites contained formal and informal settlements of varying building densities. The SSEI values ranged from −0.3 to 0.54. Seven assessed areas are in the worst ecological condition with an SSEI below zero. Only three settlement types had an SSEI index value of 0.2 and above, and two of these areas were informal settlements. The formal low-density settlement with higher tree coverage displayed the highest index value of 0.54, slightly higher than the medium-density informal settlement. Overall, there is no significant difference in the SSEI values between the surface ecological condition of formal and informal settlements. The results achieved in this study can be used to understand urban ecology better and develop urban greening strategies at a city or settlement level.

Keywords: informal settlements; land surface temperature; urban ecology

6.1 Introduction

The urban ecosystem provides services that directly impact human health and security, including runoff mitigation, urban cooling, and air purification (Bolund & Hunhammar, 1999). The availability of vegetation in urban areas can help improve air quality and reduce flood severity (Gallagher et al., 2015). In addition, improving green infrastructure in informal settlements can help enhance social and cultural interaction (Adegun, 2021; Haase et al., 2017). In addition, an increase in the impervious surface and low vegetation cover negatively affects the local microclimate and increases the formation of surface urban heat island (SUHI) (Morabito et al., 2021). Exposure to excessive heat in certain areas can cause physiological and socio-economic stress, amplify existing health issues, and increase premature death or disability (Anderson & Bell, 2009). Populations in informal settlements are likely to be affected the most by increased heat exposure as the dwelling structures in these areas lack cooling services (Anderson & Bell, 2009; Ramsay et al., 2021). Urbanization can also result in soil erosion or contamination, which may threaten human health (Wang et al., 2018).

Satellite images have been widely used to assess and detect land use features such as human settlement developments (Kemper et al., 2015; Marconcini et al., 2020; Mudau et al., 2022), informal settlements (Gram-Hansen et al., 2019; Luo et al., 2022; Owusu et al., 2021) and urban growth rates (Borana et al., 2020; Yadav & Ghosh, 2021). Vegetation cover and density of impervious surface are the two land cover classes that have been thoroughly investigated in an attempt to automatically detect informal settlements from satellite imagery (Fallatah et al., 2019a; Hofmann et al., 2001; Mudau & Mhangara, 2021a). Other studies have used satellite images to map and measure urban morphology (Chen et al., 2021; Wang et al., 2023).

Urban surfaces and their characteristics play an important role in achieving sustainable and resilient cities as they can influence the people's quality of life and the settlements' environmental conditions (Croce & Vettorato, 2021). Several studies have assessed the environmental conditions of cities using a vegetation-impervious surface-soil (VIS) model (RIDD, 1995) and medium spatial resolution images (Aina et al., 2019; Phinn et al., 2002). In addition to the VIS model, assessing other biophysical characteristics such as surface temperature, wetness, and air quality provides more variables to assess the surface ecological status of cities. The remote sensing ecological index (RSEI) is the first model that utilizes remotely sensed data to assess the status of the urban ecology of cities (Zheng et al., 2022). RSEI uses vegetation index, humidity, land surface temperature, and built-up and bareness index (Zheng et al., 2022). Researchers have explored the RSEI to evaluate the status of urban ecology across cities (Firozjaei et al., 2020; Li et al., 2021; Yue et al., 2019).

The methodologies commonly used for mapping the land cover biophysical characteristics include the thresholding radiometric values and the maximum-likelihood algorithm (MLA). Due to the heterogeneity of land use features in urban areas, these methods suffer from spectral mixing issues. A hierarchical algorithm that uses textural features has proven to perform better than MLA (Setiawan et al., 2006). Using object-based image analysis (OBIA) in mapping urban land cover using high-resolution imagery improves the results significantly compared to pixel-based classification and MLA (Myint et al., 2011).

The previous studies conducted on the assessment of ecological studies are limited to a city level, providing data required to develop a city-level intervention. Since informal settlements are illegal and may lack essential services such as sanitation, water, and waste removal (UN-Habitat, 2004), they pose several social and environmental challenges. Environmental challenges such as land degradation and pollution of natural resources have been associated with informal settlements (Devi et al., 2017). This may be attributed to unmanaged land use activities and lack of access to basic services (UN-Habitat, 2004). In addition, the effect of climate change and global change may be more severe in informal settlements than in formal settlements as they are located in undesirable locations such as flood-prone or high-slope areas (Ramin, 2009). With future urbanization expected to take place mostly in developing countries that are already struggling with informal settlement developments, understanding the vulnerability of informal settlements can help develop interventions to improve the wellbeing of people living in informal settlements.

The studies that used RSEI to assess the ecological conditions of the cities assess the broad land-use classes. Since human settlements are not the same, a detailed analysis of urban ecological conditions is required to improve understanding of urban environments and develop necessary solutions to build green infrastructure across a city. This study builds on RSEI and develops a settlement surface ecological index (SSEI) that uses the tree, grassland, impervious surface, soil, land surface temperature, and vegetation moisture to assess the ecological status of informal and formal settlements using biophysical parameters derived from high and medium spatial resolution imagery.

6.2 Study area

The study area covers residential, commercial, and industrial areas in the eastern part of the City of Tshwane, Gauteng, South Africa, and lies between −25°41′ and −25°46′ latitude and 28°17′ and 28°26′ longitude. The study area contains low- and high-density residential areas on the eastern side of the metropolitan municipality and formal high-density and informal settlements in Mamelodi township, located about 30 km from the city's central business district, see Figure 6-1 for the location of the study area and different human settlement types assessed in the study.

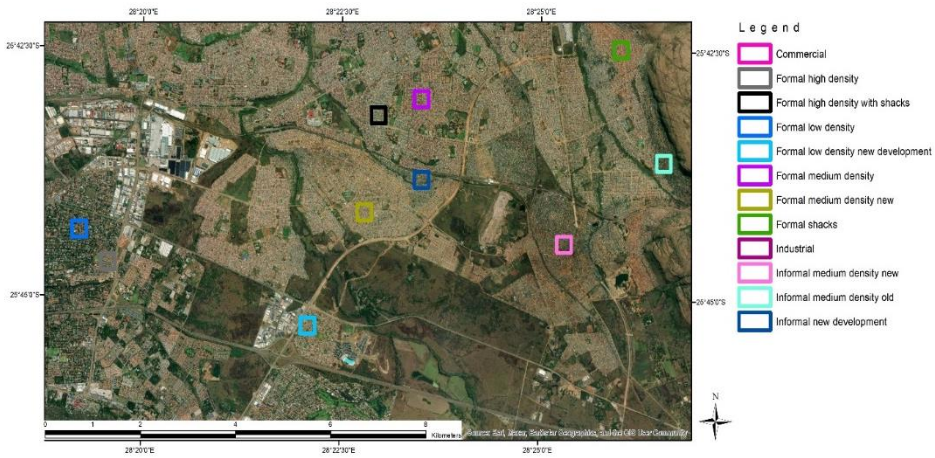


Figure 6-1**.** Location of the study area and different human settlement types assessed in the study

The main economic activities in the municipality are finance and manufacturing. About 16% of municipal households were informal settlements in 2016 (Department of Cooperative Governance and the Department of Traditional Affairs, 2020a). Mamelodi is one of the townships experiencing increased development of informal settlements (Mudau & Mhangara, 2022). The municipality plans to upgrade informal settlements by providing essential services or top structures (Department of Environmental Affairs, 2016). In addition, several initiatives are aimed at greening the cities to improve air quality and sociocultural interaction, especially in townships. The zoom-in pictures of selected areas are shown in APPENDIX A.

The selection of the different human settlement types was performed through visual interpretation using the Google Earth platform. The maps of the selected settlement were generated using Esri base maps. The description of the selected settlements was guided by Census 2011 metadata (Statistics South Africa, 2012) and the South African National Land Cover Classification standard, 19144-2:2014.

6.3 Data

We used Satellite Pour Observation de la Terre (SPOT) 7 images acquired on 8 November 2017 to classify urban land cover classes. The SPOT 7 sensor acquires images both in multispectral and panchromatic modes. The scene IDs of the images used are IMG_SPOT7_MS_201711070754099_ORT_SPOT7_20180925_0743431nq51eejut843_1_R3C2 and img_spot7_ms_201711070754099_ort_spot7_20180925_0743431nq51eejut843_1_r3c2. The spectral bands, wavelength, and spatial resolution of SPOT 7 are presented in Table 6-1. A Landsat 8 image acquired on 08 November 2017, scene ID LC81700782017312LGN00, was used to derive land surface temperature and vegetation moisture information.

Table 6-1**.** List of the spectral band, bandwidth, and spatial resolutions of SPOT 7 and Landsat 8 satellite images.

Spectral Band	**Wavelength (μm)**	**Spatial Resolution (m)**
SPOT 7		
Panchromatic	0.45–0.75	1.5
Blue	0.45–0.52	6
Green	0.53–0.06	6
Red	0.62–0.69	6
Near-Infrared	0.76–0.89	6
Landsat 8		
Panchromatic	0.50–0.68	15
Coastal Blue	0.43–0.45	30
Blue	0.45–0.67	30
Green	0.53–0.59	30
Red	0.64–0.67	30
Near-Infrared	0.85–0.88	30
Short-wave Infrared1	1.57–1.65	30
Short-wave Infrared 2	2.11–2.29	30
Cirrus	1.36–1.38	30
Thermal Infrared 1	10.6–11.19	100
Thermal Infrared 2	11.50–12.51	100

6.4 Methodology

6.4.1 Classification of Urban Land-Use Classes

The classification of impervious surface tree, grass, and soil cover and features from the SPOT 7 satellite image was performed using the object-based image analysis (OBIA) technique in Trimble eCognition Software. The OBIA technique has been widely used to detect urban land cover and land use classes from high spatial resolution satellite imagery (de Pinho et al., 2012; Mudau & Mhangara, 2021a). This technique has generated more accurate results than pixel-based urban land use classification (Myint et al., 2011). The first fundamental step of OBIA is image segmentation. This process partitions an image into image objects that represent desired land use or land cover features with similar spectral and spatial properties

(Definiens, 2007). The quality of results achieved using OBIA techniques depends on the image objects created during image segmentation (Definiens, 2007).

The multiresolution segmentation method was used to partition the image into image objects. This bottom-up, region-merging technique partitions an image into objects based on the user-defined homogeneity criteria, i.e., scale, compactness, and shape (Baatz, 2000). Two segmentation levels were created using 400 and 25 scale parameters using the multispectral bands. Segmentation parameters were selected using the trial-and-error method by visually inspecting segmentation results. The scale parameter 400 generated Level 1 image objects representing non-built-up and built-up land cover and land use classes. In contrast, the scale parameter 25 generated Level 2 image objects representing urban land use objects. The compactness and shape parameters of 0.5 and 0.1 were selected for both segmentation levels. The scale, compactness, and shape parameters were selected using trial and error by visually inspecting the results and adjusting the segmentation parameters (Liu et al., 2022; Mugiraneza et al., 2019).

The OBIA rule-based classification technique was used to classify level 1 image objects into built-up and non-built-up classes. A ruleset that uses radiometric values, vegetation indices and textural features was developed to classify built-up and non-built-up classes. Classifying built-up and non-built-up areas using the gray-level co-occurrence matrix (GLCM) dissimilarity texture (Haralick et al., 1973). The GLCM dissimilarity texture measures the distance between pairs of pixels within an image object (Haralick et al., 1973). Due to the heterogeneity of land use features in urban areas, the dissimilarity values are expected to be higher dissimilarity texture values than in non-built-up areas (Mudau et al., 2014). Most image objects in urban areas are also expected to have higher brightness values than non-built-up areas (Huete, 1988). A rule set that uses GLCM dissimilarity and brightness values is expected to separate built-up and non-built-up areas.

Level 2 image objects were classified into trees, grass, impervious surface, and soil using the soil-adjusted vegetation index (SAVI) (Huete, 1988), GLCM dissimilarity texture (Haralick et al., 1973), Pantex (Pesaresi et al., 2008), and iron oxide index (White et al., 1997). The SAVI is a vegetation index that minimizes the impact of soil properties in vegetated areas (Huete, 1988). The SAVI has been widely used to map vegetation from other land cover classes, such as impervious surfaces, soil, and water (Chen et al., 2015; Stefanov et al., 2001). The impervious surfaces, including roads and building structures, are expected to have lower SAVI values than soil and vegetation classes (Ukhnaa et al., 2019). SAVI was used to classify trees from grass features.

Pantex is a texture-derived built-up presence that uses GLCM for different directions and displacements and has proven to improve the classification of human settlement land use types compared to other built-up indices (Pesaresi et al., 2008). Building structures are expected to have higher Pantex values than other land-use classes (Pesaresi et al., 2008). The GLCM dissimilarity texture was used to distinguish open areas from building structures. The iron oxide or iron index measures the amount of iron on the surface using the red and blue bands (White et al., 1997). This index was used to distinguish grass from soil classes. SAVI was used to classify trees from grass features.

6.4.2 Mapping of LST

LST was derived using band 10 of the Landsat 8 satellite. The LST was calculated using the following formula:

$$LST = \frac{BT}{1+(\lambda BT/\rho) ln\varepsilon} \qquad (6\text{-}1)$$

where BT is brightness temperature, λ is the length of emitted wavelength, ρ is a constant obtained using the formula $h * \frac{c}{\sigma}$, where h is Plank's constant, c is the velocity of light, σ is the Boltzmann constant, and $\mathcal{E}$ is land surface emissivity.

6.4.3 Mapping of vegetation moisture

The assessment of vegetation moisture in the study area was done by analyzing the normalized difference moisture index (NDMI) which measures vegetation water content. The NDMI was derived using the following formula:

$$NDMI = (NIR - SWIR1) / (NIR + SWIR1) \qquad (6\text{-}2)$$

6.4.4 The assessment of settlement surface ecological index

The SSEI is a function of the urban land cover classes, LST, and vegetation moisture, and it was calculated using the following formula:

$$SSEI = (Tree\ cover + Grass\ cover + vegetation\ moistures) - (Impervious\ surface + LST) \quad (6\text{-}3)$$

The assessment of SSEI index was performed over 300 m × 300 m of the selected urban land-use classes. The assessed biophysical characteristics were standardized to the 0–1 range. The index is defined as the difference between characteristics that improve urban ecology and those that negatively alter the urban ecosystem. The values of SSEI range from 0 to 1. Values closer to one represent a better settlement ecological condition, and values closer to zero represent the worst.

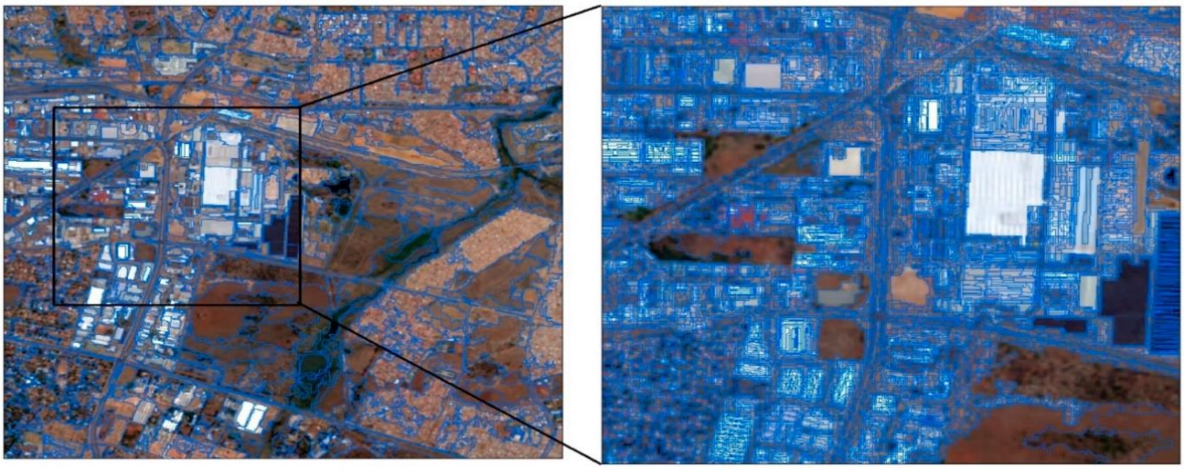
6.4.5 Quality assurance

Quality assurance of mapped VIS classes was performed by assessing the classification results with the manually selected image objects representing the mapped classes. A total of 588 impervious surfaces, 71 trees, 42 grasses, and 99 soil samples were created through visual image interpretation using a random sampling method. The accuracy assessment used Trimble eCognition 9.0 software (Definiens, 2007). We assessed overall, producer and user accuracies. These producer and user accuracy measurements assess the errors of omission and commission of selected samples on the classified image.

6.5 Results

6.5.1 Image segmentation

Multiresolution image segmentation process with scale parameter, compactness and shape values of 400, 0.1, and 0.5, respectively, was able to generate built-up and non-built-up image objects; see Figure 6-2. The segmentation results show that non-built-up areas adjacent to built-up areas were accurately separated from built-up areas. The segmentation parameters also created image objects that represent different human settlement types. Some of the open spaces within settlements were separated from the residential area. There were, however, a few cases where open spaces objects were merged within residential areas image objects. The image objects in industrial and primarily commercial areas contained individual building structures since the building structures have clear contrast from the surrounding areas.



(a) (b)

Figure 6-2: Level 1 multiresolution segmentation results over SPOT 7 images (**a**) and Level 2 multiresolution segmentation results over SPOT 7 images (**b**)

The Level 2 multiresolution segmentation separated impervious surface, soil, and vegetation image objects. However, impervious surfaces, such as roads and building structures in industrial areas and in low-density settlements, experienced oversegmentation. Oversegmentation in low-density formal settlements may be attributed to the different orientations of the building structures. Undersegmentation was observed in informal settlements where more than one building structure was merged into one image object.

6.5.2 Classification results

The OBIA ruleset-based classification method that uses GLCM dissimilarity texture successfully classified built-up areas from non-built-up land cover classes, Figure 6-3 and Table 6-2. The major roads were successfully classified as built-up areas. Some areas with bare soil without building structures were classified as built-up areas. Image objects formed in such areas had apparent contrast differences from the surrounding non-built-up areas. Some open-space image objects with small human settlement segments were classified as non-built-up areas. Non-built-up areas are primarily found in the bottom left of the study area.

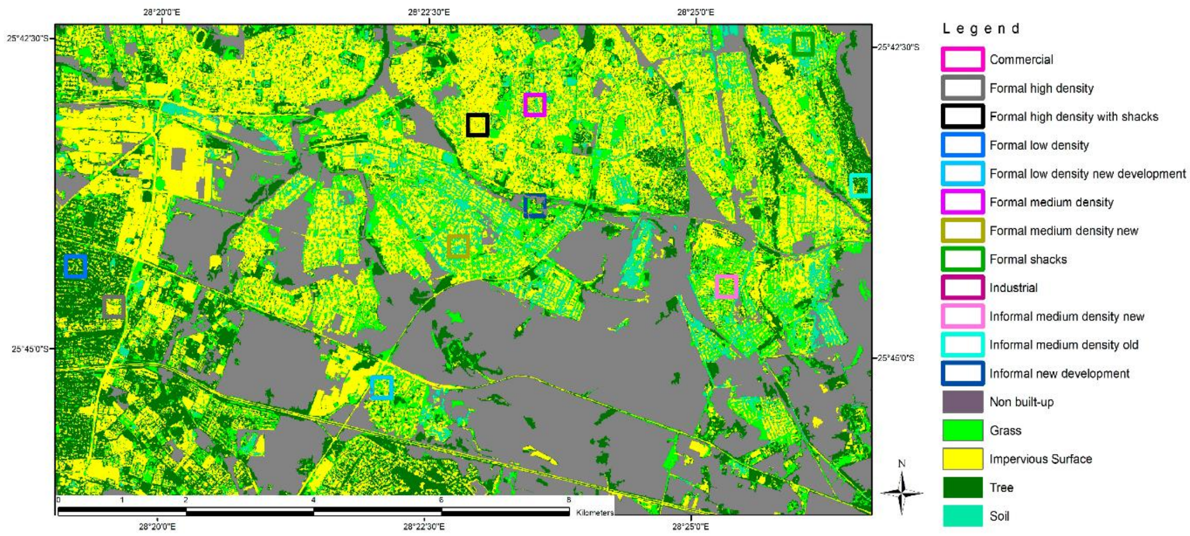


Figure 6-3: Classification results and the location of assessed settlements

Table 6-2: Producer and user accuracies achieved during classification

Class	User accuracy %	Producer accuracy %
Impervious surface	97.9	94.4
Soil	87.2	82.8
Trees	89.7	98.6
Grass	66.6	63.6

The use of Pantex and dissimilarity texture was able to distinguish building structures from vegetation and soil because building structures in the study areas contain a clear contrast from the surrounding land use classes. The use of SAVI was able to separate trees from the grass class. The separation of bare soil and vegetated areas was successfully achieved using the iron index. The results show that the built-up areas on the bottom left of the study area contained higher tree coverage than the other built-up areas. In contrast, the rest of the built-up areas in the middle and top of the study area contain a higher percentage of impervious surface; see Figure 6-3. The soil class can be seen mainly from the centre to the left and top right corner of the study area.

An overall accuracy of 91.1% was achieved in classifying trees, grass, impervious surface, and soil cover; see Table 6-2. The soil class achieved producer and user accuracies of less than 90% compared to the other classes. The error of omission in this class was found in the formal and informal settlements where gravel road segments were merged and classified as an impervious surface class or vegetation class.

The grass class achieved poor accuracy compared to other classes. Some of the grass objects were misclassified as trees. Some of the grass image objects were classified as trees. Some of the grass segments were misclassified as open spaces. Some of the building structures in informal settlements were not classified as impervious surfaces but misclassified as soil. That may be attributed to the fact that some of the dwelling structures in informal settlements are small structures and were merged with the soil image objects.

6.5.3 Assessment of Biophysical Characteristics

The spatial distribution of the assessed human settlement types over LST and vegetation moisture is shown in Figure 6-4 and Figure 6-5.

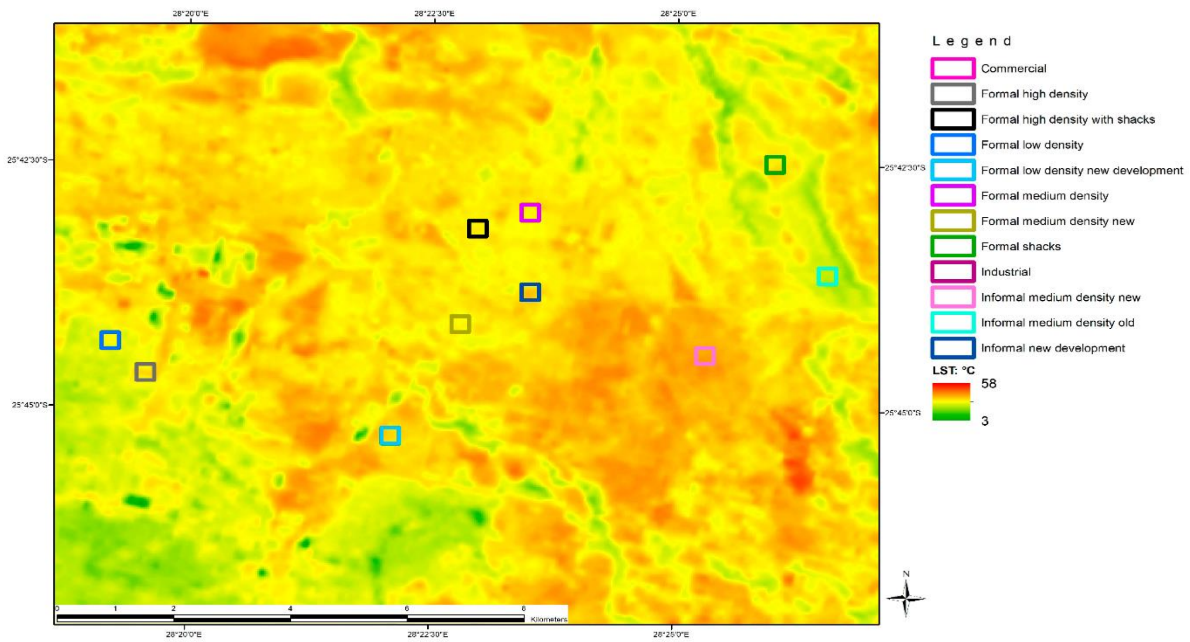


Figure 6-4: Spatial distribution of the different settlement types over the LST layer

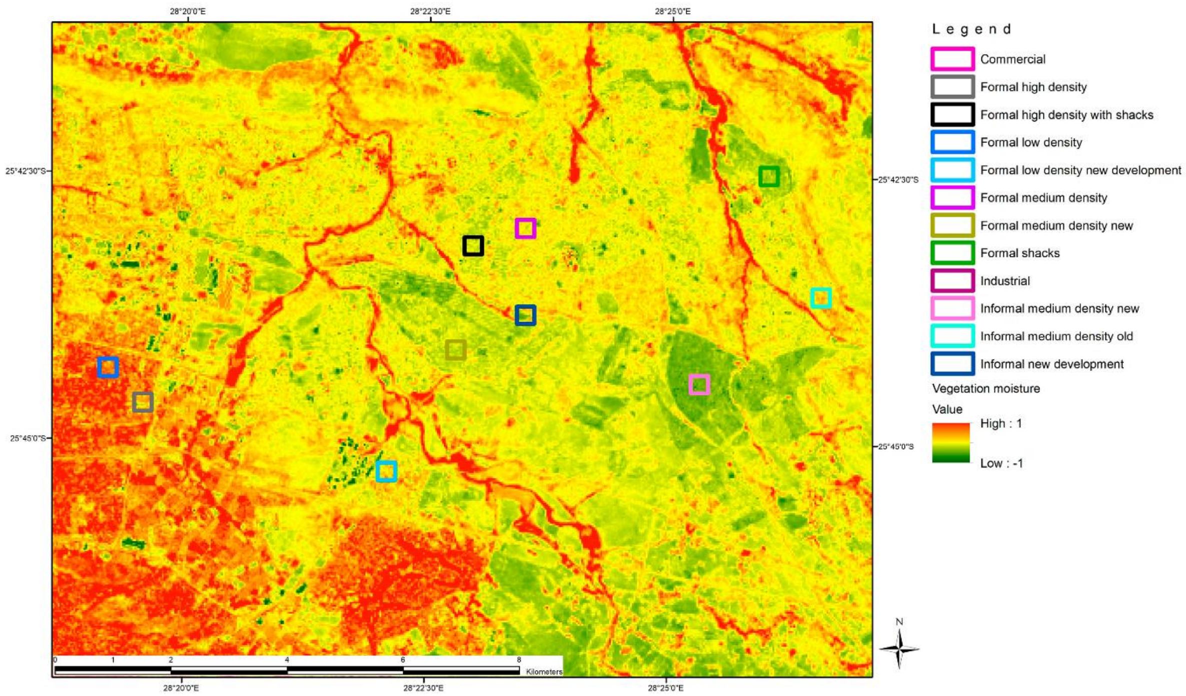


Figure 6-5: Spatial distribution of assessed settlement types over vegetation moisture layer

The medium-density informal settlement experienced the highest LST of over 40 °C, and the old medium-density informal settlement experienced the lowest LST of 34 °C compared to other formal and informal settlement types; see Figure 6-4. The lower LST in such an area may be attributed to the settlement located next to the mountain (Peng et al., 2020). The formal settlements experienced LST of 36-39 °C on the assessment day. The low-density formal settlement with high tree cover experienced the lowest LST, while the formal low-density new development experienced the highest LST. The LST in industrial areas was 1 °C higher than in commercial areas.

Table 6-3: Proportions and values of biophysical characteristics assessed during the study.

Settlement type	**LST _mean**	**Soil %**	**Vegetation Moisture**	**Impervious Surface %**	**tree %**	**grass %**
Commercial	36,90	0	0,00	77	19	3
Industrial	38,67	0	-0,02	90	4	6
Formal high-density with shacks	38,31	1	-0,07	91	2	5
Formal medium density	37,88	16	-0,05	66	6	11
Formal shacks	38,70	48	-0,09	43	1	7
Old informal medium density	34,41	0	-0,02	31	63	6

Informal medium-density new development	42,67	3	-0,14	47	8	42
Formal low density	36,05	1	0,07	24	69	5
Formal low-density new development	39,16	3	-0,03	53	8	37
Formal medium-density new development	37,76	46	-0,08	49	0	4
Formal high-density (clusters)	37,81	3	0,00	65	23	8
Informal new development	39,77	3	-0,06	17	47	33

The vegetation moisture was very low in all the settlement types, with values lower than 0.1; see Figure 6-5 and Table 6-3. The settlements with the highest tree cover experienced the highest vegetation moisture of 0.07 compared to other settlement types.

The results show that the informal settlement class comprised less than 50% of the impervious surface, with new medium-density informal settlements containing the highest impervious surface cover of 49%. In comparison, the new informal settlements development contained the least impervious cover of 17%. The tree cover in informal settlements varied from 8% to 63%, with old informal settlements having the highest tree cover while the new medium-density informal settlement contained only 8% of tree cover. The soil cover in the informal settlements was extremely low, with a maximum cover of only 3%. The grass cover varied from 6% to 42%, with medium-density informal settlements having the highest grass cover compared to other informal settlement types.

Table 6-4 shows the normalized values of the assessed parameters. The normalized values were used to calculate the SSEI.

Table 6-4: Normalized classification and mapping results

Settlement type	LST	Vegetation Moisture	Soil	Impervious Surface	Tree	Grass
Commercial	0,30	0,00	0,66	0,81	0,28	0,28
Industrial	0,52	0,00	0,59	0,99	0,06	0,06
Formal high-density with shacks	0,47	0,00	0,30	1,00	0,03	0,03
Formal medium density	0,42	0,33	0,42	0,66	0,09	0,09
Formal shacks	0,52	1,00	0,20	0,35	0,01	0,01
Old informal medium density	0,00	0,00	0,59	0,19	0,91	0,91
Informal medium-density new development	1,00	0,06	0,00	0,41	0,12	0,12
Formal low density						
Formal low-density new	0,20	0,02	1,00	0,09	1,00	1,00
development	0,58	0,06	0,54	0,49	0,00	0,12
Formal medium-density						
new development	0,41	0,96	0,25	0,43	0,00	0,00
Formal high-density						
(clusters)	0,41	0,06	0,67	0,65	0,33	0,33
Informal new						
development	0,65	0,06	0,37	0,00	0,68	0,68

The low-density formal settlements had the highest composition of tree cover, 69%, compared to other settlement types. In contrast, medium formal density with backyard shacks and formal settlements with shacks had the lowest composition of trees. The soil cover was low in formal areas except in new formal density and formal settlements, with shacks with 46% and 48% cover. The impervious surface cover in formal settlements ranged between 24 and 91%. The low-density formal with a high cover of trees had the least impervious surface cover. The formal medium density with shacks had the highest impervious surface cover. Industrial areas had the second highest impervious surface cover of 90%, while the commercial area had the most impervious surface cover of 77%. Industrial and commercial areas had zero soil cover, with 10% and 22% vegetation, respectively.

6.5.4 Assessment of Settlement Surface Ecological Index (SSEI)

The status of urban surface ecology is good in low-density formal settlements compared to other settlement types; see Figure 6-6. The assessment of SSEI in informal settlements in the study areas varies according to the composition of the biophysical characteristics. The old medium-density informal settlement with a high cover of trees is in a better condition than the new medium-density informal settlement with a very low coverage of trees.

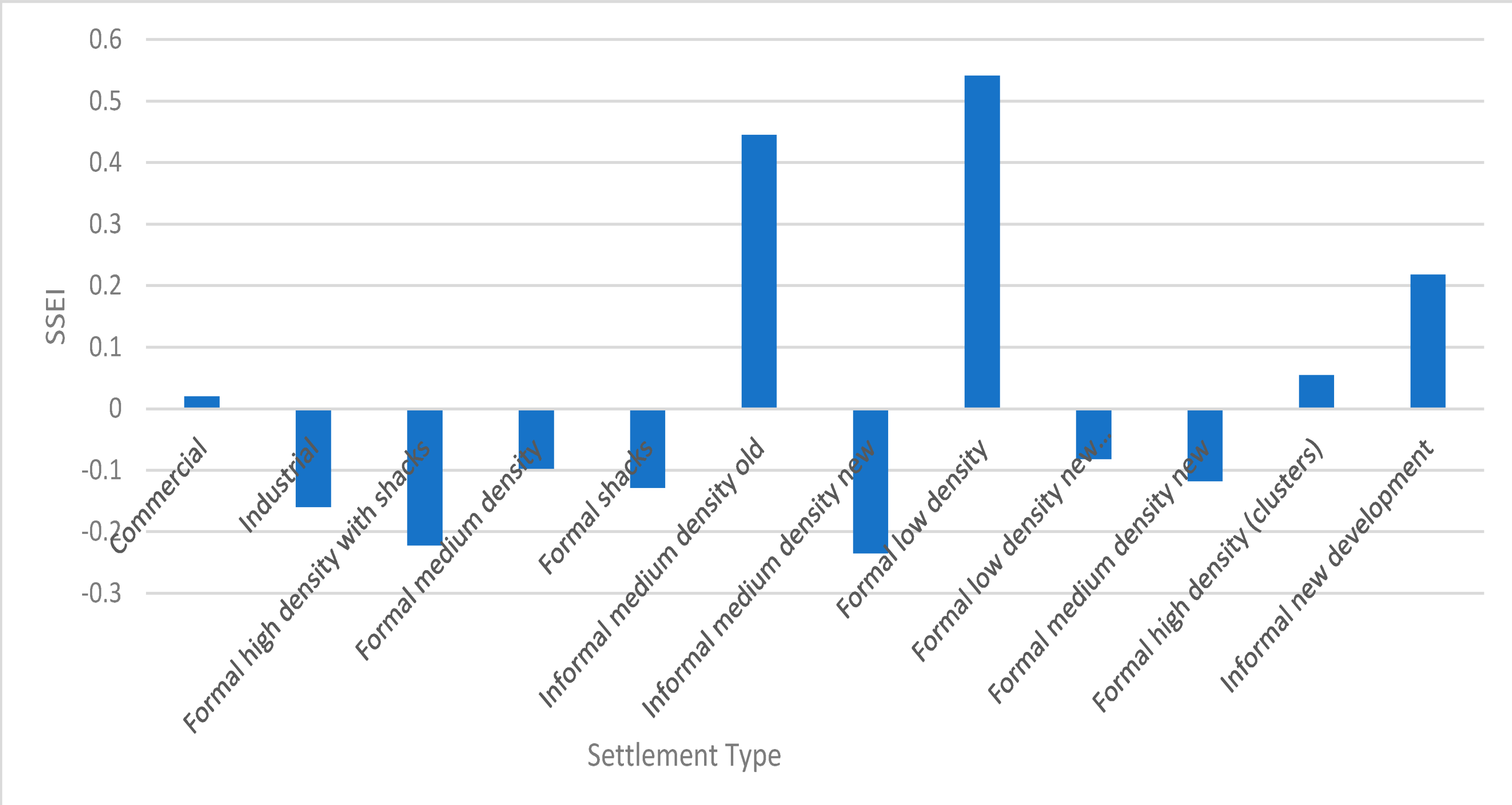


Figure 6-6: SSEI values of different settlement types

Commercial area and formal medium-density clusters have the lowest positive SSEI values. All other settlement types have negative SSEI values, with the formal settlement with backyard shacks and new informal settlements having the worst ecological condition. Grass cover and soil cover have an insignificant negative correlation with the SSEI. Since moisture cover is positively correlated with tree cover, the results show that increasing the coverage of trees can improve the ecological conditions of the settlements, reduce surface temperature, reduce soil erosion, and reduce the impact of flooding.

6.6 Discussions

The condition of surface ecology is influenced by the physical, chemical, and biological characteristics of the area of interest and is affected by natural processes and land use activities. Several studies have assessed the ecological conditions of cities using VIS and RSEI extracted from medium spatial resolution images. The studies show that impervious surface cover affects the quality of the condition of surface ecology, with higher cover resulting in unhealthy surface ecological conditions (Li et al., 2021; Yue et al., 2019). These studies generated information that can support initiatives to manage and improve urban ecosystems at the city level. This study demonstrated that using biophysical parameters derived from high and medium spatial resolution images provides detailed information on the surface ecological conditions of different settlement types. The study shows that the surface ecological condition varies from one informal settlement to another.

The results show that informal settlements with lower impervious surface and high tree cover have better ecological conditions than those with lower vegetation cover. The same trend was seen in formal settlements. This is well aligned with the previous studies that assessed ecological conditions using RSEI using medium spatial resolution conditions (Firozjaei et al., 2020; Li et al., 2021). The results show that some of the formal settlements have unhealthy environmental conditions than some of the informal settlements. Such areas have higher impervious surface cover and lower tree cover. The assessment of the results shows that settlements with higher tree cover have better ecological conditions than those with higher grass cover. Informal settlements with higher grass cover and higher impervious surface were at an unhealthy surface ecological state compared to other assessed informal settlements. Further investigation on the impact of classifying grass from trees on SSEI needs to be conducted. The assessment of the index at different informal settlement types has the potential to provide valuable information that can be incorporated during the planning of upgrade projects. High spatial resolution imagery and information on the location of informal settlements are not always available and may be a limitation in assessing this index in certain countries or cities.

6.7 Conclusions

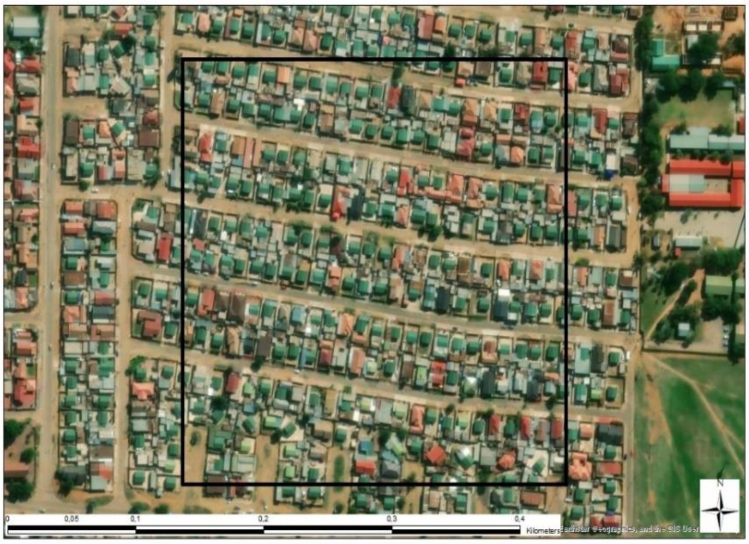
The study assessed the surface ecological conditions of informal settlements. The analysis of impervious surface, tree and grass cover, LST, and vegetation moisture provides valuable information on the environmental vulnerability of informal settlements and other settlement types. The results achieved in this study can be used to develop green strategies suitable for the different informal settlements to improve wellbeing. The results can also be used to develop disaster management strategies to reduce the impact of disasters on informal settlements. In addition, the information provided in this study can be used as input during the planning of informal settlement upgrade projects to ensure that the planning of services takes into account the need to reduce the environmental vulnerability of the settlements. As urbanization and the effects of climate change continue to be challenges for many city authorities, addressing the environmental challenges of informal and formal settlements is key to achieving sustainable development. The developed index contributes to ongoing research to build resilient settlements and offers practical measurements that can be used as the foundation for further work to understand the resilience of the cities.

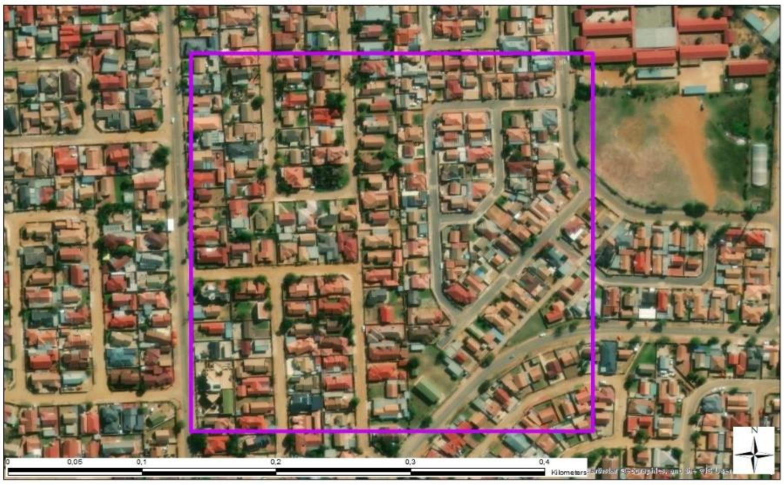
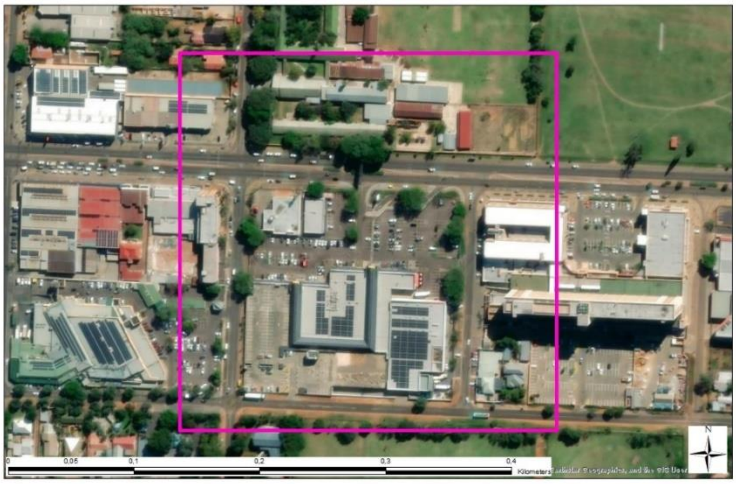
APPENDIX A : List of settlement types assessed during the study

Settlement Type	Description	Picture
Old, informal medium density	Medium-density informal settlements with trees	
Informal medium density, new	Less than five-year-old informal settlement with medium building density	

Informal settlement density, new development	New, informal settlement developments, less than a year old	
Formal low density	Old suburb with a low building density of single- or double-story houses and big yards	

Formal low-density, new development	New development of formal low building density	
Formal medium density (cluster)	A formal medium building density where dwellings have private grounds within a common ground of other dwellings, located in a suburb	

Formal medium density with backyard shacks	Formal townships with medium building density, located beyond the city limits, with backyard shacks	
Formal shacks	Serviced informal settlement, located in a township. Majority of the structures are shacks	

Formal medium density	Formal townships with medium building density located beyond the city limits	
Formal medium density, new	Formal medium building density, less than five years old	
Commercial	A non-residential built-up surface area used to conduct commerce, and other areas. The selected area is located outside the central business district (CBD)	

Industrial	A non-residential built-up surface area used for manufacturing or processing of products	

Chapter 7 ASSESSMENT OF LOCATION INFORMAL SETTLEMENT GROWTH AND LOCATION CHARACTERISTICS OF INFORMAL SETTLEMENTS

Abstract

This study assessed the growth of the informal settlements and their location characteristics between 2015 and 2020 in a densely populated township. The mapping of informal settlements was done using very high spatial resolution satellite images and the Object-Based Image Analysis (OBIA) technique that uses asymmetry of sub-objects. The location characteristics assessed were slope and proximity to water bodies, major transport infrastructure, mining activities, industrial areas, formal areas, wetlands and flood inundation areas. The results show the aerial extent of informal settlements in the study area almost tripled between 2015 and 2020. The assessment of location characteristics of informal settlements in the study area shows that in 2015, informal settlements were in gentle to strong steep slopes and within 100m of all assessed land cover and land use features with a higher extent of the informal settlements located closer to formal settlements. In 2020, the extent of informal settlements located on a steep slope more than tripled and a smaller extent of informal settlements developed was located within 100m of the flood inundation. The higher extent of informal settlements continued to develop closer to formal settlements, railways lines and rivers in 2020. The information derived in this study can be used to understand the informal settlement growth and location characteristics of informal settlements. This information can be used as input during the development of strategies to better manage informal settlements and during the planning of informal settlement upgrade projects.

Keywords: Informal settlements; WorldView; location characteristics

7.1 Introduction

Informal settlements or slums remain a challenge for many developing countries. These settlements lack access to basic services such as water and sanitation, security of tenure and sufficient living space, are located in environmentally sensitive areas and lack or have poor durability of the dwelling structures (UN-Habitat, 2004). Even though a lot of progress has been achieved toward improving the livelihood of people living in informal settlements through the implementation of the Millennium Development Goals, the absolute number of people living in informal settlements increased from 689 million to 883 million between 2000 and 2014 (United Nations, 2015). More than 1 billion people lived in informal settlements or slums in 2018 (UN-Habitat, 2018a). More than 80% of the informal settlement dwellers lived in Eastern, South-Eastern Asia, Central and Southern Asia and South-Saharan Africa in 2020 (United Nations, 2021). Future urbanization is expected to take place mostly around cities and towns in developing countries around Asia and Sub-Saharan Africa (United Nations, 2021). While urbanization is linked to human capital and economic development, urbanization in developing countries results in increased inequality, overloaded infrastructure and proliferation of informal settlements (Arouri et al., 2014).

Rapid urbanization remains a challenge in many developing countries including South Africa with more than 60% percent of the population living in urban areas in 2011 (South African Cities Network, 2022). According to Statistics South Africa, the number of people living in urban areas in South Africa increased by 10 % between 1996 and 2011. Rapid urbanization puts enormous pressure on the urban environment, especially around the cities. Urbanization in South Africa can be attributed to population growth and the abolishment of pass laws and restrictions of influx of black population into the cities (Ogura, 1996) which resulted in the rapid development of informal settlements. The backlog of housing delivery, lack of affordable rental and higher migration rates to cities are among some of the factors contributing to the increased development of informal settlements. Living conditions in informal settlements are below acceptable levels (Hofmann et al., 2008) with high levels of poverty, crime and violence (Kohli, Sliuzas, et al., 2016; South African Cities Network, 2022). Informal settlements are usually developed in areas that are not surveyed for human settlement development. Consequently, these settlements are located in environmental risk areas and also contribute to environmental degradation (South African Cities Network, 2022).

Information on the extent of informal settlements is not always up to date. This might be attributed to the fact that informal settlements are illegal (UN-Habitat, 2004) and are not part of urban or municipal plans except during the upgrade process (Isandla Institue, 2014). The reliance on ground surveys also contributes to the temporal gap of informal settlement data (Statistics South Africa, 2022). In addition, little information is known about the factors that influence the development of informal settlements in certain geographic locations. Limited studies have investigated the environmental and socioeconomic factors that attribute to the development of informal settlements in certain areas through empirical methods (John-Nsa, 2021; Takyi et al., 2021). These studies have concluded that the decision to settle in certain informal settlements is influenced by several factors including environmental and socio-economic factors.

To close the data gap on informal settlements, several studies have investigated the use of remote sensing to detect informal settlements the extent of informal settlements (Fan et al., 2021; Hofmann et al., 2001; Kuffer & Barros, 2011; Mudau & Mhangara, 2021a). The success of the developed methodologies varies from one region to the other and in certain areas within a city due to the varying physical characteristics of informal settlements (Fallatah et al., 2019a; Mudau & Mhangara, 2021a). Consequently, limited studies have assessed the informal settlement growth patterns using remotely sensed data (Fallatah et al., 2022; Mudau & Mhangara, 2022).

Few studies have assessed locations characteristics of informal settlements. The study done by Takyi et al, 2021 concluded that majority of informal settlements in Kumasi, Ghana, are closer to central business district (CBD) whereas few are located closer to water bodies and on steep slopes (Takyi et al., 2021). In Kisumu, Kenya, most of the informal settlements are located in flood-prone areas closer to farmlands and highways whereas, in Ahmedabad, informal settlements are mainly located closer to the major transport infrastructure, lakes and rivers (Kohli et al., 2012). Vacant land accessible without restriction has been found to influence the location of informal settlements more than other location-driving factors in Nairobi (Githira, 2016); Dar es Salaam (Abebe & Sliuzas, 2011); and Sancaktepe, Istanbul (Dubovyk et al., 2010). Proximity to water bodies and railway lines has been found to positively influence the development of informal settlements in Enugu City, Nigeria (John-Nsa, 2021) and in Dar es Salaam (Abebe & Sliuzas, 2011). Informal settlements have been found to develop in low-slope terrain in Sancaktepe, Instabul (Dubovyk et al., 2010) while in other cities informal settlements are on both gentle and steep slopes (Sirueri, 2015). In certain areas, the new informal settlement developments are observed on steeper slopes than on gentle slopes (Han et al., 2017). This shows that the location characteristics of informal settlements vary from one city to the other. to the other. Human activities undertaken by informal settlement dwellers can contribute to land degradation and water pollution depending on the locations (Darkey & Donaldson, 2000; Mahabir et al., 2016; Takyi et al., 2021).

There is, therefore, a need to assess land used as informal settlements to understand the location characteristics of informal settlements. Assessing the location characteristics can help identify infrastructure and services required by informal settlements. This study assesses the spatial growth of informal settlements between 2015 and 2020 and analyses the location characteristics of informal settlements in Mamelodi township, City of Tshwane, South Africa. The study contributes toward understanding the location characteristics of informal settlements using satellite images and Geographic Information System (GIS). Understanding the informal settlement growth and spatial location of informal settlement developments is crucial for the provision of services and mitigation of health, fire, flood and other natural and manmade disasters.

7.2 Study area

The study area is located in Mamelodi township, City of Tshwane (CoT) metropolitan municipality, Gauteng Province, South Africa, Figure 7-1. The city had around 227 informal settlements in 2020 (Department of Cooperative Governance and the

Department of Traditional Affairs, 2020b; Mudau & Mhangara, 2022). Mamelodi township contains both formal and informal settlements and is one of the most underserviced townships in CoT with some of the settlements having the lowest access to services (Department of Cooperative Governance and the Department of Traditional Affairs, 2020b). The aerial extent of informal settlements in Mamelodi more than doubled between 2005 and 2020 with higher expansion rates in recent years (Mudau & Mhangara, 2022).

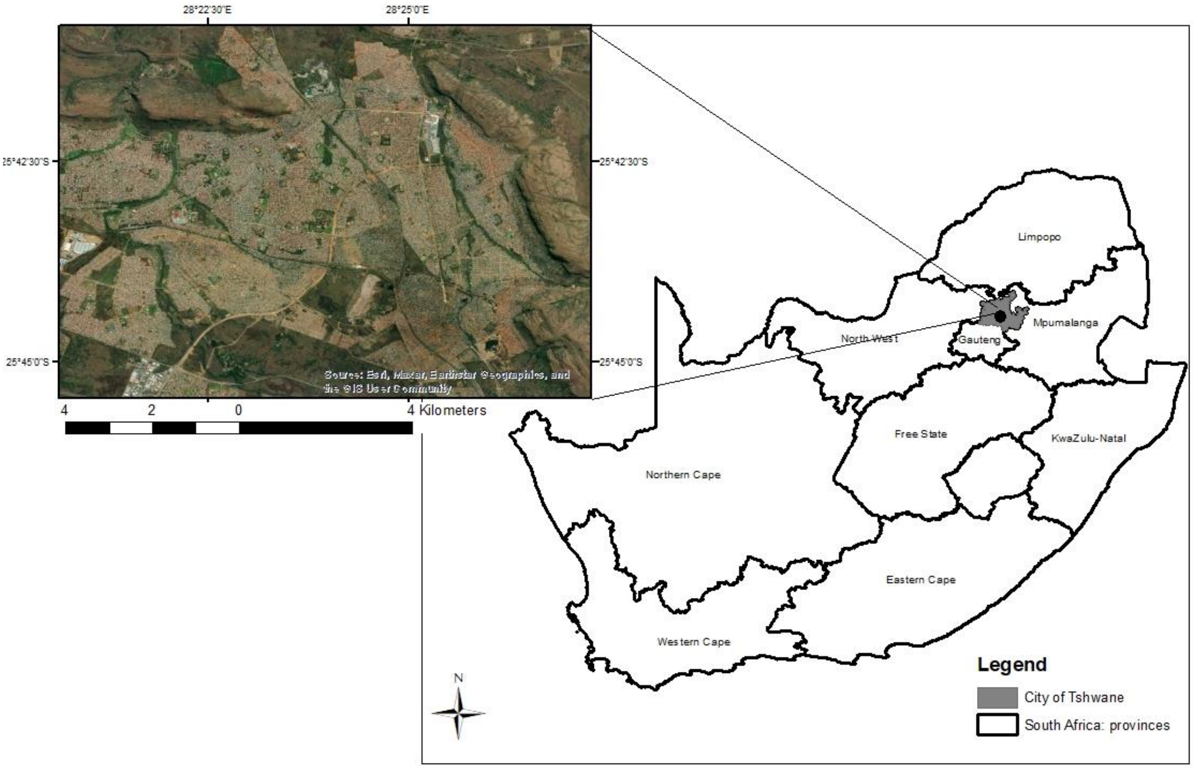


Figure 7-1: Location of the study area

7.3 Data and methodology

7.3.1 Data

WorldView 2 images acquired on 29 July 2015 and 06 May 2020 were used in this study. The WorldView 2 sensor acquires images in multispectral and panchromatic modes. The 8 bands multispectral images and 0.46 cm panchromatic images were used to detect informal settlements. The images were received georeferenced to a geographic coordinate system, WGS 84 Datum and WGS 84 Spheroid. The spectral and spatial specifications of the Worldview images are listed in Table 7-1.

Table 7-1: Spectral bands, spectral range and spatial resolution of Worldview 2 images

Spectral band	Spectral range (nm)	Spatial resolution
Panchromatic	450-800	0.46cm
Coastal blue	400-450	1.85m
Blue	450-510	1.85m
Green	510-580	1.85m
Yellow	585-625	1.85m
Red	630-690	1.85m
Red Edge	705-745	1.85m
Near Infrared 1	770-895	1.85m
Near Infrared 2	860-1040	1.85m

A 2020 Land cover dataset was used to extract land cover and land use features used in this study. The data was sourced from the Department of Forestry, Fisheries, and the Environment, accessed using https://egis.environment.gov.za. The 2020 land cover dataset was derived using Sentinel 2 images acquired in 2020 and contains 73 land cover and land use classes. The land use classes used are formal settlements, industrial areas mines and herbaceous wetlands.

The 30m SRTM was used to derive the slope of informal settlements. The SRTM DEM was sourced from United States Geological Services (USGS) using https://earthexplorer.usgs.gov/ website. The wetland and rivers Freshwater Priority Areas (FEPAs) datasets were sourced from South African National Biodiversity Institute and were used to assess the proximity of informal settlements to national strategic spatial priority for conserving freshwater. Major roads and railway lines were used to assess the proximity of informal settlements to transport infrastructure. The 1m flood inundation was sourced from the South African National Space Agency. The layer was developed using Height above Nearest Drainage.

7.3.2 Method

shows the workflow that was used to assess the location characteristics of informal settlements between 2015 and 2020.

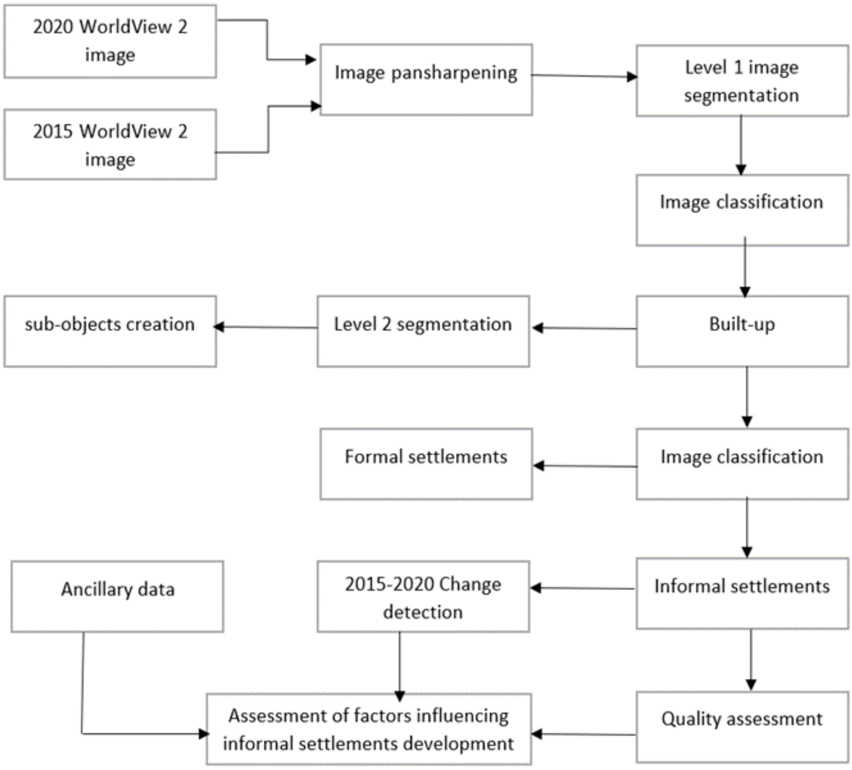


Figure 7-2: Workflow followed to assess the location characteristics of informal settlements.

7.3.2.1 Image classification

The images were pansharpened using Gram-Schmidt image fusion technique using ArcGIS software. This technique maximizes image sharpness and minimizes image distortion. Gram-Schmidt is the most robust pansharpening method than other image fusion techniques (Jawak & Luis, 2013; Maurer, 2013).

The detection of informal settlements was done using OBIA using Trible eCognition software. Unlike pixel-based classification, in addition to spectral information, OBIA uses contextual, textural and spatial characteristics of image objects during the classification process (Castilla & Hay, 2008). Pixel-based classification in urban areas suffers from spectral confusion resulting from land use features that exhibit similar spectral features and limited spectral bands (Moran, 2010). OBIA has been proven to increase land cover and land use classification results in urban environments (Myint et al., 2011).

The first step in OBIA classification method is image segmentation. The image segmentation process segments an image into meaningful image objects that will be used during classification. In this study, we used the multiresolution segmentation method to segment the image into desired image objects. The supervised segmentation method was used to determine the optimum segmentation parameters to generate desired image objects. Two segmentation levels, i.e., level 1 and level 2, were created. The level 1 image objects were created using scale parameter, shape and compactness values of 100, 0.1 and 0.5 respectively. These segmentation parameters created image objects that represented non built-up, formal and informal settlement land use features. These image objects were classified as built-up and non built-up areas using gray-level co-occurrence matrix (GLCM) dissimilarity textural features.

The level 2 image objects were created using the built-up area class created using level 1 image objects. The level 2 image objects were created by segmenting level 1 built-up class using scale parameter, shape and compactness values of 30, 0.1 and 0.5 respectively.

The classification of informal settlements was done using the asymmetry of level 2 image objects. Informal settlements are expected to contain greater angular variability and shorter length structures than formal settlements, therefore the texture based on the asymmetry of image objects in informal settlements is expected to be lower than that of formal settlements.

7.3.2.2 Quality assessment

Quality assessment of informal settlement classification was done by assessing manually selected informal settlement samples against the classification results using eCognition software (Definiens, 2007).

7.3.2.3 Assessment of the location characteristics of informal settlements

The assessment of the location characteristics of informal settlements was done in an ArcGIS environment using zonal analysis and intersection functions. The proximity analysis of informal settlements to rivers, water bodies, wetlands, herbaceous wetlands, 1m flood inundation, major roads, railway line and mining activities was done using 100m buffer of the features assessed. A buffer of 300m was used to assess the proximity of informal settlements to formal settlements. The analysis of the slope where informal settlements are located was done using the SRTM DEM values.

7.4 Results

7.4.1 Classification of informal settlements

The selected segmentation parameters for Level 1 were able to partition the image into image objects that represented built-up and non built-up land use classes, Figure 7-3 The selected parameters were also able to create open space, informal and informal settlement image objects. There were, however, few cases where informal settlement objects located adjacent to formal settlements were merged into one image object.

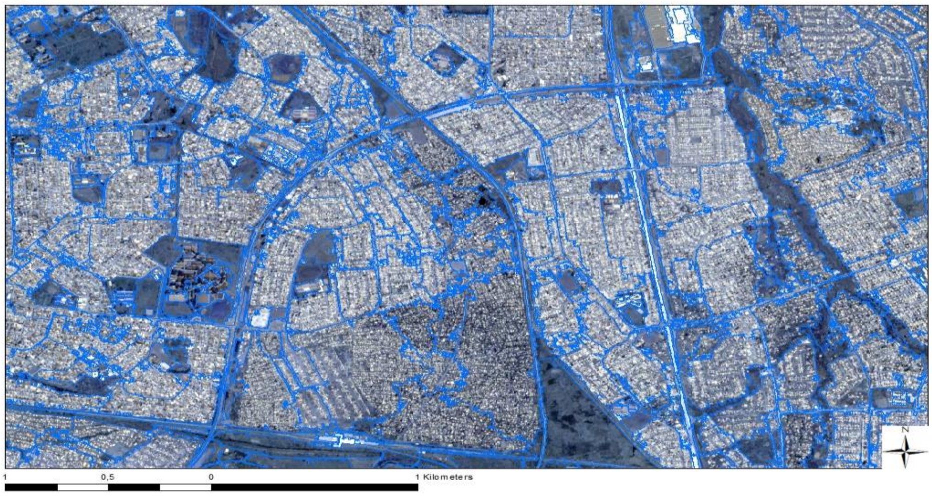


Figure 7-3: Zoom picture of Level 1 segmentation results over a 2020 panchromatic image

The classification results are shown in Figure 7-4. The results show that in 2015, the detected informal settlements were located in the north-eastern part of the township and around formal settlements covering a total area of 4.99 km^2. The land used as informal settlement increased to 12.06 km^2 in 2020, see Figure 7-4. More than 50% of the growth took place in the southern part of the study area. Some of the new informal settlements were developed on open spaces within formal settlements.

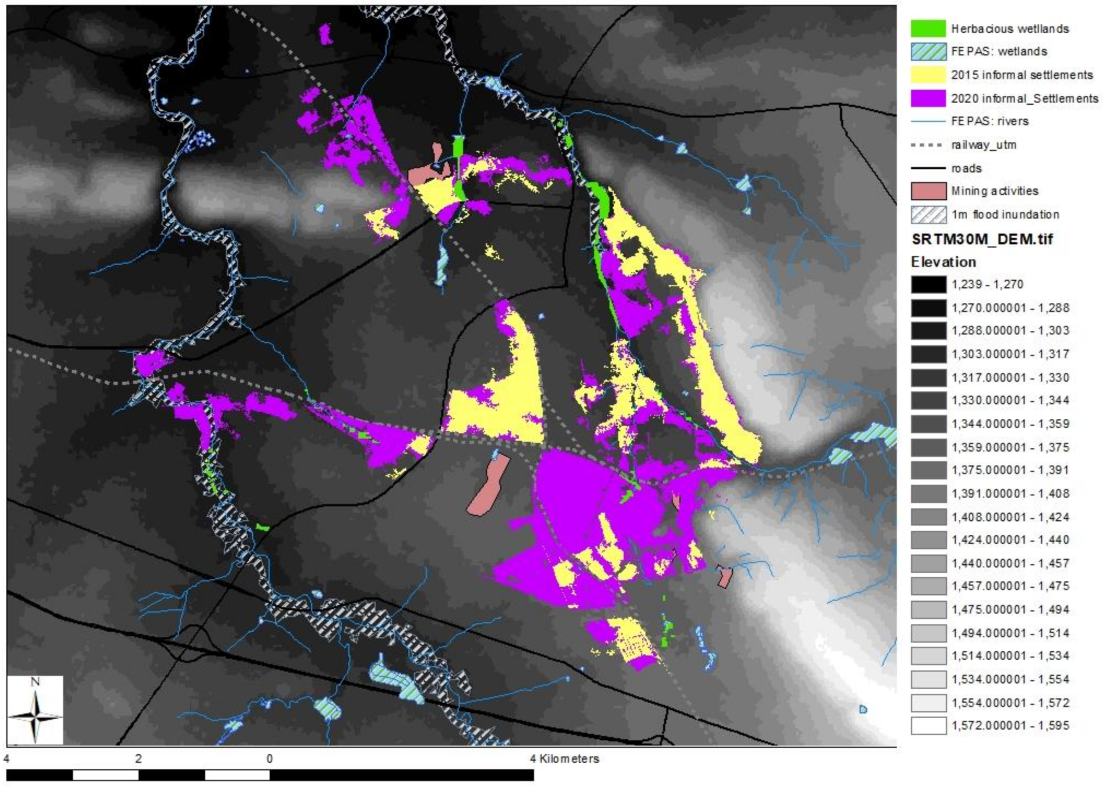


Figure 7-4: 2015 and 2020 informal settlement classification results, location of features and resources assessed.

7.4.2 Location characteristics assessment results

Table 7-2 lists the results of the location characteristics assessment of informal settlements in 2015 and 2020 In 2015, informal settlements were found at 1298 m-1400 m altitudes. The informal settlements at high altitudes are situated in the north-eastern part of the study area in both years, Figure 7-4. The informal settlement land in lower altitudes more than doubled between 2015 and 2020, with an aerial extent of 2.6 km^2 in 2020, representing 20% of the total informal settlement land. The new informal settlement development at lower altitudes can be seen in open areas around the formal settlements toward the western side of the study area. The percentage of informal settlement land located in steep terrain remained the same in 2020, however, the aerial extent more than tripled between 2015 and 2020.

Table 7-2: Spatial location of informal settlements assessment results

Land cover land use feature	Aerial extent of informal 2015 (km^2)	Aerial extent of informal 2020 (km^2)
Elevation		
1290 m-1320 m	0.10	1.8
1360 m-1447 m	1.40	3.94
Slope	1.4˚-37˚	0˚-26˚
Rivers	0.75	2.60
Water bodies	0	0
Wetland	0	0.1
Major roads	0.15	0.3
Railway lines	0.53	1.97
Mining	0.13	0.4
Herbaceous wetland	0.16	0.84
Industrial area	3.8 km-10 km	2.1 km-10 km
Formal settlements	3.8	6.85
1m flood inundation	0	0.25

The informal settlements in the study areas are in gentle to strong steep slope, ranging from 0˚-37˚ Figure 7-5. Most of the informal settlements are located at gentle slopes i.e. less than 9˚. In 2015 the informal settlements on strong steep slopes are located on the eastern side of the study area. Informal settlement growth was observed between 2015 and 2020 resulting in some informal settlements developing in strong steep slopes. This can be observed around the south-eastern part of the study area and towards the northern part of the study area.

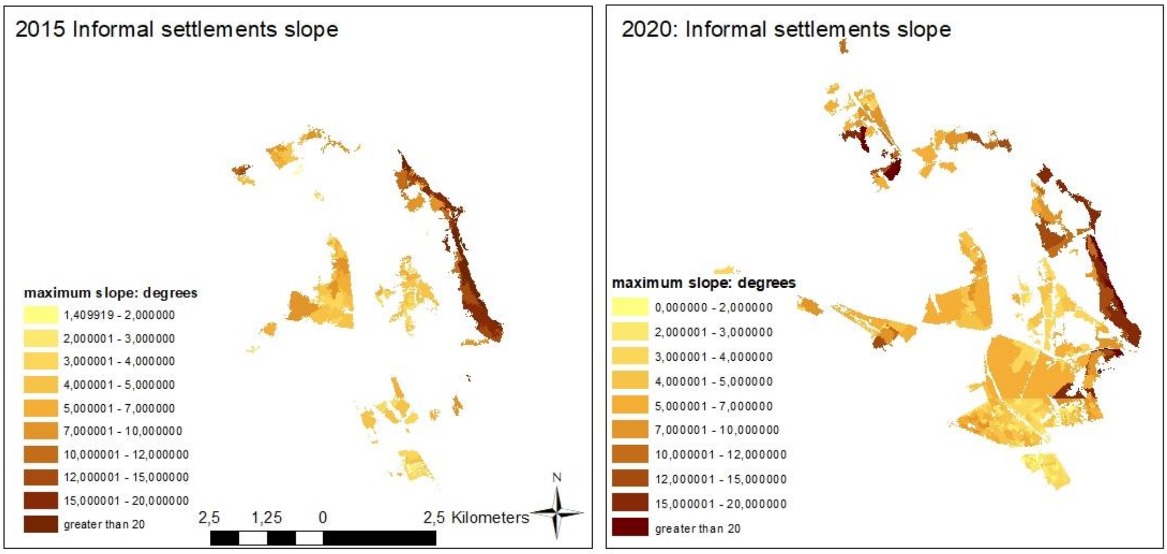


Figure 7-5: Location of informal settlements in 2015 and 2020 with corresponding slope values

In 2015, no informal settlement was located within a 1m flood inundation area, whereas in 2020, a land of 0.25 km of informal settlement was located within 1 m flood inundation area. Such areas have an altitude that ranges from 1290 m-1304 m.

Less than 10% of informal settlement land in the study area was located far away from NFEPA and herbaceous wetlands during the two years. Less than 1km^2 of informal settlement land was located within 100m of NFEPA rivers in 2015. However, in 2020, the area increased to 2.6 km^2. Less than 0.01 km^2 of the informal settlement land was located within 100 m of NFEPA wetlands compared to 0,1 km^2 in 2020. About 3% of informal settlement land was located within 100m of herbaceous wetland in 2015 compared to 6% in 2020. Developments of informal settlements along the rivers and wetlands can result in higher water pollution due to a lack of refuse collection and sanitation infrastructure (Darkey & Donaldson, 2000).

The assessment of the results shows that in 2015, more than 75% of informal settlement land was located within 300m of formal settlements. In 2020, just over half of the informal settlement land was located within 300 m of formal settlements. This shows that a significant amount of informal settlement land developed over five years was located far from formal settlements. These settlements are observed in the southern-eastern part of the study area.

The results show that the informal settlements in the study area are located far from the major transport infrastructure. More than 80% of informal settlement land was located more than 100m from the railway lines. The informal settlement development in the study area continued to develop further away from the railway line, with about 85% of informal settlement land located more than 100 m away from the railway line in 2020. Less than 3% of informal settlement land is located within 100 m of the major road infrastructure. Informal settlements are located between 2,1 km and 10 km of the major industrial areas and between 16km and 25km from the CBD.

7.4.3 Accuracy assessment

The 2020 informal settlement mapping achieved overall, user and producer accuracies of 93%, 83% and 95% respectively compared to 91%, 100% and 76% achieved during the 2015 mapping. The errors of commission can be observed in formalized settlements with shack building structures both in 2015 and 2020, while errors of omission can be found in some informal settlements that are merged with a small portion of formal areas.

7.5 Discussions

The study focused on assessing informal settlement growth and location characteristics of informal settlements over five years. The results showed that the aerial ex-tent of informal settlement more than tripled during the assessed period. The location characteristics analysis of the informal settlements indicated that informal settlements in the study area are located around roads, railway lines, mining activities, wetlands, rivers, formal built-up areas and on gentle to strong steep slopes. The analysis showed that there were no informal settlements closer to man-made water features. The aerial extent of informal settlements developed closer to the assessed features increased between 2015 and 2020 at varying extents. A larger extent of informal settlement land was developed on open spaces with level, gentle to strong steep slopes closer to formal settlements, rivers, and railway lines. A significant extent of informal settlement land was developed in areas that were more than 100m of formal settlements and railway lines. Even though a small extent of informal settlement land was developed closer to wetlands, mining activities and along the flood lines, there is a need to manage such areas to conserve the natural environment and to protect informal settlement dwellers from pollution and the impact of natural disasters such as floods.

Unlike informal settlements in cities such as Kumasi (Takyi et al., 2021), most of the informal settlements in the study areas were located far away from CBD, major commercial and industrial areas. The high extent of informal settlements was closer to existing residential areas as was the case in Nairobi and Dar es Salaam in the study done by Sirueri, 2015. Although access to available land and densification of structures were not assessed, the expansion of informal settlements took place on undeveloped vacant land. This is aligned with studies conducted by (Dubovyk et al., 2010; Githira, 2016; Abebe & Sliuzas, 2011). The high extent of informal settlements was closer to existing residential areas as was the case in Nairobi and Dar es Salaam in the study done by Sirueri, 2015.

7.6 Conclusions

The effective management of informal settlements requires an understanding of the location of informal settlements and the influence of location on development. The information on the spatial location of the informal settlement is collected using ground survey methods over a settlement targeted for an upgrade, leaving the rest of the in-formal settlements not surveyed since these settlements are not part of urban plans. The study demonstrated the use of remote sensing images and GIS to assess the spatial location of informal settlements. In this study, the proximity to formal settlements was identified as a neighborhood characteristic with the highest extent of informal settlements compared to other location characteristics. The availability of informal settlements along rivers, mining activities, lakes and wetlands highlights settlements at risk of air and water pollution, flooding and land degradation. The results achieved in this study can provide decision makers with the information required to effectively manage the environment, develop disaster management and informal settlement upgrade plans. Further studies could assess the relationship between morphological patterns and spatial location of the informal settlements.

Chapter 8 SYNTHESIS

The aim of the study is to investigate informal settlement dynamics and spatial characteristics to generate an understanding of housing informality and environmental conditions for designing innovative sustainable solutions.

Objective 1

To investigate settlement-based indicators to detect informal settlements from formal settlements using very high spatial resolution imagery.

The use of remote sensing technologies in the detection of informal settlements requires an understanding of the characteristics of informal settlements in areas of interest. This is attributed to the fact that informal settlements differ in characteristics from one geographic area to another and sometimes within a city. OBIA techniques integrate spectral, contextual and physical characteristics of informal settlements during the classification.

Chapter 3, therefore, investigated image proxies that can be used in OBIA to detect informal settlements in a densely populated township using WorldView 2 image. Most studies investigated the use of vegetation, the density of buildings, road surface and the tone of building structures and the pattern of land use objects to distinguish informal settlements from formal settlements. The image proxies investigated were vegetation, coastal blue, iron, road extraction and built-up indices and seven FOS and GLCM textural statistics. The results achieved in chapter 3 show that the built-up index and coastal blue index and FOS mean detected the informal settlements better than the other features. The use of these features produced higher overall accuracy of 89%. The use of NDVI and GLCM which have been widely used achieved poor results in the study area compared to other image features.

The three identified image features can potentially distinguish informal settlements in other areas with similar characteristics. The results show that most of the informal settlements in the study area have lower coverage impervious surface area than the surrounding area.

Objective 2

Assessment of informal settlement growth patterns using very high spatial resolution imagery.

Chapter 4 illustrates the use of high spatial resolution imagery and the OBIA technique in assessing the informal settlement growth patterns. Chapter 4 proposes the ratio of land consumption rate of informal settlements that uses informal settlement extent and impervious surface in informal settlements as a measure of land use efficiency of informal settlements. Even though the densification of building structures in formal areas is a positive land use activity, the higher density of structures in informal settlements increases disaster risks such as fire and as well as health risks. This measurement can be used to support reporting of SDG 11.1.1 or 11.3.1. Studies on the assessment of informal settlement growth focused on the assessment of growth extent than densification. Assessment of densification has been done using visual interpretation of aerial photography which is not always available. The study also demonstrated the use of OBIA and asymmetry sub-objects in the extraction of informal settlement extent which is one of the input data required during the computation of the proposed indicators.

Objective 3

Assessment of spatial pattern of informal settlement and backyard shacks using UAV products.

The spatial patterns of free-standing shacks in informal settlements and backyard shacks in formal areas assessed using landscape metrics are presented in chapter 5. The classification of free-standing shacks and backyard shacks was done through the use of height information derived from the very high spatial resolution DSM and DTM and orthophotos acquired by a UAV. The use of rule-based classification results in the classification of freestanding and backyard shacks yielded better classification results than the use of object-based RF method.

The assessment of the landscape metrics shows that the values of the shape metrics of backyards shacks are almost the same as those of the free-standing shacks, whereas the aggregation metrics of the two dwelling types are more distinct. The backyard shacks are less connected and more isolated compared to informal settlement dwelling structures. In addition, the density of informal dwelling structures was higher compared to the density of backyard shacks. The results achieved here show that the aggregation metrics have the potential to distinguish backyard structures from freestanding shacks than shape and landscape metrics. The results achieved here can be used to assess informality in formal areas and during the formalization of backyard rental in the townships.

Objective 4

Investigation of the surface ecological condition of informal settlements and other settlement types

Understanding the biophysical characteristics of urban areas is a prerequisite for adequate management of the urban ecological ecosystem. In Chapter 6 we present an SSEI which is derived using high and medium spatial resolution images. The SSEI uses six variables i.e. tree, soil, impervious surface and grass covers, LST and soil moisture to assess the surface condition of human settlements. The SSEI values range from 0 to 1 with 1 representing an excellent ecological condition and 0 representing a poor ecological condition. The results of the study show that 70% of the areas assessed had an SSEI of less than 0.2, which represents poor surface ecological conditions. Two of the settlements with the highest SSEI values were informal. The highest values of SSEI were achieved in settlement types with high to medium density of tree cover. The highest SSEI of 0.54 was found in low-density residential types with high-density tree cover. This was slightly higher than the SSEI of a medium-density informal settlement.

This study reveals that some of the formal settlements and new informal settlements are in very poor surface ecological conditions. This implies that the communities living in such areas may be vulnerable to heat-related diseases. The results show that there is a strong positive correlation between SSEI and tree cover and SSEI and soil moisture. The information presented in this chapter can be used to develop strategies to improve urban ecological ecosystems and during the implementation of urban greening strategies.

Objective 5
Assess the location characteristics of informal settlements

Understanding the location where informal settlements develop is crucial to managing their development and preventing the negative impact of informal settlements on the environment. In Chapter 7 we quantified the informal settlement growth in Mamelodi township, Gauteng province, South Africa and assessed the location characteristics of informal settlement developments. In Chapter 7 The location characteristics assessment was done by assessing the slope and proximity of informal settlements to the major transport infrastructure, water bodies, wetlands, economic opportunities, flood inundation area and formal settlements.

The study reveals that the extent of informal settlement more than tripled over five years. The informal settlements in the study area were located on gentle to strong steep slopes within 100 m of roads, railway lines, mining activities, wetlands, rivers and formal built-up areas. There were however no informal settlements located closer to man-made water bodies. Chapter 7 reveals a larger percentage of informal settlement developments was observed on open spaces with a level, gentle to strong steep slope closer to formal settlements, rivers, and railway lines, with a larger extent of informal settlement land developed next to formal settlements. The information presented in this study can be used to better manage informal settlement developments and during the planning of informal settlement upgrade projects. In addition, the results of the study can be used to identify areas that are likely to get flooded during heavy rains and to identify communities that may cause water pollution or alter the natural ecosystem.

Reflections

This research aimed to assess housing informality using high spatial resolution satellite imagery and UAV image products and to assess the environmental conditions of informal settlements. The first part of the aim of the research was achieved through the investigations of the image-derived proxies that are suitable for detecting informal settlements in Chapter 3 and Chapter 4. These chapters identified relevant image proxies suitable for informal settlement detection based on the local ontology in densely populated townships. Understanding the characteristic of informal settlements in different geographic areas is a requirement for developing robust methodologies to detect informal settlements from satellite imagery. The temporal analysis reveals that between 2000 and 2010 and between 2015 and 2020, the informal settlements in the study area experienced higher expansion rates than densification rates. In contrast, the low and negative ratio is attributed to the decline in impervious surface between 2010 and 2015.

The methodologies for the detection of the second form of housing informality, the backyard shack, were addressed in Chapter 5 by assessing the application of orthophotos, DTM and DSM acquired by UAV. In Chapter 5 OBIA, the rule-based classification approach has proven to perform better in the detection of backyard shacks compared to the Random Forest machine learning method. Further studies may include assessing the use of deep learning machine learning methods to detect housing informality using satellite imagery. Temporal UAV imagery may provide information to assess the rate of informality in formal areas.

The second part of the aim of the research was addressed in Chapter 6 and Chapter 7. In Chapter 6, the environmental condition of informal settlements was done by developing and assessing the settlement surface ecological index. Many studies in literature and efforts by local governments focus on generating information on the extent of informal settlements and land use information especially, the number of dwelling structures. The assessment of the surface ecological condition of informal settlements provides new information that can be used to understand the environmental condition of informal settlements. The study shows the environmental condition of informal settlements should not be generalized as the condition can vary according to the location and development stage of the settlement. In addition, formal settlements, especially those in townships, can be at the worst surface ecological conditions due to the high cover of impervious surface and low vegetation cover. Future research can investigate the integration of weather and atmospheric parameters in the settlement surface ecological index.

The management of informal settlements requires information on the growth patterns of informal settlements and the location where growth is taking place. Chapter 7 shows that, in addition to mapping the location and assessing informal settlement growth over time, the assessment of location characteristics over time provides unique important information that can be used to manage informal settlement development and to prioritize informal settlement upgrade projects. Chapter 6 and Chapter 7 demonstrated the use of satellite imagery and ancillary to understand the environmental conditions of informal settlements which have not been thoroughly investigated.

Key conclusions from this research are:

1. The OBIA classification technique that uses settlement-based indicators built-up index, coastal blue index and FOS mean can detect informal settlements from formal settlements in densely populated formal settlements using very high spatial resolution imagery.
2. The success of NDVI and GLCM which have been widely used in the detection of informal varies from one geographic area to the other.
3. Iron index derived from very high spatial resolution images can distinguish informal settlements from formal settlements better than NDVI and GLCM
4. Backyard shacks can be detected using Orthophotos, DTM and DSM acquired by a UAV
5. Object-based RF classification that uses estimated height and radiometric information yields poor less accurate classification techniques in backyard shack classification than the rule-based classification method.
6. UAV image products can be used to detect free-standing shacks and backyard shacks.
7. The aggregation metrics of free-standing shacks and backyard shacks are more distinct than shape and landscape metrics.
8. The surface ecological conditions of informal settlements vary according to the development stage of the informal settlements.

9. The surface ecological conditions of some of the formal settlements are poor compared to those of some of the informal settlements.
10. Most of the informal settlements in the study area are located on a level, gentle to strong steep slope, close to formal settlements, rivers, and railway lines.

Conclusion

Informal settlements in the study area can be detected using an OBIA approach, which integrates the built-up index, coastal blue index, and FOS mean derived from very high spatial resolution data. The extent of informal settlements more than quadrupled between 2000 and 2020. Notably, these settlements expanded with lower impervious density. The study reveals that informal settlements were developing even on steep slopes, particularly in proximity to rivers, railway lines, roads, and formal settlements during 2000-2022 period. Some formal settlements contain backyard shacks. The backyard shacks in the study areas are less connected compared to freestanding shacks. Additionally, the analysis indicates that certain informal settlements experienced lower LST and vegetation moisture levels on the day of assessment compared to specific formal settlements.

Limitation of the study

The study did not explore object-level indicators due to the unavailability of funds to procure 30cm spatial resolution imagery or drone imagery covering all informal settlements in the study area. The use of 30cm or higher spatial resolution may provide deep insights into settlement-level and object-level image proxies that can be used to detect informal settlements in the study area. Covering more than one township would have provided an opportunity to test the robustness of the developed OBIA approach in the city. Future work can test the transferability of the developed approach in other townships or cities in the country.

Additionally, there is a need to conduct field surveys and gather information on why people choose to stay in certain areas to add a social dimension to the spatio-temporal patterns results. There is also a need to test the developed OBIA methodology to detect backyard shacks over a different area to investigate the robustness its robustness in classifying backyard shacks from freestanding shacks.

The investigation of the detection of more land use classes formal and informal settlements using drone can improve the understanding of the physical characteristics of informal settlements and formal settlements with backyard shacks.

The lack of high spatial resolution multispectral data with a thermal band resulted in the analysis of informal settlements at a coarse scale. High spatial resolution remote surface temperature and vegetation moisture data can improve the understanding of the ecological conditions of informal settlements. Future work can also assess the ecological conditions derived in this study and gather field data on health and disaster vulnerability in the communities. More variables can be integrated to the settlement ecological index to improve the understanding surface ecological conditions of informal settlements and other settlements.

REFERENCES

Abebe, F., Sliuzas, J., 2011. Modelling informal settlement growth in Dar es Salaam Tanzania. Unpublished Msc thesis. University of Twente Faculty of Geo-Information and Earth Observation. https://doi.org/10.13140/RG.2.1.4392.7282

Abebe, M.S., Derebew, K.T., Gemeda, D.O., 2019. Exploiting temporal-spatial patterns of informal settlements using GIS and remote sensing technique: a case study of Jimma city, Southwestern Ethiopia. Environmental Systems Research 8. https://doi.org/10.1186/s40068-019-0133-5

Abunyewah, M., Gajendran, T., Maund, K., 2018. Profiling Informal Settlements for Disaster Risks, in: Procedia Engineering. Elsevier Ltd, pp. 238–245. https://doi.org/10.1016/j.proeng.2018.01.031

Adegun, O.B., 2021. Green Infrastructure Can Improve the Lives of Slum Dwellers in African Cities. Frontiers in Sustainable Cities 3. https://doi.org/10.3389/frsc.2021.621051

Aggarwal, N., Agrawal, R., 2012. First and Second Order Statistics Features for Classification of Magnetic Resonance Brain Images. Journal of Signal and Information Processing 03. https://doi.org/10.4236/jsip.2012.32019

Aina, Y.A., Adam, E., Ahmed, F., Wafer, A., Alshuwaikhat, H.M., 2019. Using multisource data and the V-I-S model in assessing the urban expansion of Riyadh city, Saudi Arabia. Eur J Remote Sens 52, 557–571. https://doi.org/10.1080/22797254.2019.1691469

Ajayakumar, J., Curtis, A.J., Rouzier, V., Pape, J.W., Bempah, S., Alam, M.T., Alam, M., Rashid, M.H., Ali, A., Morris, J.G., others, 2021. Exploring convolutional neural networks and spatial video for on-the-ground mapping in informal settlements. Int J Health Geogr 20, 1–17. https://doi.org/10.1186/s12942-021-00259-z

Al-Bilbisi, H., 2019. Spatial monitoring of urban expansion using satellite remote sensing images: A case study of Amman City, Jordan. Sustainability 11, 2260. https://doi.org/10.3390/su11082260

Anderson, B., Bell, M., 2009. Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiology. https://doi:org /10.1097/EDE.0b013e318190ee08

Ansari, R., Buddhiraju, K.M., 2019. Textural segmentation of remotely sensed images using multiresolution analysis for slum area identification. Eur J Remote Sens 52, 1–15. https://doi.org/10.1080/22797254.2019.1565419

Arouri, M., Youssef, B., Nguyen-Viet, C., Soucat, A., 2014. Effects of urbanization on economic growth and human capital formation in Africa Effects of urbanization on economic growth and human capital formation in Africa; Working Papers halshs-01068271.

Ashilah, Q.P., Rokhmatuloh, Hernina, R., 2021. Urban slum identification in Bogor Tengah Sub-District, Bogor City using Unmanned Aerial Vehicle (UAV) Images and Object-Based Image Analysis. IOP Conf Ser Earth Environ Sci 716, 12133. https://doi.org/10.1088/1755-1315/716/1/012133

Baatz, M., Schape, A., 2000. Multi resolution segmentation: an optimum approach for high quality multi scale image segmentation, in: Beutrage Zum AGIT-Symposium. Salzburg, Heidelberg, pp. 12–23.

Bank, L., 2007. The Rhythms of the Yards: Urbanism, Backyards and Housing Policy in South Africa. Journal of Contemporary African Studies 25, 205–228. https://doi.org/10.1080/02589000701396298

Belal, A.A., Moghanm, F.S., 2011. Detecting urban growth using remote sensing and GIS techniques in Al Gharbiya governorate, Egypt. Egypt J Remote Sens Space Sci. 14: 73–79. https://doi.org/10.1016/j.ejrs.2011.09.001

Bhatti, S.S., Tripathi, N.K., 2014. Built-up area extraction using Landsat 8 OLI imagery. GIsci Remote Sens 51, 445–467. https://doi.org/10.1080/15481603.2014.939539

Bolund, P., Hunhammar, S., 1999. Ecosystem services in urban areas. Ecol Econ. https://doi.org/10.1016/S0921-8009(99)00013-0.

Boori, M.S., Netzband, M., Choudhary, K., Voženilek, V., 2015. Monitoring and modeling of urban sprawl through remote sensing and GIS in Kuala Lumpur, Malaysia. Ecol Process 4: 1–10. https://doi.org/10.1186/s13717-015-0040-2

Borana, s. L., Vaishnav, A., Yadav, s. K., Parihar, S.K., 2020. Urban Growth Assessment Using Remote Sensing, GIS and Shannon's Entropy Model: A Case Study of Bhilwara City, Rajasthan. pp. 1–6. https://doi.org/10.1109/ICETCE48199.2020.9091771

Breiman, L., 2001. Random Forest. Mach Learn 45, 5–32. https://doi.org/http://dx.doi.org/10.1023/A:1010933404324

Castilla G. and Hay, G.J., 2008. Image objects and geographic objects, in: Blaschke Thomas and Lang, S. and H.G.J. (Ed.), Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 91–110. https://doi.org/10.1007/978-3-540-77058-9_5

Chaudhry, M.H., Ahmad, A., Gulzar, Q., 2020. Impact of uav surveying parameters on mixed urban landuse surface modelling. ISPRS Int J Geoinf 9. https://doi.org/10.3390/ijgi9110656

Chen, W., Wu, A.N., Biljecki, F., 2021. Classification of Urban Morphology with Deep Learning: Application on Urban Vitality. https://doi.org/10.1016/j

Chen, X., Sun, G., Wang, Z., 2015. A case study on the urban impervious surface distribution based on a BCI index, in: International Symposium on Multispectral Image Processing and Pattern Recognition. https://api.semanticscholar.org/CorpusID:130192599

Christopher, J., 2019. The science of rule-based classifiers, in: Proceedings of the 9th International Conference On Cloud Computing, Data Science and Engineering, Confluence 2019. Institute of Electrical and Electronics Engineers Inc., pp. 299–303. https://doi.org/10.1109/CONFLUENCE.2019.8776954

Center for International Earth Science Information Network - CIESIN - Columbia University, 2016. Documentation for the Gridded Population of the World, Version 4 (GPWv4), Revision 11 Data Sets. Palisades NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H4D50JX4

City of Tshwane, 2020. A City of Tshwane integrated development plan: revision for 2020/21 and service delivery and budget implementation (SDBIP) scorecard. Pretoria. https://www.tshwane.gov.za/?wpfd_file=proposed-revision-idp-for-2020-21-for-public-comments60079-4

City of Tshwane, 2018. 2017/18 Built Environment Performance Plan (BEPP). https://ia801005.us.archive.org/9/items/2018-

19_03_final_bepp_documents_tsh_city_of_tshwane_201819_bepp_e_implementation_v3-00_20180517_pdf/Documents/02.%20Built%20Environment%20Performance%20Plans/2018-19/03.%20Final%20BEPP%20documents/TSH%20City%20of%20Tshwane/201819_BEPP_E_Implementation_V3-00_20180517.pdf

Croce, S., Vettorato, D., 2021. Urban surface uses for climate resilient and sustainable cities: A catalogue of solutions. Sustain Cities Soc 75. https://doi.org/10.1016/j.scs.2021.103313

Dahiya, S., Garg, P.K., Jat, M.K., 2020. Automated Extraction of Slum Built-up Areas from Multispectral Imageries. Journal of the Indian Society of Remote Sensing 48, 113–119. https://doi.org/10.1007/s12524-019-01066-7

Darkey, D.&, Donaldson, 2000. Water pollution and community perceptions in Mamelodi, Pretoria. In : Proceedings of WISA 2000 Biennial Conference, Sun City, p. 28.

de Kadt, J., Hamann, C., Mkhize, S.P., Parker, A., 2021. Quality of Life Survey 6 (2020/21): Overview Report. Johannesburg. https://doi.org/10.36634/2021.db.1

de Pinho, C.M.D., Fonseca, L.M.G., Korting, T.S., de Almeida, C.M., Kux, H.J.H., 2012. Land-cover classification of an intra-urban environment using high-resolution images and object-based image analysis. Int J Remote Sens 33, 5973–5995. https://doi.org/10.1080/01431161.2012.675451

Definiens, 2007. Definiens Developer 7 Reference Book. https://vdocuments.mx/ecognition-reference-book.html?page=1

Department of Cooperative Governance and the Department of Traditional Affairs, 2020a. Profile: City of Tshwane. Pretoria. https://www.cogta.gov.za/ddm/wp-content/uploads/2020/08/2nd-Take_Final_DistrictProfile_TSHWANE2306-1-002.pdf

Department of Cooperative Governance and the Department of Traditional Affairs, 2014. COGTA Strategic Plan 2014-2019. https://www.cogta.fs.gov.za/wp-content/uploads/2012/07/STRAT-PLAN-2014-19-print2.pdf

Department of Environmental Affairs, 2016. South Africa Environment Outlook. https://www.dffe.gov.za/sites/default/files/reports/environmentoutlook_executivesummary.pdf

Devi, P.P., Lowry, J.H., Weber, E., 2017. Global environmental impact of informal settlements and perceptions of local environmental threats: An empirical case study in Suva, Fiji. Habitat Int 69, 58–67. https://doi.org/https://doi.org/10.1016/j.habitatint.2017.08.005

Drăguţ, L., Tiede, D., Levick, S.R., 2010. ESP: A tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. Int J Geogr Inf Sci 24, 859–871. https://doi.org/10.1080/13658810903174803

Dubovyk, O., Sliuzas, R., Flacke, J., 2010. Spatio-temporal analysis of informal settlements development: a case study of Istanbul, Turkey. ISPRS J. Photogramm. Remote Sens. 120(6). https://doi.org/10.1016/j.isprsjprs.2010.10.002

Duque, J.C., Patino, J.E., Betancourt, A., 2017. Exploring the potential of machine learning for automatic slum identification from VHR imagery. Remote Sens (Basel) 9. https://doi.org/10.3390/rs9090895

Eckstein, S., 1990. Urbanization Revisited: Inner-City Slum of Hope and Squatter Settlement of Despair, World Development 18(2). https://doi.org/10.1016/0305-750X(90)90046-Z

Esch, T., Thiel, M., Bock, M., Roth, A., Dech, S., 2008. Improvement of image segmentation accuracy based on multiscale optimization procedure. IEEE Geosci. Remote. Sens. Lett. 5, 463–467. https://doi.org/10.1109/LGRS.2008.919622

European Commission Joint Research Centre, 2018. Global Human Settlement Population Model (GHS-POP). https://ghsl.jrc.ec.europa.eu/ghs_pop.php

Fallatah, A., Jones, S., Mitchell, D., 2020. Object-based random forest classification for informal settlements identification in the Middle East: Jeddah a case study. Int J Remote Sens 41, 4421–4445. https://doi.org/10.1080/01431161.2020.1718237

Fallatah, A., Jones, S., Mitchell, D., Kohli, D., 2019a. Mapping informal settlement indicators using object-oriented analysis in the Middle East. Int J Digit Earth 12, 802–824. https://doi.org/10.1080/17538947.2018.1485753

Fallatah, A., Jones, S., Wallace, L., Mitchell, D., 2022. Combining Object-Based Machine Learning with Long-Term Time-Series Analysis for Informal Settlement Identification. Remote Sens (Basel) 14. https://doi.org/10.3390/rs14051226

Fan, Y., Ding, X., Wu, J., Ge, J., Li, Y., 2021. High spatial-resolution classification of urban surfaces using a deep learning method. Build Environ 200, 107949. https://doi.org/https://doi.org/10.1016/j.buildenv.2021.107949

Moran, E., 2010. Land Cover Classification in a Complex Urban-Rural Landscape with Quickbird Imagery. Photogramm Eng Remote Sensing 76, 1159–1168. https://doi: 10.14358/pers.76.10.1159.

Firozjaei, M.K., Fathololoumi, S., Weng, Q., Kiavarz, M., Alavipanah, S.K., 2020. Remotely sensed urban surface ecological index (RSUSEI): An analytical framework for assessing the surface ecological status in urban environments. Remote Sens (Basel) 12. https://doi.org/10.3390/rs12122029

Frankenhoff, C.A., 1967. Elements of an Economic Model for Slums in a Developing Economy. Econ Dev Cult Change 16, 27–36.

Gadiraju, K.K., Vatsavai, R.R., Kaza, N., Wibbels, E., Krishna, A., 2019. Machine learning approaches for slum detection using very high resolution satellite images, in: IEEE International Conference on Data Mining Workshops, ICDMW. IEEE Computer Society, pp. 1397–1404. https://doi.org/10.1109/ICDMW.2018.00198

Galeon, F., 2008. Estimation of Population in informal settlement communities using high resolution satellite image. XXI ISPRS Congress, Commission IV. Beijing.

Gallagher, J., Baldauf, R., Fuller, C.H., Kumar, P., Gill, L.W., McNabola, A., 2015. Passive methods for improving air quality in the built environment: A review of porous and solid barriers. Atmos Environ 120, 61–70. https://doi.org/https://doi.org/10.1016/j.atmosenv.2015.08.075

Gauteng City-Region Observatory, 2018. Backyard and informal dwellings (2001-2016); Gauteng City-Region Observatory; https://gcro.ac.za/outputs/map-of-the-month/detail/backyard-and-informal-dwellings-2001-2016/ (accessed 8.12.23)

Gefen, Y., Meir, Y., Mandelbrot, B.B., Aharony, A., 1983. Geometric Implementation of Hypercubic Lattices with Noninteger Dimensionality by Use of Low Lacunarity Fractal Lattices. Phys Rev Lett. https://link.aps.org/doi/10.1103/PhysRevLett.50.145.

Gevaert, C., Sliuzas, R., Persello, C., Vosselman, G., 2016. Opportunities for UAV mapping to support unplanned settlement upgrading. Rwanda Journal 1. https://doi.org/10.4314/rj.v1i1s.4d

Gevaert, C.M., Persello, C., Sliuzas, R., Vosselman, G., 2020. Monitoring household upgrading in unplanned settlements with unmanned aerial vehicles. International Journal of Applied Earth Observation and Geoinformation 90. https://doi.org/10.1016/j.jag.2020.102117

Gevaert, C.M., Persello, C., Sliuzas, R., Vosselman, G., 2017. Informal settlement classification using point-cloud and image-based features from UAV data. ISPRS Journal of Photogrammetry and Remote Sensing 125, 225–236. https://doi.org/10.1016/j.isprsjprs.2017.01.017

Gevaert, C.M., Persello, C., Sliuzas, R., Vosselman, G., 2016. Classification of informal settlements through the integration of 2D and 3D features extracted from UAV data. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences III–3, 317–324. https://doi.org/10.5194/isprsannals-iii-3-317-2016

Ribeiro, B.M., 2015. Mapping informal settlements using WorldView-2 imagery and C4.5 decision tree classifier, in: 2015 Joint Urban Remote Sensing Event (JURSE). pp. 1–4. https://doi.org/10.1109/JURSE.2015.7120470

Gibson, L., Adeleke, A., Hadden, R., Rush, D., 2021. Spatial metrics from LiDAR roof mapping for fire spread risk assessment of informal settlements in Cape Town, South Africa. Fire Saf J 120. https://doi.org/10.1016/j.firesaf.2020.103053

Girija, G., Nikhila, R., 2018. Slum extraction approaches from high resolution satellite data – A case study of Madurai city. nt.J. Pure. Appl. Math 119. 14509–14514.

Githira, D.N., 2016. Growth and eviction of informal settlements in Nairobi. Unpublished Msc thesis. University of Twente Faculty of Geo-Information and Earth Observation. https://essay.utwente.nl/83895/1/githira.pdf

Graesser, J., Cheriyadat, A., Vatsavai, R.R., Chandola, V., Long, J., Bright, E., 2012. Image Based Characterization of Formal and Informal Neighborhoods in an Urban Landscape. IEEE J Sel Top Appl Earth Obs Remote Sens 5, 1164–1176. https://doi.org/10.1109/JSTARS.2012.2190383

Gram-Hansen, B.J., Helber, P., Varatharajan, I., Azam, F., Coca-Castro, A., Kopackova, V., Bilinski, P., 2019. Mapping informal settlements in developing countries using machine learning and low resolution multi-spectral data, in: Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society. pp. 361–368.

Haase, D., Kabisch, S., Haase, A., Andersson, E., Banzhaf, E., Baró, F., Brenck, M., Fischer, L.K., Frantzeskaki, N., Kabisch, N., Krellenberg, K., Kremer, P., Kronenberg, J., Larondelle, N., Mathey, J., Pauleit, S., Ring, I., Rink, D., Schwarz, N., Wolff, M., 2017. Greening cities – To be socially inclusive? About the alleged paradox of society and ecology in cities. Habitat Int 64, 41–48. https://doi.org/https://doi.org/10.1016/j.habitatint.2017.04.005

Han, Y., Song, Y., Burnette, L., Lammers, D., 2017. Spatiotemporal analysis of the formation of informal settlements in a metropolitan fringe: Seoul (1950-2015). Sustainability (Switzerland) 9. https://doi.org/10.3390/su9071190

Hao, P., Geertman, S.C.M., Hooimeijer, P., Sliuzas, R. V, 2013. Spatial Analyses of the Urban Village Development Process in Shenzhen, China. Int J Urban Reg Res 37, 2177–2197. https://doi.org/10.1111/j.1468-2427.2012.01109.x

Haralick, R.M., Shanmugam, K., Dinstein, I.H., 1973. Textural features for image classification. IEEE Trans Syst Man Cybern 610–621. https://doi/org/10.1109/TSMC.1973.4309314

He, C., Peijun, S., Dingyong, X., Zhao, Y., 2010. Improving the normalized difference built-up index to map urban built-up areas using a semiautomatic segmentation approach. Remote Sens Lett 1, 213–221. https://doi.org/10.1080/01431161.2010.481681

Hegazy, I.R., Kaloop, M.R., 2015. Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. Int. J. Sustain 4, 117–124. https://doi.org/10.1016/j.ijsbe.2015.02.005

Ho, T. Van, Rao, P.J., 2016. Feature Selection Methods for Object-Based Classification of Tropical Forest Using Spot 5 Imagery. Jorsg 7, 41-49

Hofmann, P., others, 2001. Detecting informal settlements from IKONOS image data using methods of object oriented image analysis-an example from Cape Town (South Africa). Jürgens, C.(Ed.): Remote Sensing of Urban Areas/Fernerkundung in urbanen Räumen 41–42.

Hofmann, P., Strobl, J., Blaschke, T., Kux, H., 2008. Detecting informal settlements from QuickBird data in Rio de Janeiro using an object based approach, in: Object-Based Image Analysis. Springer, pp. 531–553.

Hofmann, P., Taubenböck, H., Werthmann, C., 2015. Monitoring and modelling of informal settlements - A review on recent developments and challenges, in: 2015 Joint Urban Remote Sensing Event, JURSE 2015. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/JURSE.2015.7120513

Housing Development Agency, 2012. South Africa: Informal settlements status http://www.thehda.co.za/uploads/files/HDA_Informal_settlements_status_South_Africa.pdf

Huang, Y., Zhuo, L., Tao, H., Shi, Q., Liu, K., 2017. A Novel Building Type Classification Scheme Based on Integrated LiDAR and High-Resolution Images. Remote Sens (Basel) 9. https://doi.org/10.3390/rs9070679

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens Environ 25, 295–309. https://doi.org/https://doi.org/10.1016/0034-4257(88)90106-X

Hund, J., Kotu-Rammopo, M., 1983. Justice in a South African township: the sociology of Makgotla. Comparative and International Law Journal of Southern Africa 16, 179–208.

Isandla Institue, 2014. Participatory informal settlement upgrading in South Africa. https://isandla.org.za/en/resources/item/download/146_9dbadd7c008d58eb3e9ae0cb46dd007b

Jain, S., 2007. Use of IKONOS satellite data to identify informal settlements in Dehradun, India. Int J Remote Sens 28, 3227–3233.

Jawak, S.D., Luis, A.J., 2013. A Comprehensive Evaluation of PAN-Sharpening Algorithms Coupled with Resampling Methods for Image Synthesis of Very High Resolution Remotely Sensed Satellite Data. Adv. remote sens 02, 332–344. https://doi.org/10.4236/ars.2013.24036

Jeevalakshmi, D., Reddy, S.N., Manikiam, B., 2016. Land cover classification based on NDVI using LANDSAT8 time series: A case study Tirupati region, in: International Conference on Communication and Signal Processing, ICCSP 2016. Institute of Electrical and Electronics Engineers Inc., pp. 1332–1335. https://doi.org/10.1109/ICCSP.2016.7754369

Jing, Y., Cui, J., Chen, Y., Ma, D. (Eds.), 2023. Towards sustainable urban development: Use of geographic big data for spatial planning. Frontiers Media SA, Lausanne, Switzerland. https://doi.org/10.3389/fenvs.2023.1202661

Jinli, L., Chen, J., Gao; Xianlian, Gao ; Zhongqiu, Sun; Zhao, 2019. Research on the method of determining the optimal segmentation scale for tree species classification of high-resolution image. Scientia Silvae Sinicae 55, 95–104.

John-Nsa, C., 2021. Understanding the factors influencing the spatial dynamics of informal settlements: The case of Enugu city, Nigeria. Town and Regional Planning 79, 29–43. https://doi.org/10.18820/2415-0495/trp79i1.5

Jovanović, D., Gavrilović, M., Sladić, D., Radulović, A., Govedarica, M., 2021. Building change detection method to support register of identified changes on buildings. Remote Sens (Basel) 13. https://doi.org/10.3390/rs13163150

Kakembo, V., van Niekerk, S., 2014. The integration of GIS into demographic surveying of informal settlements: The case of Nelson Mandela Bay Municipality, South Africa. Habitat Int 44, 451–460. https://doi.org/10.1016/j.habitatint.2014.09.004

Kemper, T., Mudau, N., Mangara, P., Pesaresi, M., 2015. Towards an automated monitoring of human settlements in South Africa using high resolution SPOT satellite imagery, in: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, pp. 1389–1394. https://doi.org/10.5194/isprsarchives-XL-7-W3-1389-2015

Kessides, C., 2007. The urban transition in Sub-Saharan Africa: Challenges and opportunities. Environ Plann C Gov Policy 25, 466–485. https://doi.org/10.1068/c3p

Khawte, S.S., Koeva, M.N., Gevaert, C.M., Oude Elberink, S., Pedro, A.A., 2022. Digital Twin Creation For Slums In Brazil Based On Uav Data, in: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, pp. 75–81. https://doi.org/10.5194/isprs-archives-XLVIII-4-W4-2022-75-2022

Kit, O., Lüdeke, M., 2013. Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery. ISPRS Journal of Photogrammetry and Remote Sensing 83, 130–137. https://doi.org/10.1016/j.isprsjprs.2013.06.009

Kit, O., Lüdeke, M., Reckien, D., 2012. Texture-based identification of urban slums in Hyderabad, India using remote sensing data. Applied Geography 32, 660–667. https://doi.org/10.1016/j.apgeog.2011.07.016

Koeva, M., Muneza, M., Gevaert, C., Gerke, M., Nex, F., 2018. Using UAVs for map creation and updating. A case study in Rwanda. Survey Review 50, 312–325. https://doi.org/10.1080/00396265.2016.1268756

Kohli, D., 2015. Identifying and classifying slum areas using remote sensing. Unpublished PhD thesis. University of Twente Faculty of Geo-Information and Earth Observation. https://doi.org/10.3990/1.97 89036540087

Kohli, D., Sliuzas, R., Kerle, N., Stein, A., 2012. An ontology of slums for image-based classification. Comput Environ Urban Syst 36, 154–163. https://doi.org/10.1016/j.compenvurbsys.2011.11.001

Kohli, D., Sliuzas, R., Stein, A., 2016a. Urban slum detection using texture and spatial metrics derived from satellite imagery. J Spat Sci. https://doi.org/10.1080/14498596.2016.1138247

Kohli, D., Stein, A., Sliuzas, R., 2016b. Uncertainty analysis for image interpretations of urban slums. Comput Environ Urban Syst 60, 37–49. https://doi.org/10.1016/j.compenvurbsys.2016.07.010

Kohli, D., Warwadekar, P., Kerle, N., Sliuzas, R., Stein, A., 2013. Transferability of object-oriented image analysis methods for slum identification. Remote Sens (Basel) 5, 4209–4228. https://doi.org/10.3390/rs5094209

Kruk, M.E., Gage, A.D., Arsenault, C., Jordan, K., Leslie, H.H., Roder-DeWan, S., Adeyi, O., Barker, P., Daelmans, B., Doubova, S. v, others, 2018. High-quality health systems in the Sustainable Development Goals era: time for a revolution. Lancet Glob Health 6, e1196–e1252. https://doi.org/10.1016/S2214-109X(18)30386-3

Kuffer, M., Barros, J., 2011. Urban morphology of unplanned settlements: The use of spatial metrics in VHR remotely sensed images, in: Procedia Environmental Sciences. Elsevier B.V., pp. 152–157. https://doi.org/10.1016/j.proenv.2011.07.027

Kuffer, M., Pfeffer, K., Sliuzas, R., 2016a. Slums from space-15 years of slum mapping using remote sensing. Remote Sens (Basel). https://doi.org/10.3390/rs8060455

Kuffer, M., Pfeffer, K., Sliuzas, R., Baud, I., 2016b. Extraction of Slum Areas From VHR Imagery Using GLCM Variance. IEEE J Sel Top Appl Earth Obs Remote Sens 9, 1830–1840. https://doi.org/10.1109/JSTARS.2016.2538563

Kumar, V., Gupta, P., 2012. Importance of Statistical Measures in Digital Image Processing. International Journal of Emerging Technology and Advanced Engineering 2. https://api.semanticscholar.org/CorpusID:2062243

Kurfess, F.J., 2003. Artificial Intelligence, in: Meyers, R.A. (Ed.), Encyclopedia of Physical Science and Technology (Third Edition). Academic Press, New York, pp. 609–629. https://doi.org/https://doi.org/10.1016/B0-12-227410-5/00027-2

Leonita, G., Kuffer, M., Sliuzas, R., Persello, C., 2018. Machine learning-based slum mapping in support of slum upgrading programs: The case of Bandung City, Indonesia. Remote Sens (Basel) 10. https://doi.org/10.3390/rs10101522

Li, J., Gong, J., Guldmann, J.M., Yang, J., 2021. Assessment of urban ecological quality and spatial heterogeneity based on remote sensing: A case study of the rapid urbanization of wuhan city. Remote Sens (Basel) 13. https://doi.org/10.3390/rs13214440

Li, J., Li, Y., Chapman, M., Rüther, H., 2005. Small Format Digital Imaging for Informal Settlement Mapping. Photogramm Eng Remote Sensing 71, 435–442. https://doi.org/10.14358/PERS.71.4.435

Liu, H., Huang, X., Wen, D., Li, J., 2017. The use of landscape metrics and transfer learning to explore urban villages in China. Remote Sens (Basel) 9. https://doi.org/10.3390/rs9040365

Liu, H., Liu, J., Li, M., Gou, P., Cheng, Y., 2022. Assessing the evolution of PM2.5 and related health impacts resulting from air quality policies in China. Environ Impact Assess Rev 93, 106727. https://doi.org/https://doi.org/10.1016/j.eiar.2021.106727

Liu, R., Kuffer, M., Persello, C., 2019. The temporal dynamics of slums employing a CNN-based change detection approach. Remote Sens (Basel) 11. https://doi.org/10.3390/rs11232844

Lizarazo, I., 2014. Accuracy assessment of object-based image classification: another STEP. Int J Remote Sens 35, 6135–6156. https://doi.org/10.1080/01431161.2014.943328

Lu, Z., Im, J., Rhee, J., Hodgson, M., 2014. Building type classification using spatial and landscape attributes derived from LiDAR remote sensing data. Landsc Urban Plan 130, 134–148. https://doi.org/https://doi.org/10.1016/j.landurbplan.2014.07.005

Lucieer, A., 2004. Uncertainties in Segmentation and their Visualisation. Unpublished PhD thesis. Utrecht University and International Institute for Geo-Information Science. https://research.utwente.nl/en/publications/uncertainties-in-segmentation-and-their-visualisation

Luo, E., Kuffer, M., Wang, J., 2022. Urban poverty maps - From characterising deprivation using geo-spatial data to capturing deprivation from space. Sustain Cities Soc 84, 104033. https://doi.org/https://doi.org/10.1016/j.scs.2022.104033

Mahabir, R., Crooks, A., Croitoru, A., Agouris, P., 2016. The study of slums as social and physical constructs: Challenges and emerging research opportunities. Reg Stud Reg Sci 3, 399–419. https://doi.org/10.1080/21681376.2016.1229130

Mahlakanya, I., Willemse, L., 2022. A living conditions index for main and backyard shacks and backyard rooms in Gauteng's metropolitan municipalities: 2001 to 2011. Town and Regional Planning 80. https://doi.org/10.18820/2415-0495/trp80i1.4

Maiya, S.R., Babu, S.C., 2018. Slum segmentation and change detection: A deep learning approach. arXiv preprint arXiv:1811.07896.

Maluleke, R. van E.A., 2013. The relationship between settlement type and undercount in the South African census of 2011.Research Articles, https://scholar.ufs.ac.za/server/api/core/bitstreams/c440af40-6431-4523-a0c0-007f57e029f5/content

Marconcini, M., Metz-Marconcini, A., Üreyen, S., Palacios-Lopez, D., Hanke, W., Bachofer, F., Zeidler, J., Esch, T., Gorelick, N., Kakarla, A., others, 2020. Outlining where humans live, the World Settlement Footprint 2015. Sci Data 7, 1–14. https://doi.org/10.1038/s41597-020-00580-5

Martino, P., Daniele, E., 2009. A methodology to quantify built-up structures from optical VHR imagery. " in Global Mapping of H uman Settle-ment Experiences, Datasets, and Prospects,P.GambaandM.Herold,Eds. Boca Raton , FL, USA: CRC Press, 2009, ch. 3, pp. 27–58 DOI:10.1201/9781420083408-c3

Marutlulle, N.K., 2021. A critical analysis of housing inadequacy in South Africa and its ramifications. Africa's Public Service Delivery and Performance Review 9. https://doi.org/10.4102/apsdpr.v9i1.372

Matarira, D., Mutanga, O., Naidu, M., Vizzari, M., 2022. Object-Based Informal Settlement Mapping in Google Earth Engine Using the Integration of Sentinel-1, Sentinel-2, and PlanetScope Satellite Data. Land (Basel) 12, 99. https://doi.org/10.3390/land12010099

Maurer, T., 2013. How to pan-sharpen images using the Gram-Schmidt pan-sharpen method - A recipe. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL-1/W1, 239–244. https://doi.org/10.5194/isprsarchives-XL-1-W1-239-2013

Mayunga, S.D., Coleman, D.J., Zhang, Y., 2010. Semi-automatic building extraction in dense urban settlement areas from high-resolution satellite images. Survey Review 42, 50–61. https://doi.org/10.1179/003962609X451690

Mboga, N., Persello, C., Bergado, J.R., Stein, A., 2017. Detection of informal settlements from VHR images using convolutional neural networks. Remote Sens (Basel) 9. https://doi.org/10.3390/rs9111106

McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/pnw-gtr-351

Mhangara, P., Odindi, J., Kleyn, L., Remas, H., 2011. Road extraction using object oriented classification. https://api.semanticscholar.org/CorpusID:14388201

Mitra, S., Aithal, Dr.B., 2020. Automatic Extraction of Buildings from UAV-Based Imagery Using Artificial Neural Networks. Journal of the Indian Society of Remote Sensing 49, 1–7. https://doi.org/10.1007/s12524-020-01235-z

Mohd Noor, N., Abdullah, A., Hashim, M., 2018. Remote sensing UAV/drones and its applications for urban areas: A review, in: IOP Conference Series: Earth and Environmental Science. Institute of Physics Publishing. https://doi.org/10.1088/1755-1315/169/1/012003

Morabito, M., Crisci, A., Guerri, G., Messeri, A., Congedo, L., Munafò, M., 2021. Surface urban heat islands in Italian metropolitan cities: Tree cover and impervious surface influences. Science of The Total Environment 751, 142334. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.142334

Mudau, N., Mapurisa, W., Tsoeleng, T., Mashalane, M., 2022. Towards development of a national human settlement layer using high resolution imagery: a contribution to SDG reporting. South African Journal of Geomatics 9, 1–12. https://doi.org/10.4314/sajg.v9i1.1

Mudau, N., Mhangara, P., 2022. Towards understanding informal settlement growth patterns: Contribution to SDG reporting and spatial planning. Remote Sens Appl 27. https://doi.org/10.1016/j.rsase.2022.100801

Mudau, N., Mhangara, P., 2021. Investigation of informal settlement indicators in a densely populated area using very high spatial resolution satellite imagery. Sustainability 13. https://doi.org/10.3390/su13094735

Mudau, N., Mhangara, P., Gebreslasie, M., 2014. Monitoring urban growth around Rustenburg, South Africa, using SPOT 5. South African Journal of Geomatics 3, 185–196. http://dx.doi.org/10.4314/sajg.v3i2.5

Mugiraneza, T., Nascetti, A., Ban, Y., 2019. WorldView-2 data for hierarchical object-based urban land cover classification in Kigali: Integrating rule-based approach with urban density and greenness indices. Remote Sens (Basel) 11. https://doi.org/10.3390/rs11182128

Myint, S.W., Gober, P., Brazel, A., Grossman-Clarke, S., Weng, Q., 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sens Environ 115, 1145–1161. https://doi.org/10.1016/j.rse.2010.12.017

Najmi, A., Gevaert, C.M., Kohli, D., Kuffer, M., Pratomo, J., 2022. Integrating Remote Sensing and Street View Imagery for Mapping Slums. ISPRS Int J Geoinf 11. https://doi.org/10.3390/ijgi11120631

Naorem, V., Kuffer, M., Verplanke, J., Kohli, D., 2016. Robustness Of Rule Sets Using Vhr Imagery To Detect Informal Settlements-A Case Of Mumbai, India, In: Geobia 2016 : Solutions and Synergies. University of Twente Faculty of Geo-Information and Earth Observation (ITC). https://doi.org/https://doi.org/10.3990/2.416

Nassar, D.M., Elsayed, H.G., 2018a. From Informal Settlements to sustainable communities. Alexandria Engineering Journal 57, 2367–2376. https://doi.org/10.1016/j.aej.2017.09.004

Nassar, D.M., Elsayed, H.G., 2018b. From informal settlements to sustainable communities. Alexandria engineering journal 57, 2367–2376. https://doi.org/10.1016/j.aej.2017.09.004

Nex, F., Remondino, F., 2014. UAV for 3D mapping applications: A review. Applied Geomatics. https://doi.org/10.1007/s12518-013-0120-x

Nicolau, R., David, J., Caetano, M., Pereira, J.M.C., 2018. Ratio of land consumption rate to population growth rate—Analysis of different formulations applied to mainland Portugal. ISPRS Int J Geoinf 8, 10.

Nobrega, R.A.A., O'hara, C.G., Quintanilha, J.A., 2006. Detecting Roads In Informal Settlements Surrounding Sao Paulo City By Using Object-Based Classification, in: Proceedings of the 1st International Conference on Object-Based Image Analysis . Proceedings of the 1st International Conference on Object-based Image Analysis (OBIA 2006), Salzburg, Austria.

Norman, M., Shahar, H.M., Mohamad, Z., Rahim, A., Mohd, F.A., Shafri, H.Z.M., 2021. Urban building detection using object-based image analysis (OBIA) and machine learning (ML) algorithms, in: IOP Conference Series: Earth and Environmental Science. IOP Publishing Ltd. https://doi.org/10.1088/1755-1315/620/1/012010

Norton, B., Evans, K., Warren, P., 2016. Urban Biodiversity and Landscape Ecology: Patterns, Processes and Planning. Current Landscape Ecology Reports 1, 178–192. https://doi.org/10.1007/s40823-016-0018-5

Ogura, L., 1996. Urbanization and apartheid in South Africa: influx controls and their abolition. Dev Econ 34. https://doi.org/10.1111/j.1746-1049.1996.tb01178.x

Okpala, D.C.I., 2009. Regional Overview of the Status of Urban Planning and Planning Practice in Anglophone (Sub-Saharan) African Countries. https://api.semanticscholar.org/CorpusID:37084080

Oksiutycz, A., Azionya, C.M. 2022. Informal Settlements: A Manifestation of Internal and Cross-Border Migration. In: Rugunanan, P., Xulu-Gama, N. (eds) Migration in Southern Africa. IMISCOE Research Series. Springer, Cham. https://doi.org/10.1007/978-3-030-92114-9_8

Owen, K.K., Wong, D.W., 2013. An approach to differentiate informal settlements using spectral, texture, geomorphology and road accessibility metrics. Applied Geography 38, 107–118. https://doi.org/10.1016/j.apgeog.2012.11.016

Owusu, M., Kuffer, M., Belgiu, M., Grippa, T., Lennert, M., Georganos, S., Vanhuysse, S., 2021. Towards user-driven earth observation-based slum mapping. Comput Environ Urban Syst 89, 101681. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2021.101681

Panigrahi, N., Tiwari, A., Dixit, A., 2021. Image Pan-Sharpening and Sub-pixel Classification Enabled Building Detection in Strategically Challenged Forest Neighborhood Environment. J Indian Soc Remote Sens 49, 2113–2123. https://doi.org/10.1007/s12524-021-01380-z

Patel, S., Baptist, C., 2012. Editorial: Documenting by the undocumented. Environ Urban. https://doi.org/10.1177/0956247812438364

Patino, J.E., Duque, J.C., 2013. A review of regional science applications of satellite remote sensing in urban settings. Comput Environ Urban Syst. https://doi.org/10.1016/j.compenvurbsys.2012.06.003

Peeroo, U., Idrees, M.O., Saeidi, V., 2017. Building extraction for 3D city modelling using airborne laser scanning data and high-resolution aerial photo. South African Journal of Geomatics 6, 363. https://doi.org/10.4314/sajg.v6i3.7

Pellikka, P.K.E., Hurskainen, P., Pellikka, P., 2004. Change detection of informal settlements using multi-temporal aerial photographs: the case of Voi, in: 5th African Association of Remote Sensing of the Environment conference (Ed.). Nairobi, Kenya, pp. 17–22.

Peng, X., Wu, W., Zheng, Y., Sun, J., Hu, T., Wang, P., 2020. Correlation analysis of land surface temperature and topographic elements in Hangzhou, China. Sci Rep 10, 10451. https://doi.org/10.1038/s41598-020-67423-6

Pesaresi, M., Ehrlich, D., Ferri, S., Florczyk, A., Freire, S., Halkia, M., Julea, A., Kemper, T., Soille, P., Syrris, V., others, 2016. Operating procedure for the production of the Global Human Settlement Layer from Landsat data of the epochs 1975, 1990, 2000, and 2014. Publications Office of the European Union 1–62.

Pesaresi, M., Gerhardinger, A., Kayitakire, F., 2008. A Robust Built-Up Area Presence Index by Anisotropic Rotation-Invariant Textural Measure. IEEE J Sel Top Appl Earth Obs Remote Sens 1, 180–192. https://doi.org/10.1109/JSTARS.2008.2002869

Phinn, S., Stanford, M., Scarth, P., Murray, A.T., Shyy, P.T., 2002. Monitoring the composition of urban environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. Int J Remote Sens 23, 4131–4153. https://doi.org/10.1080/01431160110114998

Prabhu, R., Parvathavarthini, B., 2022. Morphological slum index for slum extraction from high-resolution remote sensing imagery over urban areas. Geocarto Int. https://doi.org/10.1080/10106049.2022.2086624

Pratomo, J., Kuffer, M., Kohli, D., Martinez, J., 2018. Application of the trajectory error matrix for assessing the temporal transferability of OBIA for slum detection. Eur J Remote Sens 51, 838–849. https://doi.org/10.1080/22797254.2018.1496798

Preethi, T., Naga Sundari, K., Cherukuri, S., Prasad, M.V.V.S.V., 2019. Remote sensing UAV/drone technology as a tool for urban development measures in Apcrda, in: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, pp. 525–529. https://doi.org/10.5194/isprs-archives-XLII-2-W13-525-2019

Pryce, G., Ya, ·, Wang, P., Chen, · Yu, Shan, J., Houkai, ·, Editors, W., 2021. Urban Inequality and Segregation in Europe and China. Springer, Switzerland. https://doi.org/https://doi.org/10.1007/978-3-030-74544-8

Ramin, B., 2009. Slums, climate change and human health in sub-Saharan Africa. Bull World Health Organ 87, 886. https://doi.org/10.2471/blt.09.073445

Ramsay, E.E., Fleming, G.M., Faber, P.A., Barker, S.F., Sweeney, R., Taruc, R.R., Chown, S.L., Duffy, G.A., 2021. Chronic heat stress in tropical urban informal settlements. iScience 24, 103248. https://doi.org/https://doi.org/10.1016/j.isci.2021.103248

RIDD, M.K., 1995. Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities†. Int J Remote Sens 16, 2165–2185. https://doi.org/10.1080/01431169508954549

Ruwaimana, M., Satyanarayana, B., Otero, V., Muslim, A.M., Muhammad Syafiq, A., Ibrahim, S., Raymaekers, D., Koedam, N., Dahdouh-Guebas, F., 2018. The advantages of using drones over space-borne imagery in the mapping of mangrove forests. PLoS One 13. https://doi.org/10.1371/journal.pone.0200288

Salem, M., Tsurusaki, N., Eissa, A., Osman, T., 2020. Detection of Slums from Very High-Resolution Satellite Images Using Machine Learning Algorithms: A Case Study of Fustat Area in Cairo, Egypt.

Samper, J., Shelby, J.A., Behary, D., 2020. The paradox of informal settlements revealed in an ATLAS of informality: Findings from mapping growth in the most common yet unmapped forms of urbanization. Sustainability 12, 9510.

Satterthwaite, David., 2005. The scale of urban change worldwide 1950-2000 and its underpinnings. International Institute for Environment and Development. http://www.jstor.org/stable/resrep01817.1

Setiawan, H., Mathieu, R., Thompson-Fawcett, M., 2006. Assessing the applicability of the V–I–S model to map urban land use in the developing world: Case study of Yogyakarta, Indonesia. Comput Environ Urban Syst 30, 503–522. https://doi.org/10.1016/j.compenvurbsys.2005.04.003

Shahi, K., Shafri, H.Z.M., Taherzadeh, E., Mansor, S., Muniandy, R., 2015. A novel spectral index to automatically extract road networks from WorldView-2 satellite imagery. The Egyptian Journal of Remote Sensing and Space Science 18, 27–33. https://doi.org/https://doi.org/10.1016/j.ejrs.2014.12.003

Shapurjee, Y., le Roux, A., Coetzee, M., 2014. Backyard housing in Gauteng: An analysis of spatial dynamics. Town and Regional Planning 64, 19–30. http://hdl.handle.net/10204/8229

Shekhar, S., 2012. Detecting Slums From Quick Bird Data In Pune Using An Object Oriented Approach. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XXXIX-B8, 2012 . https://doi.org/10.5194/isprsarchives-XXXIX-B8-519-2012

Shih, H., Stow, D.A., Chang, K.-C., Roberts, D.A., Goulias, K.G., 2022. From land cover to land use: applying random forest classifier to Landsat imagery for urban land-use change mapping. Geocarto Int 37, 5523–5546. https://doi.org/10.1080/10106049.2021.1923827

Sibaruddin, H.I., Zulhaidi, H., Shafri, M., Pradhan, B., Haron, N.A., 2018. UAV-based Approach to Extract Topographic and As-built Information by Utilising the OBIA Technique. Journal of Geosciences and Geomatics 6, 103–123. https://doi.org/10.12691/jgg-6-3-2

Sirueri, F.O., 2015. Comparing Spatial Patterns Of Informal Settlements Between Nairobi And Dar Es Salaam. Unpublished Msc thesis; University of Twente Faculty of Geo-Information and Earth Observation; https://webapps.itc.utwente.nl/librarywww/papers_2015/msc/upm/sirueri.pdf (accessed 8.12.23).

Sliuzas, R., 2008. Report of the Expert Group Meeting on Slum Identification and Mapping. Sliuzas, R., 2008. Report of the Expert Group Meeting on Slum Identification and Mapping. Proceedings in Expert group meeting on slum identification and mapping, Faculty ITC, University of Twente, Enschede The Netherland. https://www.researchgate.net/publication/271074739_Report_of_the_Expert_Group_Meeting_on_Slum_Identification_and_Mapping/link/54bd1a650cf218da93918aa6/download?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19

Sliuzas, R., Kuffer. Monika, Gevaert, C., Persello, C., Pfeffer, K., 2017. Slum mapping From space to unmanned aerial vehicle based approaches, in: Joint Urban Remote Sensing Event (JURSE). Dubai, United Arab Emirates.

Snehmani, Gore, A., Ganju, A., Kumar, S., Srivastava, P.K., RP, H.R., 2017. A comparative analysis of pansharpening techniques on QuickBird and WorldView-3 images. Geocarto Int 32, 1268–1284.

Socio-Economic Rights Institute of South Africa, 2018. Informal Settlements and Human Rights in South Africa. https://www.ohchr.org/sites/default/files/Documents/Issues/Housing/InformalSettlements/SERI.pdf

Soman, S., Beukes, A., Nederhood, C., Marchio, N., Bettencourt, L., 2020. Worldwide detection of informal settlements via topological analysis of crowdsourced digital maps. ISPRS Int J Geoinf 9, 685.

South African Cities Network, 2022. A report of the Urban Safety. Socio-Economic Rights Institute of South Africa, 2018. Informal Settlements and Human Rights in South Africa. https://www.ohchr.org/sites/default/files/Documents/Issues/Housing/InformalSettlements/SERI.pdf

South African Local Government Agency, 2014. Local Government Position on Municipal Responses to Backyarders and Backyard Dwellings Specialist: Sustainable Human Settlements. https://static.pmg.org.za/150606SALGA_policy.pdf

Spence, M., Clarke Annez, P., Buckley, R.M., 2009. Urbanization and Growth. https://api.semanticscholar.org/CorpusID:152706002

Statistics South Africa, 2022. General Household Survey 2021. https://www.statssa.gov.za/?p=15482

Statistics South Africa, 2020. General Household Survey 2019. https://www.statssa.gov.za/publications/P0318/P03182019.pdf

Statistics South Africa, 2016. GHS Series Volume VII, Housing from a Human Settlement Perspective. https://www.statssa.gov.za/?p=6429

Statistics South Africa, 2012. Census 2011 metadata. https://www.statssa.gov.za/?page_id=3839

Statistics South Africa, 2011. Census 2011. https://www.statssa.gov.za/?page_id=4286&id=11377 https://www.statssa.gov.za/census/census_2011/census_products/Census_2011_Statistical%20release.pdf

Stefanov, W.L., Ramsey, M.S., Christensen, P.R., 2001. Monitoring urban land cover change: An expert system approach to land cover classification of semiarid to arid urban centers. Remote Sens Environ 77, 173–185. https://doi.org/https://doi.org/10.1016/S0034-4257(01)00204-8

Strauss, M., 2019. A historical exposition of spatial injustice and segregated urban settlement in South Africa. Fundamina 25. https://doi.org/10.17159/2411-7870/2019/v25n2a6

Street, G.M., Fieberg, J., Rodgers, A.R., Carstensen, M., Moen, R., Moore, S.A., Windels, S.K., Forester, J.D., 2016. Habitat functional response mitigates reduced foraging opportunity: implications for animal fitness and space use. Landsc Ecol 31, 1939–1953. https://doi.org/10.1007/s10980-016-0372-z

Takyi, S.A., Amponsah, O., Yeboah, A.S., Mantey, E., 2021. Locational analysis of slums and the effects of slum dweller's activities on the social, economic and ecological facets of the city: insights from Kumasi in Ghana. GeoJournal 86, 2467–2481. https://doi.org/10.1007/s10708-020-10196-2

Teng, Z., Li, C., Zhao, W., Wang, Z., Li, R., Zhang, L., Song, Y., 2022. Extraction and Analysis of Spatial Feature Data of Traditional Villages Based on the Unmanned Aerial Vehicle (UAV) Image. Mobile Information Systems 2022. https://doi.org/10.1155/2022/4663740

Thomson, D.R., Gaughan, A.E., Stevens, F.R., Yetman, G., Elias, P., Chen, R., 2021. Evaluating the accuracy of gridded population estimates in slums: A case study in Nigeria and Kenya. Urban sci 5, 48. https://doi.org/10.3390/urbansci5020048

Touzani, S., Pritoni, M., Singh, R., 2023. Machine Learning for Automated Extraction of Building Geometry. Lawrence Berkeley National Laboratory. https://escholarship.org/uc/item/4vr8r3vk

Turok, I., Borel-Saladin, J., 2016. Backyard shacks, informality and the urban housing crisis in South Africa: stopgap or prototype solution? Hous Stud 31, 384–409. https://doi.org/10.1080/02673037.2015.1091921

Ukhnaa, M., Huo, X., Gaudel, G., 2019. Modification of urban built-up area extraction method based on the thematic index-derived bands. IOP Conf Ser Earth Environ Sci 227, 62009. https://doi.org/10.1088/1755-1315/227/6/062009

UN-Habitat, 2022. World Cities Report: Envisaging the Future of Cities. https://digitallibrary.un.org/record/3984713

UN-Habitat, 2020. UN-Habitat Strategic Vision. https://unhabitat.org/the-strategic-plan-2020-2023

UN-Habitat, 2018a. SDG Indicator 11.3. 1 Training Module: Land Use Efficiency. https://unhabitat.org/sites/default/files/2021/08/indicator_11.3.1_training_module_land_use_efficiency.pdf

UN-Habitat, 2018b. Metadata on SDGs Indicator 11.3. 1 Indicator category: Tier II. https://unhabitat.org/sites/default/files/2020/07/metadata_on_sdg_indicator_11.3.1.pdf

UN-Habitat, 2018c. Addressing the most vulnerable first pro-poor climate action informal settlements. https://unhabitat.org/sites/default/files/2019/05/pro-poor_climate_action_in_informal_settlements-.pdf

UN-Habitat, 2016. Report of the Inter Agency and Expert Group on Sustainable Development Goal Indicators. https://tcgtest.uis.unesco.org/wp-content/uploads/sites/4/2020/10/TCG-7-REF-1.pdf

UN-Habitat, 2015. Habitat III issue paper 22—informal settlements. https://unhabitat.org/sites/default/files/download-manager-files/Habitat-III-Issue-Paper-22_Informal-Settlements-2.0%20%282%29.pdf

UN-Habitat, 2004. The challenge of slums: global report on human settlements 2003. https://unhabitat.org/the-challenge-of-slums-global-report-on-human-settlements-2003

United Nations, 2021.The Sustainable Development Goals Report, https://sdgs.un.org/sites/default/files/2020-09/The-Sustainable-Development-Goals-Report-2020.pdfUnited Nations, 2016. New Urban Agenda. New York.

United Nations, 2015. The Millennium Development Goals Report. https://www.un.org/millenniumgoals/2015_MDG_Report/pdf/MDG%202015%20rev%20(July%201).pdf

United Nations Department of Economic and Social Affairs, 2019. World Urbanization Prospects 2018 Highlights. https://population.un.org/wup/Publications/Files/WUP2018-Highlights.pdf

United Nations Department of Economic and Social Affairs., 2013. World economic and social survey 2013 : sustainable development challenges. https://www.un.org/en/development/desa/policy/wess/wess_current/wess2013/WESS2013.pdf

United Nations: DESA, 2019. Guidelines on the use of electronic data collection technologies in population and housing censuses. https://unstats.un.org/unsd/demographic/standmeth/handbooks/data-collection-census-201901.pdf

United Nations Population Fund, 2002. Population And Housing Census Strategies For Reducing Costs Number 4 | 2002. https://unfpa.org/sites/default/files/pub-pdf/population_census.pdf

Veljanovski, T., Kanjir, U., Pehani, P., Otir, K., Kovai, P., 2013. Object-Based Image Analysis of VHR Satellite Imagery for Population Estimation in Informal Settlement Kibera-Nairobi, Kenya. Int J Urban Reg Res 37, 2177–2197. https://api.intechopen.com/chapter/pdf-download/37546

Wang, J., Fleischmann, M., Venerandi, A., Romice, O., Kuffer, M., Porta, S., 2023. EO + Morphometrics: Understanding cities through urban morphology at large scale. Landsc Urban Plan 233. https://doi.org/10.1016/j.landurbplan.2023.104691

Wang, L.-Y., Xiao, Yi, Rao, E.-M., Jiang, L., Xiao, Yang, Ouyang, Z.-Y., 2018. An Assessment of the Impact of Urbanization on Soil Erosion in Inner Mongolia. Int J Environ Res Public Health 15. https://doi.org/10.3390/ijerph15030550

Wasisa, K.P., Santosa, S.H.M.B., Hidayati, I.N., 2016. Slums Detection On Worldview-3 Imagery Based-On Integration Of Image Sharpening And Lacunarity Algorithm. ICOIRS 2016: The 2nd

International Conference of Indonesian Society for Remote Sensing Remote Sensing for a Better Governance, Yogyakarta, Indonesi.

White, K., Walden, J., Drake, N., Eckardt, F., Settlell, J., 1997. Mapping the iron oxide content of dune sands, Namib Sand Sea, Namibia, using landsat thematic mapper data. Remote Sens Environ 62, 30–39. https://doi.org/https://doi.org/10.1016/S0034-4257(97)00068-0

Williams, N., Q.D.& S.J., 2016. Automatic Classification of Roof Objects From Aerial Imagery of Informal Settlements in Johannesburg. Appl Spat Anal Policy 6, 269–281.

Woebbecke, D.M.G.V.B.K.& M., 1995. Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the American Society of Agricultural Engineers 259–269. DOI:10.13031/2013.27838

Wu, Q., Zhong, R., Zhao, W., Song, K., Du, L., 2019. Land-cover classification using GF-2 images and airborne lidar data based on Random Forest. Int J Remote Sens 40, 2410–2426. https://doi.org/10.1080/01431161.2018.1483090

Wurm, M., Taubenböck, H., Weigand, M., Schmitt, A., 2017. Slum mapping in polarimetric SAR data using spatial features. Remote Sens Environ 194, 190–204. https://doi.org/10.1016/j.rse.2017.03.030

Xue, B., Lin, X., 2020. Water System Segmentation Method of High Resolution Remote Sensing Image Based on eCognition. J Phys Conf Ser 1651, 12162. https://doi.org/10.1088/1742-6596/1651/1/012162

Xue, J., Su, B., 2017. Significant remote sensing vegetation indices: A review of developments and applications. J Sens 2017. https://doi.org/10.1155/2017/1353691

Yadav, V., Ghosh, S.K., 2021. Assessment and prediction of urban growth for a mega-city using CA-Markov model. Geocarto Int 36, 1960–1992. https://doi.org/10.1080/10106049.2019.1690054

Yilmaz, V., Serifoglu Yilmaz, C., Güngör, O., Shan, J., 2020. A genetic algorithm solution to the gram-schmidt image fusion. Int J Remote Sens 41, 1458–1485.

Yue, H., Liu, Y., Li, Y., Lu, Y., 2019. Eco-Environmental Quality Assessment in China's 35 Major Cities Based On Remote Sensing Ecological Index. IEEE Access 7, 51295–51311. https://doi.org/10.1109/ACCESS.2019.2911627

Zahidi, I., Yusuf, B., Hamedianfar, A., Shafri, H.Z.M., Mohamed, T.A., 2015. Object-based classification of QuickBird image and low point density LIDAR for tropical trees and shrubs mapping. Eur J Remote Sens 48, 423–446. https://doi.org/10.5721/EuJRS20154824

Zambrano, L., Handel, S., Fernandez, T., Brostella, I., 2021. Landscape spatial patterns in Mexico City and New York City: contrasting territories for biodiversity planning. Landsc Ecol 37. https://doi.org/10.1007/s10980-021-01372-x

Zhang, J., Li, P., Wang, J., 2014. Urban built-Up area extraction from landsat TM/ETM+ images using spectral information and multivariate texture. Remote Sens (Basel) 6, 7339–7359. https://doi.org/10.3390/rs6087339

Zhang, Y., Liu, X., Yang, Q., Liu, Z., Li, Y., 2021. Extracting Frequent Sequential Patterns of Forest Landscape Dynamics in Fenhe River Basin, Northern China, from Landsat Time Series to Evaluate Landscape Stability. Remote Sens (Basel) 13. https://doi.org/10.3390/rs13193963

Zhao, L., Ren, H., Cui, C., Huang, Y., 2020. A partition-based detection of urban villages using high-resolution remote sensing imagery in Guangzhou, China. Remote Sens (Basel) 12. https://doi.org/10.3390/rs12142334

Zheng, X., Zou, Z., Xu, C., Lin, S., Wu, Z., Qiu, R., Hu, X., Li, J., 2022. A New Remote Sensing Index for Assessing Spatial Heterogeneity in Urban Ecoenvironmental-Quality-Associated Road Networks. Land (Basel) 11. https://doi.org/10.3390/land11010046