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Mapping illegal dumps in Soweto using object-based Image analysis

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Mapping illegal dumps in Soweto using Object-based Image Analysis.

By:

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A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirement for the degree of Master of Science GIS and Remote Sensing at the School of Geography, Archaeology & Environmental Studies.

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Johannesburg, South Africa.

Declaration

I, **Sibongiseni Selahle**, declare that this research report is my own unaided work. It is being submitted to the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.



……..
Signature of candidate

Signed on day of.....2020.....at The University of the Witwatersrand.

Abstract

The illegal dumping of waste is one of the major causes of land degradation which presents a problem for the global environment for both the developed and developing world. The illegal dumping of both building rubble and domestic waste results in groundwater pollution, air pollution and the contribution to the greenhouse gas budget. Illegal dumps cost the local municipalities a lot of money for the clean-up and removal of the illegally dumped waste. Therefore, there is a need for mapping and monitoring illegal dumps. Mapping and monitoring illegal dumps will enhance the prevention of the problem and develop technologies to aid the efficiency of service delivery.

The traditional methods of detecting and mapping illegal dumps are usually expensive and require a lot of human resources. This research report aimed at developing a remote-sensing based approach to detect and map illegal dumping in Soweto. The objectives of the report were as follows: (I) map and differentiate between illegal domestic waste and the building rubble in Soweto using Worldview-4 imagery and object-based image classification; (II) compare random forest and support vector machine algorithms for classifying the illegal dumping wastes; (III) to identify and analyse the socio-economic factors associated with the spatial distribution of illegal dumping.

The results demonstrated the ability of WorldView-4 imagery and object-based image classification techniques to detect, map, and differentiate between building rubble and domestic waste. Machine learning algorithms produced an overall accuracy of 93.98% for Random forest and 94.91% for Support Vector Machine. Additionally, factors such as population density, household size, level of education, and household income were associated with the spatial distribution of these dumps. The high accuracies of the models provide an opportunity for remote sensing tools and techniques such as the ones implemented in this

study to be tested for reliability in the greater City of Johannesburg region and other parts of the world as well.

Dedication

I dedicate this research report to my parents Buti Marcus Selahle and Marriam Selahle for their unwavering love, encouragement and support (emotionally and financially).

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Abbreviation and Acronyms

CoJ	City of Johannesburg
DT	Decision Tree
GIS	Geographical information systems
LOOCV	Leave-one-Out Cross-Validation
LULC	Land use and land cover
MDA	Mean Decrease in Accuracy
MRS	Multi-Resolution segmentation
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
OBIA	Object-based image analysis
OOB	Out-Of-Bag
PALSAR	Phased Array type L-band Synthetic Aperture Radar
RF	Random Forest
RGB	Red, Blue, Green
STATS SA	Statistics South Africa
SVM	Support Vector Machines
UN	United Nations
VHR	Very-High Resolution
WV-4	WorldView-4

Keywords: Building rubble, classification, detection, domestic waste, illegal dumping, object-based, mapping.

Chapter One: Introduction

1.1 Introduction

The concept of illegal dumping also referred to as fly dumping, fly-tipping, and night tipping is the illegal disposal of waste material in a prohibited space and it is one of the major causes of land degradation (Liu *et al.*, 2016). Waste deposited in vacant space usually comes in two forms: 1) domestic waste (i.e. yard waste, tires, electrical appliances and batteries) and building rubble (i.e. drywall, roofing, shingles, lumber, bricks, and concrete) (Liu *et al.*, 2016).

The illegal disposal of waste presents a problem for the global environment and is a huge concern for both the developed and developing world. Illegal dumps have serious environmental and public health effects (Bandara & Hettiarachi, 2010). Environmental impacts associated with illegal dumps include land degradation by toxic substances (Triassi *et al.*, 2015). Toxic substances are resultant by a complex sequence of biological and chemical reactions that occur at the dump, which lead to groundwater pollution, air pollution and the contribution to the greenhouse gas budget (Dladla *et al.*, 2016). The afore-mentioned impacts also affect human livelihoods by creating human health risks and domestic animal concerns, odour problems and loss of property value (Bandara & Hettiarachi, 2010).

According to the Arts and Humanities Research Council, 2010, the United Nations (UN) have devoted chapter 20 and 21 of the Agenda 21 programmes to promote the reduction, management and recycling of waste. The three different environmental law policies that were developed aimed at the reduction of illegal dumping. These policies include fines, vehicle impoundment, and criminal indictment by the court (Arts and Humanities Research Council, 2010).

A study conducted by Dladla *et al.*, (2016), found that in eleven African countries, 68% of the solid waste generated by communities was illegally dumped, 20.8% legally dumped through landfills and 10.7% burnt. There are factors that are associated with illegal dumping, which include but are not limited to: poor/low collection rates, bad waste management systems, lack of disposal options, household behaviour, cost of disposing waste legally, and weak enforcement and penalties of illegal dumping (Dladla *et al.*, 2016; Liu *et al.*, 2017; Polasi, 2018; Sotamenou *et al.*, 2019). These factors are similarly shared in most parts of the world.

Air pollution and groundwater contamination are the impacts that are associated with illegal dumping (Bandara & Hettiarachi, 2010). Air and groundwater pollution are resultant by a complex sequence of a biological and chemical reaction (Bandara & Hettiarachi, 2010). Both environmental impacts associated with illegal dumping are often not restricted to single states (Liu *et al.,* 2016; Nagpure, 2019). The impacts are a transboundary concern, and there is no major effective international intergovernmental organization which addresses the production and illegal disposal of solid waste on land (Nagpure, 2019). The need for effective management of illegal dumping is essential for environmental protection and sustainability of the Earth and its resources. The effective management of the illegal disposal of waste will decrease its probability of it occurring and decrease the impacts associated with it.

Conventional methods of identifying illegal dumps include the direct visitation of the dumps, direct mapping in the field, voluntary reporting and aerial photograph interpretation (visual inspection) (Silvestri & Omri, 2007; Ferrara *et al.,* 2010; Department of Environment and Heritage Protection, 2015; Zhang & Zhao, 2019). These conventional methods, however, are tedious and are often costly and require a lot of resources. They require voluntary reporting from community members which may be unsuccessful; site-visitation requires human and monetary resources; visual interpretation may be subjective and limiting (Silvestri & Omri, 2007; Ferrara *et al.,* 2010). Other recent methods for identifying illegal dumps include the usage of Geographical Information System (GIS) tools together with geostatistical modelling, GIS and multi-criteria spatial analysis, and GIS and factor analysis for determining the probability of areas of the presence of illegal landfills with remote sensing (Biotto *et al.,* 2009; Babu & Sivasankar, 2015; Taye, 2018). Recent methods are much more cost-effective and less time consuming than conventional methodologies (Sivasankar, 2015). Recent methods can be desktop based whilst conventional methods require the direct visitation of the illegal dumps often (Silvestri & Omri; Taye, 2018).

Remote Sensing, on the other hand, has been an indispensable, efficient and low-cost tool in the study of environmental management and solid waste management in recent times through its variation in data which include multispectral, hyperspectral, multi-temporal and high spatial resolution data (Mohammedshum *et al.,* 2014). The advancement of remote sensing data in terms of new generation multispectral with very high spatial resolution and hyperspectral data has made it possible and flexible enough to study and measure variables of an area extensively and at ease (Glanville & Chang, 2015). The importance of remote sensing as a tool for illegal dumping identification is a key instrument for environmental management

and for the spatially distributed characterization of possible uncontrolled illegal dumps (Silvestri & Omri, 2007).

1.2 Problem statement

According to the City of Johannesburg (2017), the CoJ produces between 1.6 and 1.8 million tons of waste per annum. Simultaneously, the city and almost all the municipalities in the country do not have illegal dumping prevention strategies in place (Polasi, 2018). Illegal dumping costs the local municipalities a lot of money for the clean-up and removal of the illegally dumped waste. Pikitup, the official integrated waste management service provider to the CoJ annually spends R60 million in efforts to deal with illegal dumping (Pikitup, 2017).

A research study conducted by Polasi (2018) in Zondi a township in Soweto identified the two factors associated with illegal dumping. These are 1) lack of irregular waste removal services and 2) lack of builder's rubble disposal options. The author also revealed that the frequency of occurrence of illegal dumping in the suburb was 79% daily, 7% weekly, and 14% sporadic (Polasi, 2018).

There is a need for identifying, mapping and monitoring illegal dumps. The detection and mapping of illegal dumps will enhance the prevention of the problem and develop technologies to aid the efficiency of service delivery (Glanville & Chang, 2015). Zorpas and Lasaridi (2013) highlight that detecting and monitoring the illegal disposal of household waste is critical since it constitutes the main tools to enable policymakers to build their strategic plans and ensure waste prevention initiatives are effective.

The traditional methods of effectively identifying illegal dumps are usually expensive and require a lot of manpower. Romeo *et al.*, (2003) concurs and highlights that a typical response to illegal dumping is for the municipality to dispatch a clean-up crew, which consists of a dump truck and a truck-mounted crane to load the waste into the dump truck. Glanville and Chang (2015) argued that conventional management strategies of illegal dumping are not comprehensive, because they rely on the voluntary reporting of incidents by the public and on-the-ground surveillance of known hotspots. Voluntary reporting can be inadequate since some of the illegal dumping's usually occurring at night (Romeo *et al.*, 2003).

Geographical Information Systems (GIS) and Remote Sensing tools and techniques such as aerial photography analysis and site suitability analysis have been used in Venice lagoon (North-East Italy) for the monitoring and management of illegal dumps (Silvestri & Omri, 2007). However, there have been challenges of using remote sensing classification techniques such as pixel-based image classification methods that lack rigorously validated approaches such as spectral mixture between similar objects when using very high resolution remotely sensed images. Traditional remote sensing pixel-based methods use a pixel as a basic unit of analysis (Jawak *et al.*, 2015). However, since the introduction of very high spatial resolution images, traditional pixel-based methods have experienced limitation as they produce undesirable classification results in extracting targeted classes (Aggerwal *et al.*, 2016). Pixel-based approaches also do not consider the size of the object where the object of interest is larger than the pixel size (Aplin & Smith, 2008).

In the City of Johannesburg, and particularly Soweto, illegal dumping is a threat to the sustainability and wellbeing of the surrounding communities (Polasi, 2018). Therefore, there is a need to develop a highly temporal, cheap, reliable and systematic method for identifying illegal dumps in CoJ. Hence, the purpose of this study is to develop a remote sensing-based model which will use object-based image classification method and the very high spatial resolution remote sensing data (Worldview-4). Object-based image classification approaches overcome the limitation of traditional pixel-based in which the processing units are no longer single pixel, but an image object (Jawak *et al.*, 2015). The change of the classification units from pixels to image objects has reduced within-class spectral variation and removes the salt and pepper effect associated with pixel-based classification (Aplin & Smith, 2008). Object-based considers object characteristics such as spectral/colour, form/shape, area/size, texture, and content whilst pixel-based only consider spectral characteristics of the object (Jawak *et al.*, 2015). This will assist the CoJ and Pikitup in coming up with effective management strategies for identifying, curbing, and managing illegal dumping.

1.3 Aims and objectives.

1.3.1 Aim:

The aim of this research is to develop a remote sensing-based approach to detect and map illegal dumping in Soweto.

1.3.1.1 Objectives:

The specific objectives of this study are to:

1. Map and differentiate between illegal domestic waste and the building rubble in Soweto using Worldview-4 imagery and object-based image classification.
2. Compare random forest and support vector machine algorithms for classifying the illegal dumping wastes in the study area.
3. Identify and analyse the socio-economic factors associated with the spatial distribution of illegal dumping.

1.4 Research Outline

This research report has five distinct chapters that detail how a remote sensing-based approach was modelled to detect and map illegal dumping. Chapter one introduces the reader to the background, concept and effects of illegal dumping, then continues to discuss and outline the problem statement and the rationale of the research study in the study area.

Chapter two reviews the relevant literature about the stated research problem. The literature reviewed includes themes such as (I) The concept of illegal dumping, (II) impacts of illegal dumping, (III) the need for illegal dumping management, (IV) mapping and monitoring illegal dumps, and (V) challenges of using remote sensing for identifying and mapping illegal dumping.

Chapter three explains and discusses the methodology that the study employed. This chapter provides the details of the study area, remote sensing data used, and the justification of the data used. The chapter also details the methodology of the study employed in achieving the three objectives.

Chapter four presents and outlines the results of the study. This chapter also synthesises the discussion with the body of literature that was highlighted in the literature review. Chapter five also concludes the research report and providing the key findings of the research, challenges and offers areas for future research.

Chapter Two: Literature Review

2.1 Concept of illegal dumping

Illegal dumping is the unlawful deposit of waste material that has been dumped onto land (open or vacant land, sources of water and other areas) where no license or approval exists to accept such waste (Glanville & Chang, 2015; Dladla *et al.*, 2016). "It is a common and prevalent though risky practice, especially among the developing communities" (Dladla *et al.*, 2016, pp. 1). The unlawful deposit of waste varies from small bags of plastics to large scale dumping of materials in isolated areas. Illegal dumps can be classified into two groups namely: 1) domestic waste and 2) building rubble. Domestic waste generally includes plastics, yard waste, electrical appliances, and batteries (Figure 1).



Figure 1: Domestic waste from one of the sites in the study area.

On the other hand, building rubble includes drywall, roofing, shingles, lumber, bricks, and concrete generated after the demolishing of households and buildings (Figure 2). This increasing amount of waste is abandoned and illegally dumped by residents, small and big

commercial and industrial businesses, municipal services, building and construction, and agricultural activities (Dladla et al, 2016; Yang *et al.*, 2019).



Figure 2: Building rubble from one of the sites in the study area.

2.1.1 Where does illegal dumping frequently occur?

The illegal dumping of waste usually occurs in densely populated suburbs and townships. According to Dladla *et al.*, (2016) and Yang *et al.*, (2019), illegal dumping is highly frequent in urban areas, where residents dump their waste in open spaces, footpaths, storm water drains, rivers, streams, streets and street corners. Nagpure (2019) concurs and emphasizes that illegal dumping is a common practice in townships surrounding cities in developing countries due to poor municipal solid waste collection efficiency. Urbanization and increase in population have contributed to waste generation, which has overwhelmed the capacity of authorities to provide adequate and equitable management services (Simatele *et al.*, 2017). Ogola et al (2011) reported that the quantity of waste generated in South Africa increased due to economic and population growth.

In a research study conducted by Nagpure (2019) in Delhi India, the author found that per capita illegally dumped waste to be the highest (61 kg) in low socio-economic status varying neighbourhoods compared to that in high socioeconomic status neighbourhoods which stood

at (2.6-3.5 kg). The author also found that, per km^2, the number of illegal dumps in low socioeconomic status neighbourhoods stood at 5336/km^2, which was 100 times higher than high socioeconomic status neighbourhoods (51 tons/km^2) (Nagpure, 2019). Bandara *et al.*, (2007) and Oyekale (2015), agree and highlight that the amount of waste generated is directly proportional to the population and the average mean living standards of the people.

2.1.2 Factors that drive illegal dumping

There are several factors that influence and drive illegal dumping ranging from climate, level of education, religious and cultural beliefs, economic, social, and attitude/behaviour of individuals or societies. Dladla *et al.,* (2016) found eight major factors associated with the prevalence of illegal dumping in eleven African countries; such factors include: 1) population growth, 2) rapid urbanization, 3) irregular refuse collection, 4) lack of resources, 5) improved standards of living, 6) increased waste generation rate, and 7) poorly planned collection routes.

Ichinose and Yamamoto (2011) state that the main factor that increases the amount of illegal dumping occurring in developing countries is due to the shortage of proper waste treatment facilities. The authors argue that the lack of proper waste treatment facilities and landfill sites result in an increase in cost for the proper disposal of household waste (Ichinose & Yamamoto, 2011). Munton (1996) agree and highlights that the increase in the demand for waste disposal facilities coupled with insufficient disposal capacity generally increases the frequency of illegal dumping and threatens human health and environmental degradation. Conversely, D'Amato *et al.,* (2018) examined the factor of insufficient waste treatment facilities from a different point of view. The authors argue that the shortage of proper waste treatment facilities does not increase illegal dumping, but the unit pricing of solid waste does (D'Amato *et al.*, 2018).

A study by Oyekale (2015) examined the factors driving solid waste disposal and recycling behaviours in South Africa. The study identified that income, attainment of formal education, payment for waste disposal, and access to social grants were the main factors which drove illegal dumping throughout the country (Oyekale, 2015). Polasi (2018) found that the main factors that influenced illegal dumping in Zondi, a township in Soweto were the lack of regular waste removal services and lack of illegal dumping prevention strategies.

2.2 Impacts of illegal dumping

The illegal disposal of waste has been regarded as one of the biggest sources of environmental damage with underlying soil quality and watercourse being under high risk of being damaged (Liu *et al.*, 2017). New South Wales Government (2011) state that there are two types of consequences associated with illegal dumping 1) environmental and social impacts, and 2) financial costs. Environmental impacts include erosion and degrading land; plant and animal habitats whilst the social impacts include fire risk posed by arson which can lead to damaged property, public health concerns, and contamination of local waterways (New South Wales Government, 2011). Glanville and Chang (2015) concur and emphasize that illegal dumping imposes significant risk such as human health, environment and to the economy. Triassi et al (2015) argued that illegal dump impacts are associated with the waste composition practices which consists of several types of substances such as toxic waste and dioxins which pollute the environment with both short term and long-term effects.

A study by Bandara and Hettiaratchi (2010) identified two common impacts that were related to illegal dumps in a municipality in Sri Lanka. The authors found that illegal dumps had an impact on both the environment and the social aspect. Environmentally, illegal dumps resulted in water that is unacceptably acidic (Bandara & Hettiaratchi, 2010). Socially, the authors identified the main problems to be: 1) unpleasant odour, 2) breeding of mosquitos and flies, 3) loss in property value and 4) children affected by various diseases such as skin diseases (Bandara &Hettiaratchi, 2010). Chen *et al.*, (2014) agrees, however, the authors argue that some social impacts of illegal dumps often lead to economic impacts. For example, illegal dumps result in a decrease in neighbourhood property values, becoming unattractive to commercial and residential developers (Chen *et al.*, 2014).

2.3 The need for illegal dumping management

There is a need for managing illegal dumping. Managing illegal dumping can help alleviate global climate change impacts and will enhance the prevention of the problem and develop technologies to aid the efficiency of service delivery. According to Nkosi (2015), waste management of illegal dumping can contribute to improving public health outcomes by reducing opportunities for disease-spreading vermin to thrive. Waste management can also contribute to enhancing environmental quality by protecting water bodies and preventing illegal dumping (Nkosi, 2015).

Munton (1996) states that in order to manage the waste of illegal dumping, it is important first to identify potential factors that cause illegal dumping. Factors include shortage of proper waste treatment facilities, landfill regulations, tax rate, enforcement power when waste regulation is violated, asymmetries of regulations between nations, price of legitimate dumping, global market of waste trading, and organized crime (Munton, 1996; Kim *et al.*, 2008; Liu *et al.*, 2016). Other Scholars such as Santos *et al.*, 2018 suggest that understanding the social life cycle of illegal dumping as a management approach for the management of illegal waste dumping in municipal services can be effective in curbing illegal dumping. On the other hand, Nagpure (2018) argues that in order to effectively and efficiently manage illegal dumping, proper management of infrastructure (waste collection centre, waste transportation, and collection efficiency) should be implemented.

2.4 The methods of identifying illegal dumps

There are different methods and procedures for identifying illegal dumps. These methods are assembled in three different eras which include: I) traditional, II) recent, and III) modern approaches. Traditional methods of identifying illegal dumps include the direct visitation of the dump itself, direct mapping in the field, voluntary reporting and aerial photograph interpretation. Indrawati and Purwaningrum (2001) identified solid waste of illegal dumping through the direct mapping in the field, by river trekking using a boat and by road using a car from Kalapa Dua Depok to Manggarai, South Jakarta. This methodology was very costly and required a lot of resources. Even though the study proved to be a success in terms of identifying the illegal dumps, its limitation was that it provided data for that small area only (Indrawati & Purwaningrum, 2001). Another limitation of this approach was identified by the Shanghai Municipal Government (2016), which proved that patrols assigned to specific dumps provides surveillance and allows dumps to be cleaned up promptly, however, this system does not reduce dumping cases and it lacks prevention mechanisms.

Salleh and Tsudagawa (2002) demonstrated an illegal dumping site detection by using features (wheat field, ground, lake, and forest) extracted from the sky using a digital video camera in Anchorage, Alaska (United States of America). Pattern classification was used to classify the ground feature in order to identify industrial illegal disposal of waste using the spectral resolution of the image (Salleh & Tsudagawa, 2002). Results showed that the correctness percentage of just 26.5% for classifying only using the spectral information and recommend that this percentage could be increased to 97.36 if spectral and spatial

information were used together in order to classify the extracted features (Salleh & Tsudagawa, 2002).

The above-mentioned traditional methods, however, are tedious and are often costly and require a lot of resources. Other recent approaches for identifying illegal dumps include the usage of Geographical Information System (GIS) tools together with geostatistical modelling, GIS and multi-criteria spatial analysis, and GIS and factor analysis for determining the probability of areas of the presence of illegal landfills. Biotto et al (2009) identified contaminated areas in Venice, Italy using GIS and multi-criteria spatial analysis. A simple weighted linear combination procedure was applied to combine suitability maps. The results revealed that GIS analysis tools allowed the quantitative study of correlations among the thematic data.

Portnov (2017) identified areas under the potential risk of illegal construction and demolition waste dumping using GIS tools and geostatistical modelling in the district of Haifa, Israel. The author used a multivariate regression to identify and measure the effect of different factors on the amount of waste accumulated in each illegal dump using the following variables as predictors: distance from the main road; distance to nearest city; depth of ravine if present; forest proximity; slope and visibility of site (Portnov, 2017). The variables were estimated using GIS layers and aerial photos. Results revealed that forested areas and locations near major roads are attractive for illegal waste dumping. The author suggests a new and relatively easy to implement assessment approach which will enable identifying and mapping specific areas characterized by elevated risks of illegal dumping (Portnov, 2017). The limitations of the identification methodologies, is that they cannot differentiate between the different kinds of the illegally dumped household waste (e.g. building rubble and domestic waste) and differentiate between spectrally similar objects.

Silvestri and Omri (2008) utilized remotely sensed data to identify unknown landfills over large areas in North-East Italy (part of the Venice lagoon watershed) using stressed vegetation as an indicator of the presence of illegal dumps. The study utilized IKONOS satellite data and the maximum likelihood classifier and achieved an overall accuracy of 74%. A study by Yonezwa (2009) investigated the usefulness of monitoring waste using data from ALOS (Advanced Land Observing Satellite) and Quickbird. Illegal dumps were examined using ALOS imagery and the results indicated that illegal dumps could be identified (Yonezwa, 2009). Selani (2017), identified and mapped illegal dumps using high-resolution

remote sensing imagery (Worldview-2) and pixel-based image analysis in Soweto, Johannesburg. The author attained an overall accuracy of 87% for Random forest and 85% for Support Vector Machine. However, in terms of identifying the two different types of dumps, the studies encountered several issues due to spectral mixture in pixel-based image analysis. Considering that Worldview-2, IKONOS, and Quickbird are high-resolution imagery with a spatial resolution of 0.46m, 1m and 2.4m, respectively delineate the complexity that image pixels are not true geographical objects and pixel topology is limited (Aggarwal *et al.*, 2016). Table 1 summaries the remote sensing-based studies and methodologies for identifying illegal dumps.

Table 1: Summary table detailing remote sensing studies that detected and mapping illegal dumping.

Author	**Data**	**Method**	**Classifiers**	**Accuracy achieved**
Silvestri and Omri (2008)	IKONOS	Pixel-based	Maximum likelihood	ML-74%
Yonezwa (2009)	ALOS (PALSAR) and Quickbird	Visual interpretation	NA	NA
Selani (2017)	Worldview-2	Pixel-based	RF and SVM	RF-84% SVM-85%.

2.5 Object-based Image Analysis

There is an increasing interest in overcoming the limitation of traditional pixel-based classification techniques. Improvements in very high-resolution remote sensing data have driven innovation in the new image-classification techniques (Blaschke, 2010). Object-based Image Analysis has been increasingly used to process high-spatial resolution images, with applications ranging from species detection to land cover mapping (Goncalves *et al*., 2019). Dornik et al (2018) utilized OBIA techniques for the delineation and classification of soil types in the western part of Romania using digital maps of topography, based on the random forest classifier. The study compared OBIA classification techniques with those a pixel-based classification using the same classifier. The study found that the OBIA classification

technique had an overall accuracy of 58%, which was 10% superior to the pixel-based approach (Dornik *et al.*, 2018).

Lichtblau and Oswald (2019) classified impervious land-use features (e.g., roads, buildings, parking lots, driveways, swimming pools, bare ground, vegetation and water) of five different areas within the Black Creek sub watershed of the Humber River, using OBIA techniques. A 0.2m resolution aerial orthoimagery with four multispectral bands (R, G, B and NIR) and 0.6m resolution LiDAR raster layers data were fused. Using a semi-automated rule-set, the authors achieved overall classification accuracies ranging from 88.7% to 94.3%, indicating the effectiveness of OBIA (Lichtblau & Oswald, 2019).

A LULC classification study comparing three classification methodologies (object-based, supervised, and unsupervised pixel-based) was conducted by (Weih & Riggan, 2016). Two multi-temporal (leaf-on and leaf of), medium resolution SPOT-5 satellite images, and a high resolution color infrared digital orthophoto were used in the analysis. Results revealed that the object-based classification method using all three image datasets produced the highest overall accuracy 82.0%, and was statistically significantly different from other classifications (Weih & Riggan, 2016).

2.6 Challenges of using remote sensing for identifying and mapping illegal dumping

The chemical composition and size of different materials makes it difficult for sensors to detect illegal dumping sites. According to Domanska and Bondar (2013) the components of waste which include: different densities, overall sizes, chemical composition, and reflecting ability cause certain complexity in the detection of illegal dumps on satellite images. Spatial objects (i.e. built-up areas, construction rubble, and road networks) that have similar spectral characteristics often cause challenges for remote sensing users (Jawak *et al.*, 2015). The spectral similarity of these spatial objects often leads to misclassification and decreasing the accuracy of the results (Salleh & Tsudagawa, 2002; Jawak *et al.*, 2015).

Yonezwa (2009) further adds that it is difficult to identify illegal dumps with a size of approximately 2 x 2m laying on bare soil which generally exhibits high reflectance. Silvestri et al (2009) on the other hand argues that identifying small illegal dumps is difficult using standard remote sensing methods.

The nature and the age of the dumps make it difficult for sensors to accurately identify and map these illegal waste dumps. Jakiel et al (2019) argues that age of dumping sites affects the visual appearance of waste in these three ways: 1) new illegal dumps means that all waste was recently disposed of on the site, 2) old and still used dumps means that some waste has been overgrown with vegetation, and 3) old and no longer used means that all waste was overgrown with vegetation and no recent waste was not noted. The second and third issues associated with the age of the dump tend to misclassify illegal dumps with vegetation or bare land areas for old and still an old and no longer used (Jakiel *et al.*, 2019).

Chapter Three: Materials and Methods.

3.1 Study area

This research was conducted in the township of Soweto in Johannesburg. Soweto is located at 26 ° 12’ 22.43” S 27 ° 59’ 02.58” E (Figure 3). The township has an area of 200.03 km^2 and has an elevation ranging from 1.500m to 1.600m. It has an average precipitation of 750 mm and an average temperature of 23^oC and is classified as a subtropical highland (Ramchander, 2004). The name was given in 1963 to the sprawling of townships that had spread adjacent to Johannesburg to accommodate black people migrating from rural areas and surrounding countries (Stewart *et al.*, 2006).

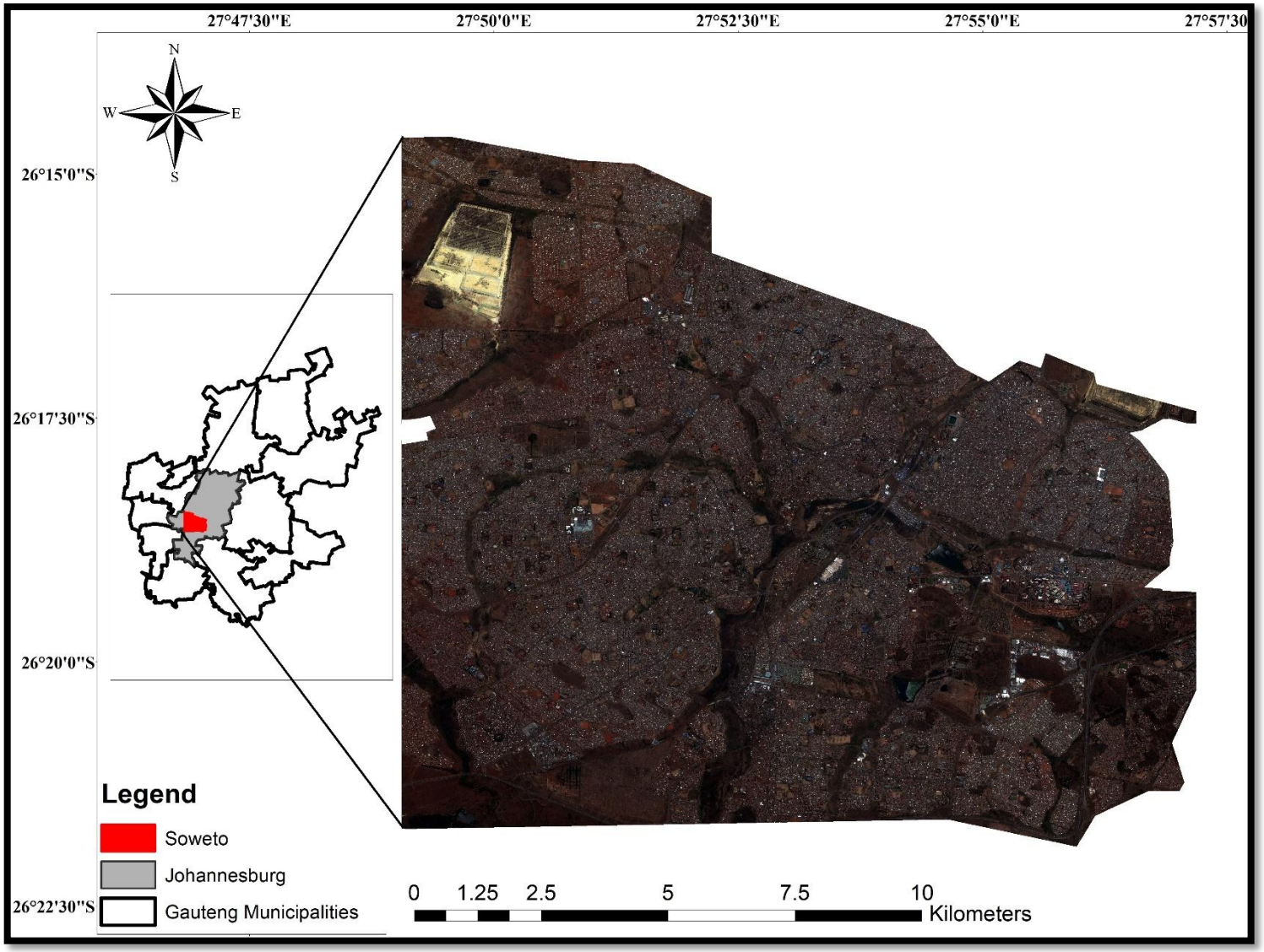

Figure 3: Location of Soweto within Johannesburg and the footprint, true colour of the Worldview-4 image used in the study.

3.1.1 Population profile and socio-economic status of Soweto

Soweto constitutes a diversity of cultural groups, particularly dominated by Zulu, Xhosa, and Sotho, nevertheless, virtually all the indigenous groups of South Africa are found (Ramchander, 2004). Soweto has a population of approximately 1 271 628, constituting about 43% of the entire population of CoJ (Statistics South Africa, 2011; Ayeleru *et al.,* 2018). It is the largest black residential area in South Africa, consisting of 34 townships and covers an area estimated at 2000.03 km^2 (Stewart *et al.,* 2006).

Soweto is a township of extreme inequality. Low-class squatter communities are characterized by abject poverty, with low levels of services and houses are made of corrugated iron accommodating approximately 7 occupants per shack (Creighton, 2003; Ramchander, 2004). Middle-class communities in which the majority fall under are characterized by smaller family sizes with only one or two children, living in two- or three-bedroom good quality houses tiled with clay roofs (Ramchander, 2004). The upper-class suburbs associated with homes valued in excess of R1 million with luxury features and swimming pools, high security of tenure and a lot of services (Ramchander, 2004).

It is estimated that 40% of the population of Soweto is unemployed, giving rise to the high number of crimes committed (Stewart *et al.,* 2006). Many try to find work as hawkers, painters, fruit and vegetable sellers, sellers of second-hand clothes, builders, and motor mechanics (Ramchander, 2004).

3.1.2 Housing

Most of the houses in Soweto are of standard design consisting of three to four rooms (Ramchander, 2004). These houses commonly referred to as "match-boxes" were built by the public authorities during the apartheid era (Ayeleru *et al.,* 2018). The houses are built on a functional floor space of 43 m^2, and consisting of two bedrooms, a dining room and a kitchen (Ramchander, 2004). The size of the yard is 330 m^2, it is quite common for up to eight people to share a house (Ramchander, 2004).

According to Gilbert and Soskolne (2003), Soweto's housing market is deeply differentiated, and the differences are easily seen. Houses are stratified by means of 1) quality of housing, 2) security of tenure, and 3) levels of services (Gilbert & Soskolne, 2003). There are six different housing domains (settlement types) namely: 1) *Council housing*— houses built by the council for the purpose of population resettlement at different periods: pre-apartheid, forced removals and squatter relocation, 2) *Private sector housing*— houses built privately by

their owners (mostly post-apartheid), 3) *Informal settlements*— dwellings put-up informally, 4) *Backyard shacks/formal backyard rooms*— found mostly in the backyards of council houses, 5) *Hostels*—these were originally built for workers from the rural areas who came to work in the city, and 6) *Site-and-service schemes*—these are post-apartheid schemes where the council provides the site and basic services, but the dwellings are informal structures put up by the owners (Gilbert & Soskolne, 2003).

3.1.3 Waste management and service delivery in Soweto

There are two landfill sites in Soweto namely: 1) Marie Louise Landfill site in Dobsinville and 2) Goudkoppies Landfill site near Pimville (Figure 4). The population density is sparsely populated in and around this landfill sites. Informal settlements tend to be located around this dumps because waste reclaimers tend to seek employment at the landfill sites (Gilbert & Soskolne, 2003). People are settled at more developed areas of the township. The location of these landfill sites makes it difficult for some members of the township to legally dispose of their waste, especially building rubble (Polasi, 2018). Christa Venter the Chief Operating Officer (COO) of Pikitup highlights that most of the illegal dumping occurs in the Northern and Southern regions where landfills are not close by and these regions have a lot of open spaces (Pikitup, 2017).

Pikitup collects on average 4 500 tonnes of illegally dumped waste per week in the CoJ (City of Johannesburg, 2017). Pikitup collects household domestic waste from different suburbs on a five-day working schedule (Figure 4)(Pikitup, 2017). According to Peter Hlubi a reporter from Pikitup (2017), residents of Soweto tend to dispose of their waste in nearby open vacant land when Pikitup trucks do not come by.

3.1.4 Selection of the focus dumps.

In this research study, domestic waste was selected because Soweto is an urban area, where residents dump their waste in footpaths, storm water drains, rivers, streams, streets and street corners which is a huge concern. Building rubble was selected because a number of building rubble illegal dumps in vacant spaces were observed in the study area during data collection. This is because the area is developing and communities are refurbishing the old “match-box” houses, which were provided by the apartheid government and Pikitup services does not collect building rubble from community households. The implications of identifying and mapping building rubble and other land-use types such us built-up-areas is the possibility of misclassification due to spectral mixture between the two materials.

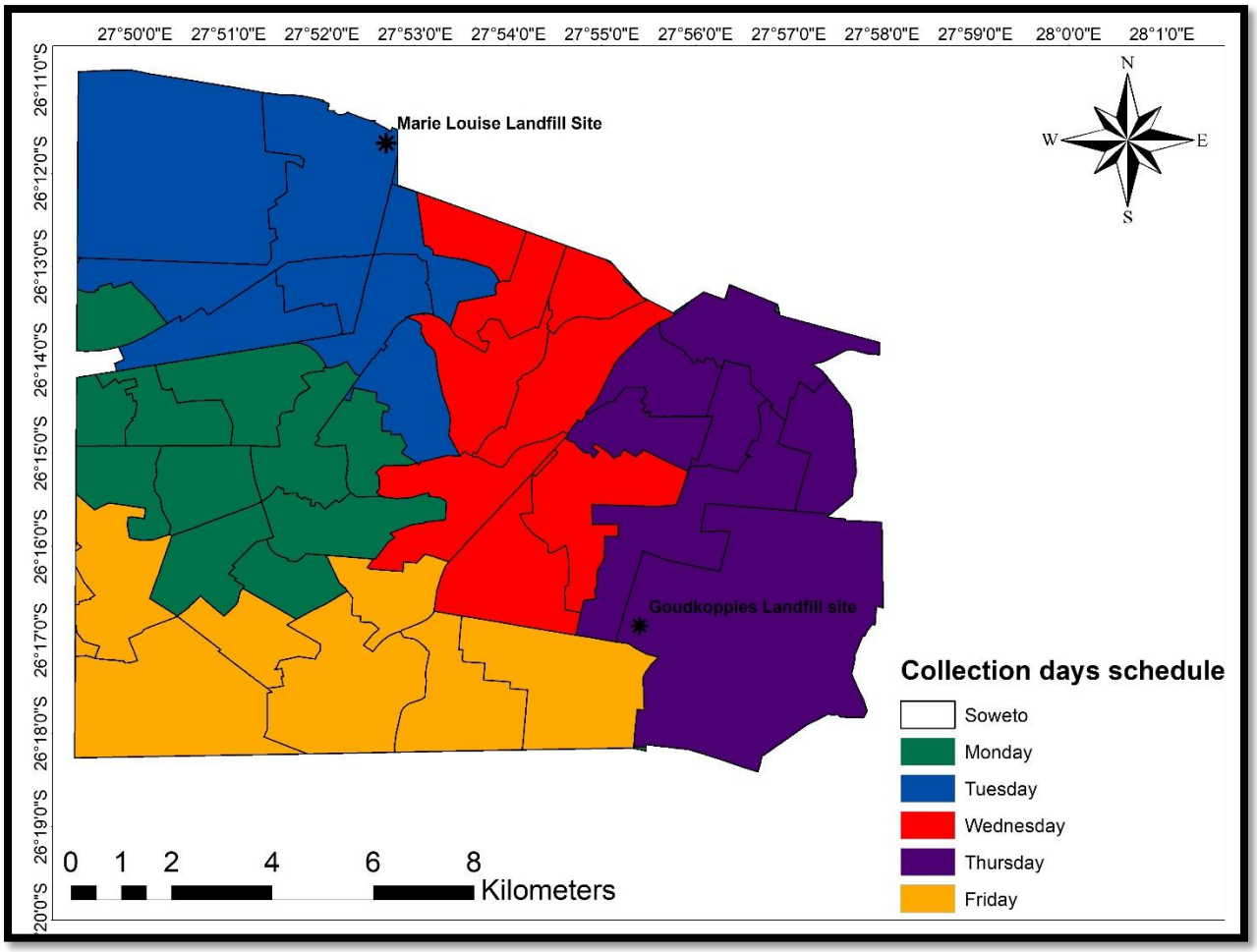

Figure 4: Pikitup collection schedule for the different suburbs of Soweto (Data source: Pikitup www.pikitup.co.za).

3.2 Remote sensing data acquisition

The study utilized WorldView-4 remote sensing imagery which was acquired from DigitalGlobe. The image acquisition date is of the 26th of September 2019. Worldview-4 is a high-resolution commercial satellite launched in 2016 by DigitalGlobe in the United States (Wang *et al.*, 2019).

Worldview-4 has an average revisit period of <1 day, running in a sun-synchronous orbit at an altitude of 617 km (Wang *et al.*, 2019). It provides panchromatic imagery with the resolution of 31 cm and a multispectral band image with a resolution of 1.24 m" (Table 2) (European Space Imaging, 2018).

Table 2: Worldview-4 specification and design (European Space Imaging, 2018).

Sensor resolution	Panochromatic:	450 – 800nm
	Four Multispectral	
	Red:	655-690 nm
	Green:	510-580 nm
	Blue:	450-510 nm
	Near IR:	780-920 nm
Sensor resolution	***Panochromatic Nadir:***	***0.31m***
	20° Off-Nadir:	0.34m
	56° Off-Nadir:	1.00m
	60° Off-Nadir:	3.51m
	Multispectral Nadir:	***1.24m***
	20° Off-Nadir:	1.38m
	56° Off-Nadir:	4.00m
	60° Off-Nadir:	14.00m

3.3 Image pre-processing

The image pre-processing of the Worldview-4 data is done by the Vendor. DigitalGlobe imagery is orthographic calibration-ready, obtained under cloudless conditions, with a series of pre-processing steps, including internal sensor geometry correction, removal of optical distortions, scan distortions and line-rate variations, and band registration, are performed (Yan *et al.*, 2018).

3.4 Identifying illegal dumping types and other land use and land cover classes

This research study employed LULC mapping in order to differentiate illegal dumps from other classes. Both building rubble and domestic waste were identified through ground-based fieldwork. The ground-based fieldwork also included the collection of different land-use and land-cover (LULC) types which were used for LULC mapping. Since most of the other LULC types were broad in size (excluding building rubble and domestic waste), the spatial resolution of the Worldview-4 with a Panochromatic nadir resolution of 0.31m made it possible to collect reference data using the image itself. The LULC classes that were identified are presented in Table 3.

Table 3: Land use and land cover classes and their description.

Land use and land cover classes	**Attributes**
1. Building rubble	Drywall, roofing, shingles, lumber, bricks, and concrete.
2. Domestic waste	Yard waste, tires, electrical appliances and batteries, plastics.
3. Bare soil	Not covered by vegetation, litter, or rocks vulnerable to erosion.
4. Built-Up Area	Residential, industrial, commercial structures, and factories.
5. Vegetation	Plants and trees collectively.
6. Bare land	Land with no buildings and it is not used.
7. Water bodies	Dams, rivers, streams, and ponds.
8. Mine dumps	The materials left-over after the processing of gold ore.
9. Roads	Streets, roads, and freeways.
10. Shadows	A dark area produced by a body coming between rays of light and a surface.

3.5 Reference data

The reference data of building rubble and domestic waste for training and validation were collected through ground-based fieldwork using a global positioning system (GPS) during the months of June and July 2019 on several illegal dumping sites in Soweto.

A random and homogeneous purposive sampling method was used to collect the training data. A random sampling method is a process whereby the selection of a sample is based on chance (Etikan *et al.*, 2016). A random sampling tool from ArcMap 10.5 was used to select 17 suburbs randomly from the 34 in the study area.

From the selected 17 suburbs, illegal dumps were identified in open/vacant space using Google Earth. This approach was based on the findings of Polasi (2018) that illegal dumps in Soweto tend to be in open/vacant spaces near schools, clinics, sports fields and cemeteries. The researcher then went to the field to collect reference data from the selected 17 suburbs in order to differentiate whether the site contained building rubble or domestic waste.

Homogeneous purposive sampling is a non-probability sampling method that is selected based on the objective of the study, and where proportionality is not the main concern (Etikan *et al.,* 2016). It is selected when there are shared characteristics or a set of characteristics. This technique was used to gather the reference data for both building rubble and domestic waste. The reference data for all identified LULC classes were split into 70% training and 30% test, resulting values are presented in Table 4.

Table 4: Reference data for training and validation for the different LULC types in the study area.

Class	**Number of training samples (70%)**	**Number of test samples (30%)**	**Total number of samples**
1. Building rubble	31	13	44
2. Domestic waste	31	13	44
3. Bare soil	68	29	97
4. Built-up area	63	27	90
5. Vegetation	57	24	81
6. Bare land	63	26	89
7. Water bodies	50	21	71
8. Mine dumps	32	13	45
9. Roads	66	27	93
10. Shadows	68	28	96

Through ground-based fieldwork and the use of Google Earth, the two types of illegal dumps which the study is interested in were identified. Building rubble is the unwanted material produced directly or incidentally during construction, such materials include drywall, roofing, shingles, lumber, bricks, and concrete (Liu *et al.,* 2016). Whilst domestic waste is waste generated as a result of the ordinary day-to-day use of a premise, such materials include yard waste, tires, electrical appliances and batteries, household litter (Liu *et al.,* 2016). The ground-based reference data for building rubble and domestic waste, and the reference points collected for other LULC types using the WorldView-4 image were randomly split into 70% training data and 30% for the test data (Table 4) (Adam *et al.,* 2014). According to (Trimble, 2014) 20 objects per class is a good rule of thumb in OBIA classification. However, the

training samples that were collected for each class were equal or more than 31 as to make the classification more efficient.

3.6 Object-based image analysis

Object-based image analysis (OBIA) is a sub-discipline of GIScience devoted to portioning remote sensing imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale (Hay & Castilla, 2006). The recognition of limitations with pixel-based approaches and the dramatic increase in commercially available very high-resolution remote sensing imagery transpired to the emergence of OBIA (Blaschke, 2010). Nassbaum and Menz (2008) concur and reveal that pixel-based methods are not effective on very high-resolution images since these include far too many details. Pixel-based methods fail to utilize the spatial variation of different land covers in very high-resolution images.

Objected based classification groups pixels with common structural, spectral and spatial characteristics, and then these segments are allocated into the correct thematic classes based on attributes (Hay & Castilla, 2006). The advantage of OBIA is that it combines both the visual interpretation and pixel-based classification (Blaschke, 2010).

3.6.1 Image segmentation

Image segmentation is defined as a method of dividing an image into homogeneous regions based on attributes such as texture, colour, shape, scale and grey level (Hossain & Chen, 2019). The scale is the most important parameter for segmentation since it controls the size of the segments (Phiri *et al.,* 2018). Image segmentation is critical and the most important step in OBIA (Mohammad *et al.,* 2019). Image segmentation highly influences the final feature extraction and image classification. According to Hossain and Chen (2019), image segmentation can be categorized into four segmentation processes: (i) pixel-based which is not suitable for OBIA, (ii) region-based, (iii) edge-based, and (iv) hybrid method depending on the identification method. Apart from pixel-based segmentation, the remaining three segmentation algorithms are classified based on hierarchy, object extraction method, object representation method and the homogeneity criteria (Auquilla *et al.,* 2014).

This study utilized the region-based (regional growing) segmentation algorithm which is based on the approach that the methods try to explore the object from the inside and then expand outward until meeting the object boundaries (Zhang, 2013). The basic approach to region-based segmentation is: (i) obtain an initial (over or under) segmentation of the image,

(ii) merge or split those adjacent segments that are similar or dissimilar, and (iii) do the second approach until no segments that should be merged or split (Bins *et al.,* 1996). The multi-resolution segmentation algorithm was used specifically for this study. This segmentation approach was chosen because it is often used as a general algorithm is remote sensing applications as it generates image objects with greater geographical significance and strong adaptability (Neubert *et al.,* 2007; Martha, 2011; Chen *et al.,* 2019).

In order to optimize the segmentation approach and minimize the errors due to over- and under-segmentation, the optimal scale factor for segmentation was obtained and optimized by iteratively changing their values and thereafter visually assessing the resulting segmented objects. Phiri *et al.,* (2018) argues that visual assessment of segmentation quality is subjective, nevertheless, it is one of the most common methods used to complement the quantitative means of defining the optimal segmentation parameters.

3.6.2 Multi-resolution segmentation

Multi-resolution segmentation (MRS) was used to segment image objects according to their different attributes. MRS arose from the idea that objects that are smaller than the resolution of the image cannot be detected, however, if objects are bigger than the spatial resolution of the image, then it will be fragmented into pixels (Mohammad *et al.,* 2019). In a not so easy process, smaller objects will be merged into larger ones and are dependent on the desired objects to be segmented. This segmentation algorithm is highly considered for environmental management-based research studies (Baatz, 2000).

When utilizing MRS algorithm to an image, three parameters namely; scale factor, shape, and compactness are crucial for the resultant image segments (Blaschke, 2010). The scale factor/parameter is the most crucial process which controls the size of the segments and affects the accuracy of the classification (Benz *et al.,* 2004). The other two parameters referred to as composition of homogeneity criterion which is shape and compactness use weights ranging from 0-1 to control the homogeneity of the image objects and regulate the spectral homogeneity and the shape of the objects (Baatz, 2000; Benz *et al.,* 2004; Trimble, 2014).

In this study, MRS was used on the Worldview-4 satellite image. The scale, compactness, and shape parameters depended on the overall aim of the study, which was the detection and mapping of illegal dumps (Table 5). The weight selection for the bands of the image was acquired from looking at the Mean Decrease Accuracy (MDA) for each band. The MDA was

achieved using the Random Forest model in R(64-bit). The Near-IR band gained the most weight, because it can express differences in the spectral signature of different objects (Gilbertson *et al.*, 2017).

Table 5: Multi-resolution segmentation parameters employed in the study.

Algorithm	**Parameters**		**Weights**	
Multi-resolution segmentation	Scale:	30	Red:	2
	Compactness:	0.98	Blue:	1
	Shape:	0.1	Green:	3
			NIR:	4

3.6.3 Feature selection

After segmenting the image, a feature selection variable was used to select object features that will be used in the image analysis. Feature selection is important because, irrelevant features induce greater computational costs, lead to overfitting and it is reasonable and important to ignore those features with little effect on the output (Guyon & Elisseeff, 2003). This study used the forward variable feature selection.

3.6.3.1 Forward variable feature selection

The forward variable feature selection evaluates all feature subsets which consists of only one input variable attribute (Guyon & Elisseeff, 2003). This feature selection methodology measures the variables through the Leave-one-Out Cross-Validation (LOOCV) error of the one component subsets so that the best individual feature(s) is found (Bengio & Chapados, 2003). Forward selection is computationally more efficient than backward elimination (Guyon & Elisseeff, 2003).

Various objects feature's such as mean and standard deviation of the layer values, geometry, extent, shape and normalized difference vegetation index (NDVI) (customized) were considered for the optimization and improvement of the classification.

3.6.3.2 Object features

In order to utilize these object features discussed below; different object features were tested using the OOB (out-of-bag) as an estimate error method. The OOB error gives an estimation of the important variables by calculating how much the error of estimate decreases when an object feature is used, whilst others remain constant (Archer & Kimes, 2008).

3.6.3.2.1 Spectral heterogeneity

The spectral heterogeneity of the objects was calculated using the standard deviation of the spectral value denoted by the formula below (Yan *et al.*, 2019):

$$h_{spectral} = \sum_{b=1}^{B} \sigma_b \quad \textbf{(1)}$$

The heterogeneity before and after the segmentation is represented by the following formula:

$$h_{spectral} = \sum_{b=1}(n_{merge} \cdot \delta_{C,merge} - (n_{obj1} \cdot \delta_{C,\ obj1} + n_{obj2}\, \delta_{C,\ obj2})) \quad \textbf{(2)}$$

$h_{spectral}$ is the difference between the spectral heterogeneity values obtained for the two different objects and the sum of the spectral heterogeneity values of obj1 and obj2, $n_{merge} \cdot \delta_{C,merge}$ denote the number and spectral variance of the merged pixels, $n_{obj2}\, \delta_{C,\ obj2}$ are the spectral variance and a pixel number of two adjacent regions (Yan *et al.*, 2019).

3.6.3.2.2 Shape heterogeneity

The measurement of the shape heterogeneity index of the objects is indicated by the following:

$$h_{shape} = \omega_{Smoothness} \cdot h_{smoothness} + \omega_{compactness} \cdot h_{compactness} \quad \textbf{(3)}$$

The measurement of the shape is composed of two sub-indexes: compactness index and smoothness index (Yan *et al.*, 2019).

3.6.3.2.3 Global heterogeneity of the object

The measure of the global heterogeneity takes into consideration the shape parameter. The formula for measuring the overall heterogeneity is as follows:

$$h = \omega_{color} \times h_{color} + \omega_{shape} \times h_{shape} + \omega_{texture} \times h_{texture} \quad \textbf{(4)}$$

As the spectral heterogeneityh_{color}, the shape heterogeneity h_{shape} and the texture heterogeneity $h_{texture}$ values are both between [0, 1], and the weight range is also between [0, 1], so the higher the similarity between the objects in the H value, the higher the similarity between the objects (Yan *et al.*, 2019).

3.6.3.2..4 Normalized difference vegetation index

The normalized difference vegetation index object feature was customized in order to differentiate between vegetated and non-vegetated classes. The formula for calculating NDVI is as follow:

$$\frac{(NIR-Red)}{(NIR+Red)} \quad \textbf{(5)}$$

Where NIR represents band 4 and Red represents band 1 of the WorldView-4 image (Zaitunah *et al.*, 2018).

3.7 Machine learning algorithms for classification

Machine learning algorithms are automated detection of meaningful patterns in data (Osisanwo *et al.,* 2017). Machine learning algorithms are often more accurate than human-crafted rules, and they do not need a human expert or programmer (Ghosh & Joshi, 2014). Machine learning algorithms are suitable because they mitigate the Hughes phenomena, which occurs when the number of variables is larger than the number of training samples, and reduce the computational time (Belgiu & Dragut, 2016). Furthermore, they deal with the nonlinearity of variables, the imbalance between the training samples and noise in both training data and unlabeled data (Gislason *et al.,* 2006; Ghosh *et al.,* 2014; Belgiu & Dragut, 2016). Two machine learning algorithms were tested in this study, Random Forest (RF) and Support Vector Machines (SVM).

3.7.1 Random forests classification algorithm

RF is one of the most effective machine learning models for predictive analysis introduced by Leo Breiman (Yu *et al.,* 2017). The algorithm has two major parts: 1) randomness and 2) ensemble learning (Yu *et al.,* 2017). RF is an ensemble of a large number (ntree) of the decision tree (DT) classifiers (Ghosh & Joshi, 2014). Within RF framework, randomness is introduced twice: first, during the bootstrap sampling of the original training data, which increases the diversity of the tree; and second, during the random selection of input predictors for splitting at nodes of each DT, thereby reducing the generalization error (Ghosh & Joshi, 2014).

The RF classifier uses a set of classification and regression of trees (CARTs) to make predictions, trees are created by drawing training samples through replacement (bagging approach) (Ghosh & Joshi, 2014; Belgiu & Dragut, 2016). Two-thirds of the samples (in-bag samples) are used to train the trees, and the remaining one-third samples (out-of-the bag) are

used as an internal cross-validation technique for estimating how the model performs (Yu *et al.*, 2017).

RF is a non-parametric supervised classifier which does not make any assumptions about the frequency distribution, overcoming the limitation of parametric classifiers which deal with unimodal data rather than multi-modal data (Belgiu & Dragut, 2016). Non-parametric classifiers are popular for classifying remotely sensed data, which rarely have a normal distribution.

This classification algorithm was considered in the study because it has become one of the most popular algorithms with the remote sensing community due to its high classification' ability (Belgiu & Dragut, 2016).

3.7.2 Support vector machines classification algorithm

SVM is a machine learning and non-parametric methodology where no prior assumptions are made as well. SVMs are linear binary classifiers that assign a given test sample a class from one of the two possible labels (Mountrakis *et al.*, 2011). The SVM training algorithm finds a hyperplane that separates the dataset into a discrete predefined number of classes in a fashion consistent with the training examples (Mountrakis *et al.*, 2011; Belgiu & Dragut, 2016; Osisanwo *et al.*, 2017). An SVM model is closely related to classical multilayer perceptron neural networks, often reported to achieve better results than other classifiers (Osisanwo *et al.*, 2017).

SVMs was considered as a classification algorithm since a limited amount of reference data is required (Mountrakis *et al.*, 2011). This study only considered the use of the radial basis function (RBF) kernel. Other kernels were not considered. The RBF requires two main parameters: sigma (C) the regularization factor, and gamma (ϒ) the width of the RBF kernel (Mountrakis *et al.*, 2011). This research study employed the methodological approach that is presented in Figure 5.

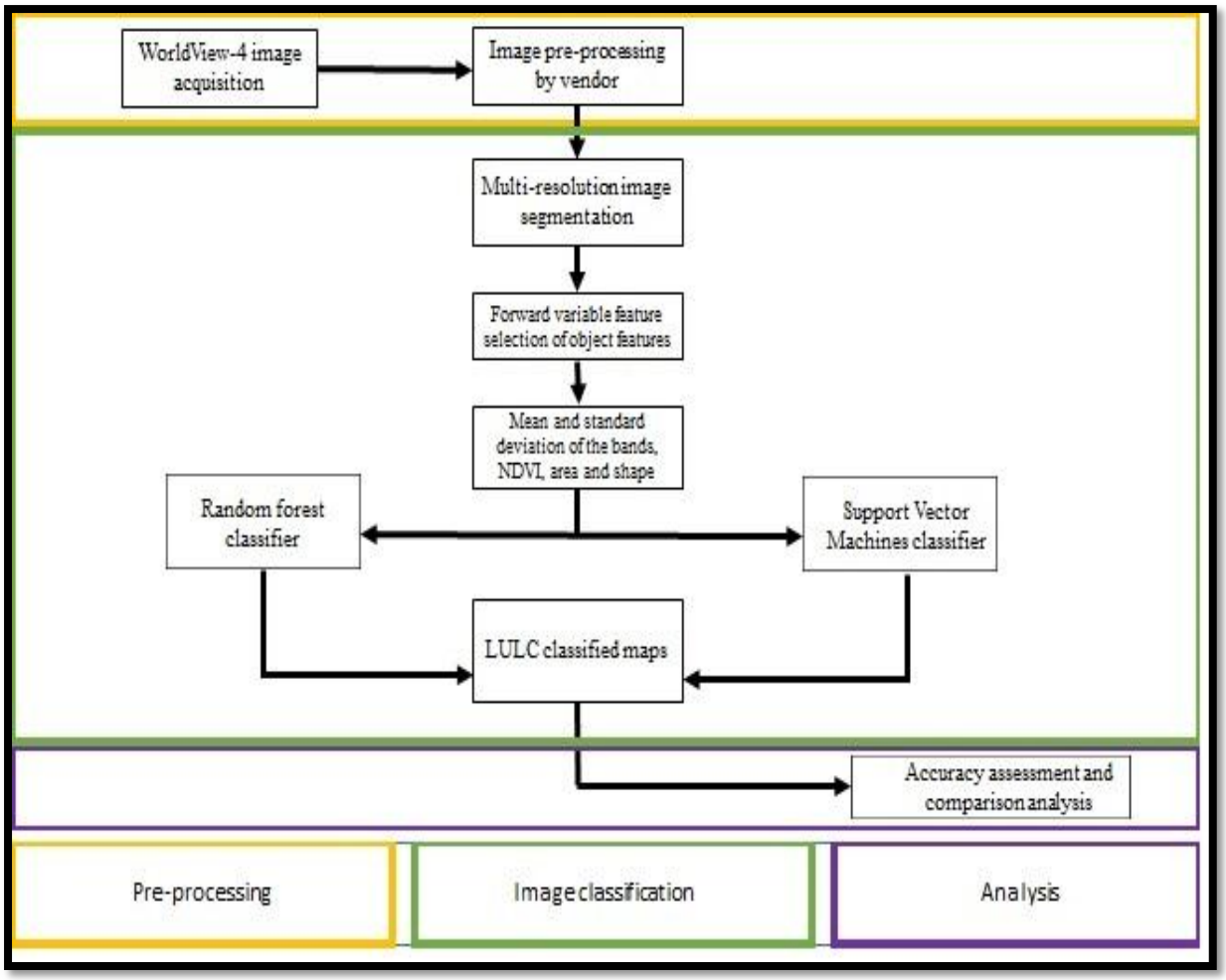

Figure 5: A flow diagram representing the methodological approach implemented in the research study.

3.8 Accuracy assessment

The validation dataset was used to test and assess the accuracy of SVM and RF algorithms in classifying the Worldview-4 image. The most common elements of the confusion matrix are the overall accuracy, user and producer accuracy and kappa coefficient; with each element having value to determine the accuracy of the classified image.

3.8.1 Overall Accuracy

Overall accuracy is a percentage which represents the probability that a randomly selected point is correctly classified on the land use and land cover map (Richards, 2012). The test dataset was used to assess the overall accuracy of the algorithms. The overall accuracy in this study was determined using the following formula (Richards, 2012):

$$Overall\ accuracy = \Sigma\ (\text{classes correctly classified})/\Sigma(\text{Column total})$$

3.8.2 Producer's Accuracy

The producer's accuracy represents the probability that the labelling of the classifier is correct in an image pixel (Richards, 2012). Richards (2012) denotes the formula for determining the producer's accuracy is as follows:

$$Producer's\ Accuracy = Number\ of\ the\ correctly\ classified\ class\ in\ a\ column / verified\ items\ total\ number\ in\ that\ column$$

3.8.3 User's Accuracy

The user's accuracy is produced by the division of the correctly classified samples number of the respective class by its total number of verified samples belonging to the class (Richards, 2012). The formula for determining the user's accuracy is as follows (Richards, 2012):

$$User's\ Accuracy = Correclty\ classified\ number\ of\ item\ in\ a\ row / verified\ items\ total\ number\ in\ that\ row$$

3.8.4 Kappa Coefficient

Kappa coefficient which lies between a value of 0 and 1 provides a measure of the difference between the actual agreement and the agreement that would have been expected by chance (Adam *et al.,* 2014). The value of 1 in the kappa coefficient shows prefect agreement between classification and ground truth pixels whereas a value of 0 shows no agreement (Dorn *et al.,* 2015).

The overall accuracy, kappa coefficient, user and producer accuracies were used to observe the level of accuracy and reliability of the LULC map produced between the two machine learning algorithms.

3.9 Census data acquisition

In order to achieve the third objective, the study also utilized census data created on the 13 March 2018 which was acquired from Statistics South Africa (statssa.gov.za) on 22 November 2019. The methodological workflow for achieving the third objective is presented in Figure 6.

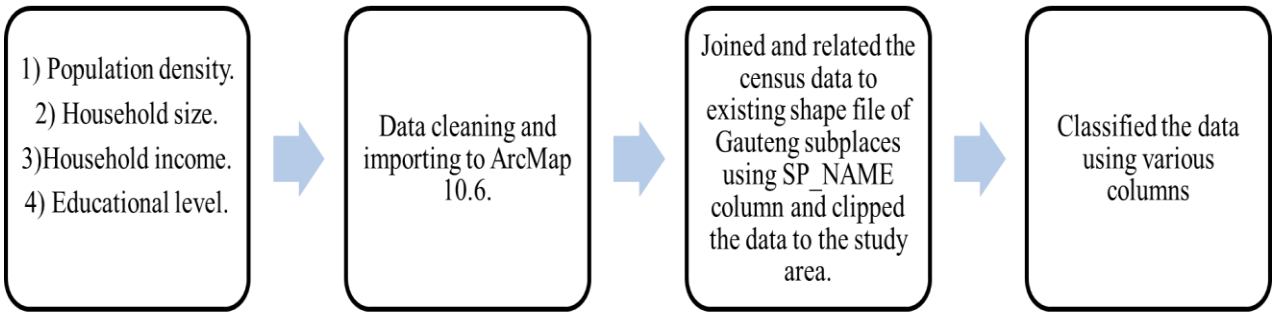

Figure 6: Diagram showing the workflow employed for identifying and analysing the factors that are associated with the spatial distribution of illegal dumping in Soweto.

After acquiring the data from STATS SA, data pre-processing was required before the data could be imported to ArcMap 10.6. Various rows were removed from excel (Xls format) file and SP_NAME (Sub-Places) was added under the places name column. A join and relate function was utilized in ArcMap in order to join the excel data with an already existing shapefile of the Gauteng sub place area. The data was clipped to the study area (Soweto) and classified using various columns such as 1) total population, 2) household size (10+), 3) household income (no income in Rands), and 4) educational level (grade 12). An effect editor tool was used to overlay and analyse the factors associated with the spatial distribution of illegal dumps in Soweto. The swipe and transparency features were utilized for the analysis.

Chapter Four: Results

4.1 The importance of the WorldView-4 bands for the assessment of the classification

The results of the mean decrease in accuracy for the individual band performance of WorldView-4 reveal that the near-infrared band was the most important band in predicting the land cover classes with the highest mean decrease in accuracy value. Whilst, the blue band was the least important band in predicting land cover classes with the lowest mean decrease accuracy value (Figure 7).

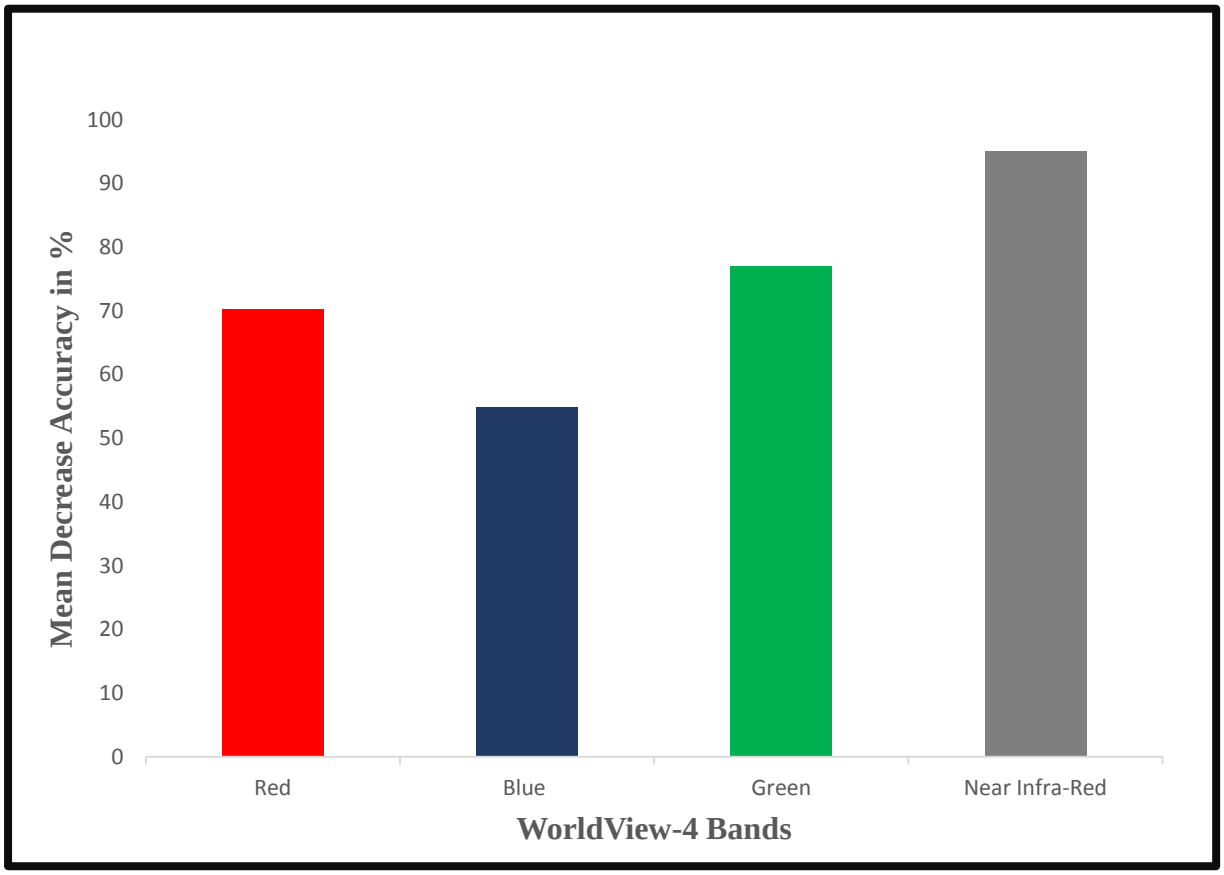

Figure 7: Histogram showing the importance of each WorldView-4 bands in LULC classification for all the classes using the mean decrease accuracy achieved using the Random Forest model.

For individual classes, the mean decrease accuracy values for the red, blue, green and near-infrared bands were assessed. The results for mapping and differentiating between the two identified illegal dumps are revealed in Figure 8. The green band was the most important band for predicting the building rubble land-cover class, followed by the red band, then the near-infrared band. Whereas the blue band was the least important band.

For domestic waste, the red band was the most important band. Followed slightly by the near-infrared band, the green and the blue band were the least important bands. For differentiating purposes, the results show that the two illegal dumps can be differentiated by the green and red bands of WorldView-4 image. For other land-cover classes such as bare soil, bare land, and mine dumps the green band is the most important band, whilst for roads, shadows, vegetation and water bodies the near-infrared band is the most important band. The red band is also important for predicting the built-up area land-cover class. Figure 8 below also reveals that the band importance for DW and BUA are almost similar. The band's importance for the two classes goes from red, near-infrared, green with the least important band being blue. However, the difference between the two classes is the decrease in the mean decrease in accuracy value in the green band. The mean decrease in accuracy for DW is lower than that of BUA.

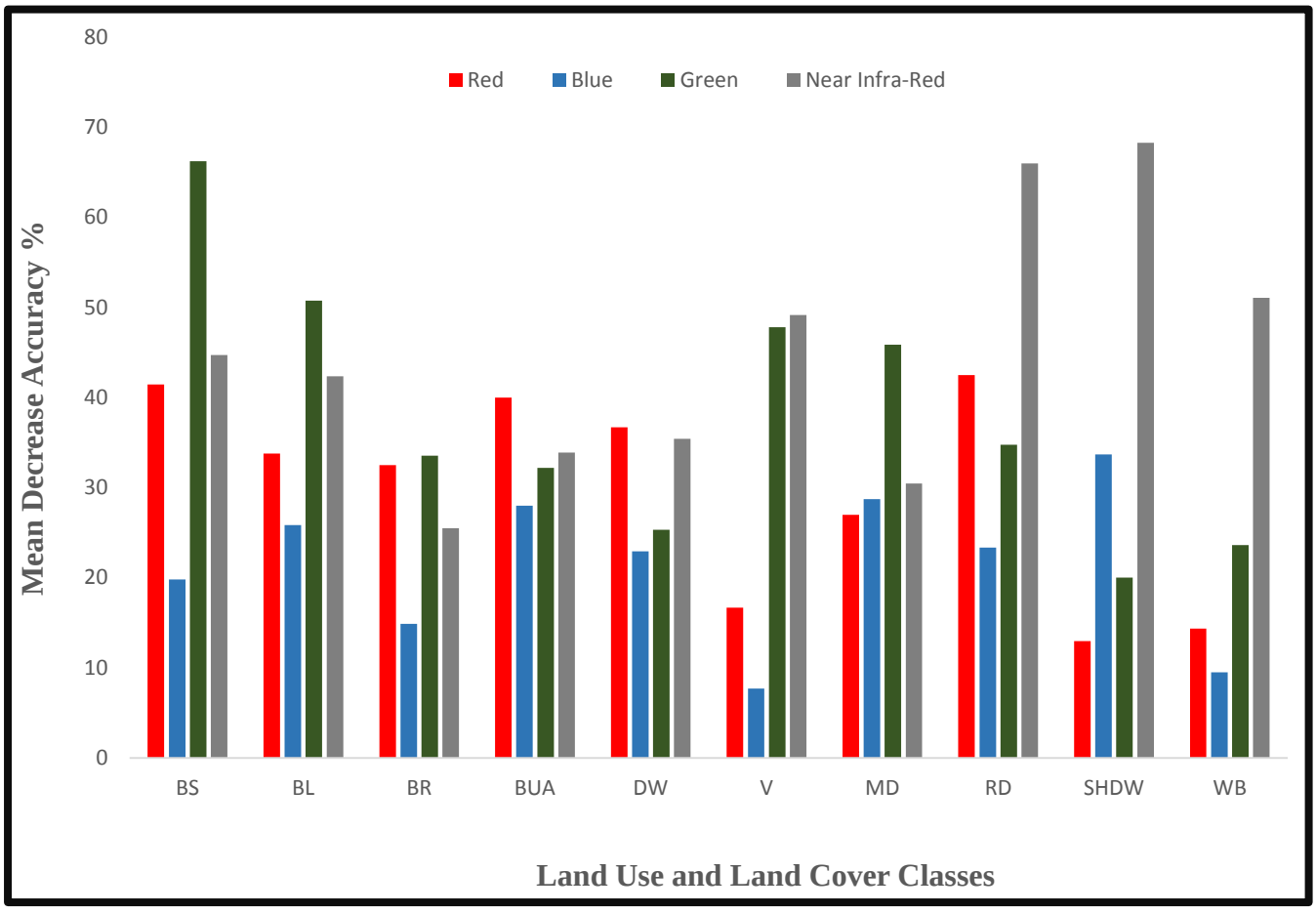

Figure 8: Histogram showing the importance of the individual bands of Worldview-4 in classifying different LULC with the highest mean decrease accuracy indicating the most important band. (BS-bare soil, BL-bare land, BR-building rubble, BUA-built-up area, DW-

domestic waste, V-vegetation, MD-mine dump, RD-roads, SHDW-shadow, WB-water bodies).

4.2 Multi-resolution image segmentation

The optimal segmentation results were achieved when the parameters were set at 30 for scale, 0.98 for compactness, and 0.1 for shape with the weight of the layers at 2,1,3,4 for the red, blue, green, and NIR bands. Segmentation results for building rubble and domestic waste are presented in Figure 9. Segments show that not only the spectral signatures of the dumps were considered, but also the shape, texture, size, and length were also considered. Figure 9C and 9D show in detail how the multi-resolution segmentation algorithm was able to differentiate between the different types of illegal dumps from other LULC classes.

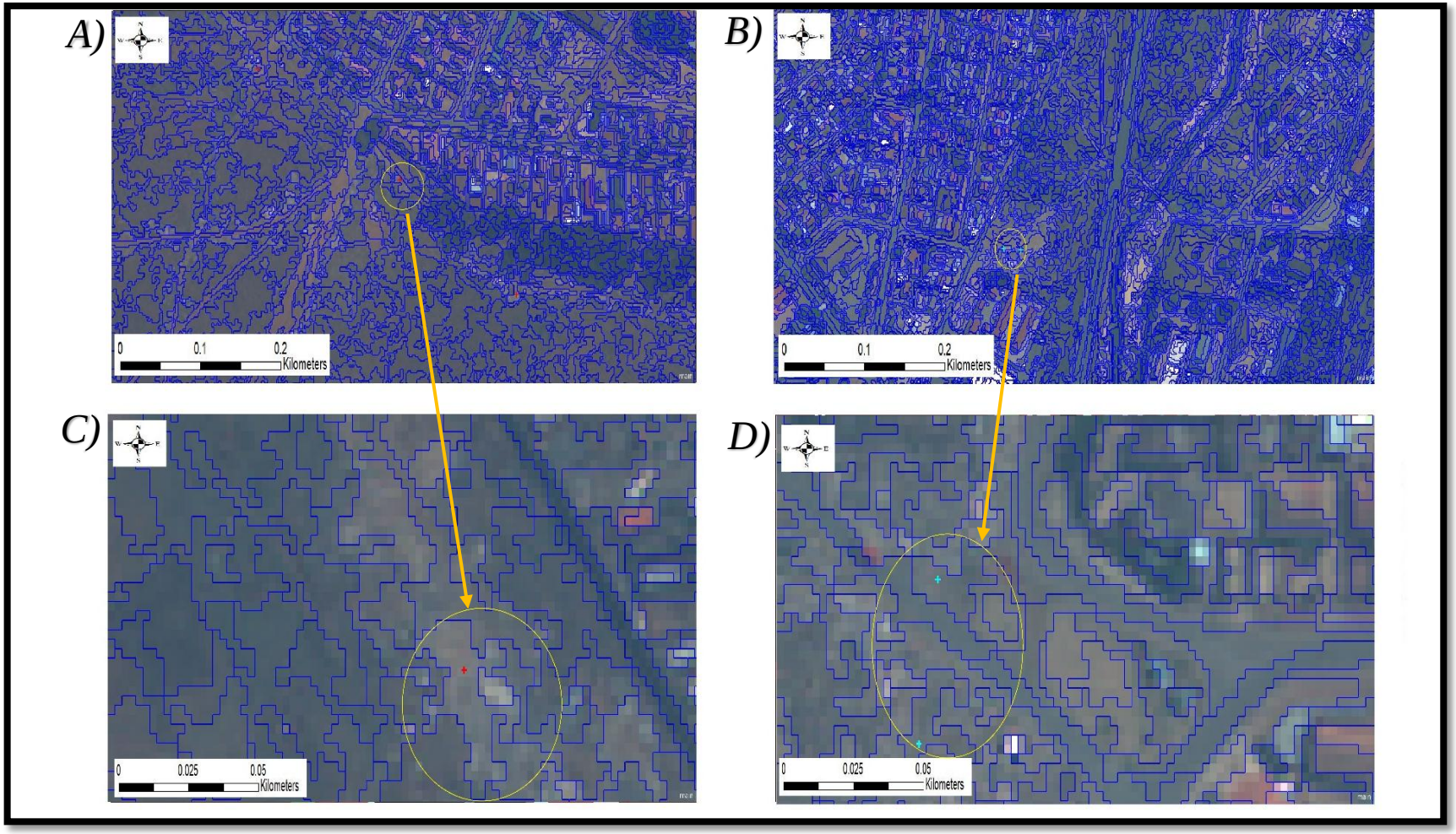

Figure 9: The results of multi-resolution segmentation of the illegal dumps and other LULC classes derived from using optimal parameters in e-Cognition. (A: Segments showing building rubble, B: Segments showing domestic waste, C: The zoomed-in segments of building rubble type of illegal dump, D: The zoomed-in segments of domestic waste type of illegal dump).

4.3 RF and SVM results for classifying building rubble and domestic waste

The classification of the Worldview-4 image using both RF and SVM was done to differentiate mainly between building rubble, domestic waste and other LULC classes, which include: bare soil, built-up area, roads, woody vegetation, green vegetation, mine dumps, shadows and water bodies. Both classifiers produced similar results of different illegal dumping sites and LULC classes in the study area.

The classification of building rubble is visually visible looking at both the reference image and both the classification algorithms as seen in Figure 10. Both the classifiers were able to differentiate and map the building rubble type of illegal dump. However, the SVM algorithm produced more accurate results in terms of classifying building rubble than the RF algorithm. Building rubble is virtually classified in open or vacant land more frequently than domestic waste.

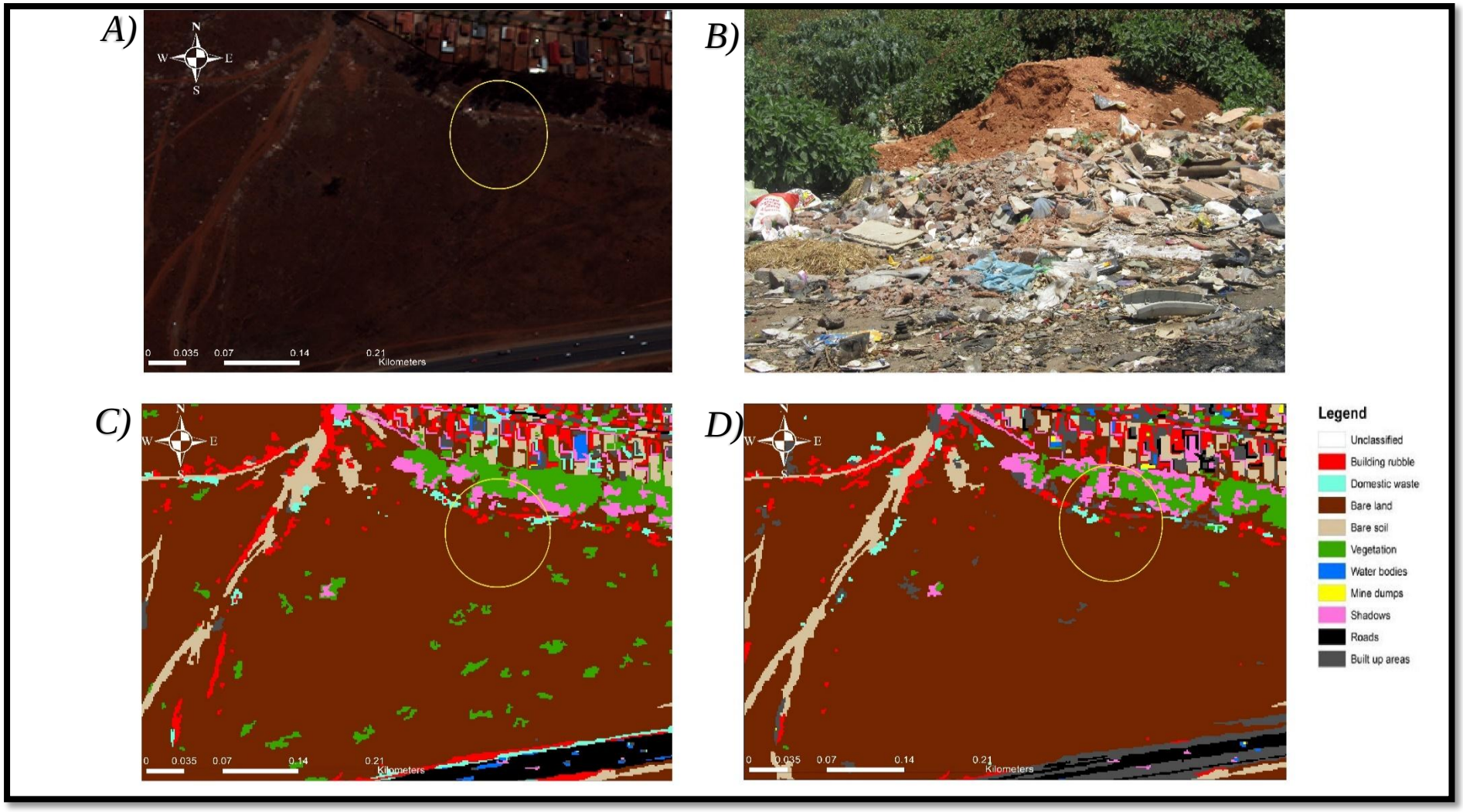

Figure 10: The zoomed-in classification of building rubble using Random Forest and Support Vector Machine models. (A: original WorldView-4 image) (B: photograph showing the map insert in the yellow colour) (C: RF classification result)(D: SVM classification result).

The classification of domestic waste is also visually visible looking at both the WorldView-4 image and both the classification algorithms as seen in Figure 11. Both the classifiers were able to differentiate and map between the domestic waste and building rubble type of illegal dumps. However, the SVM model outperformed the RF model in terms of identifying and classifying domestic waste. The visual difference between the two algorithms is that the SVM algorithm in this illegal dumping site misclassified building rubble illegal type of dump with water bodies and built up areas. The RF algorithm, on the other hand, misclassified building rubble with built-up areas and road. This type of misclassifications can be due to the type and the period of time the materials have been there in the respective illegal dump.

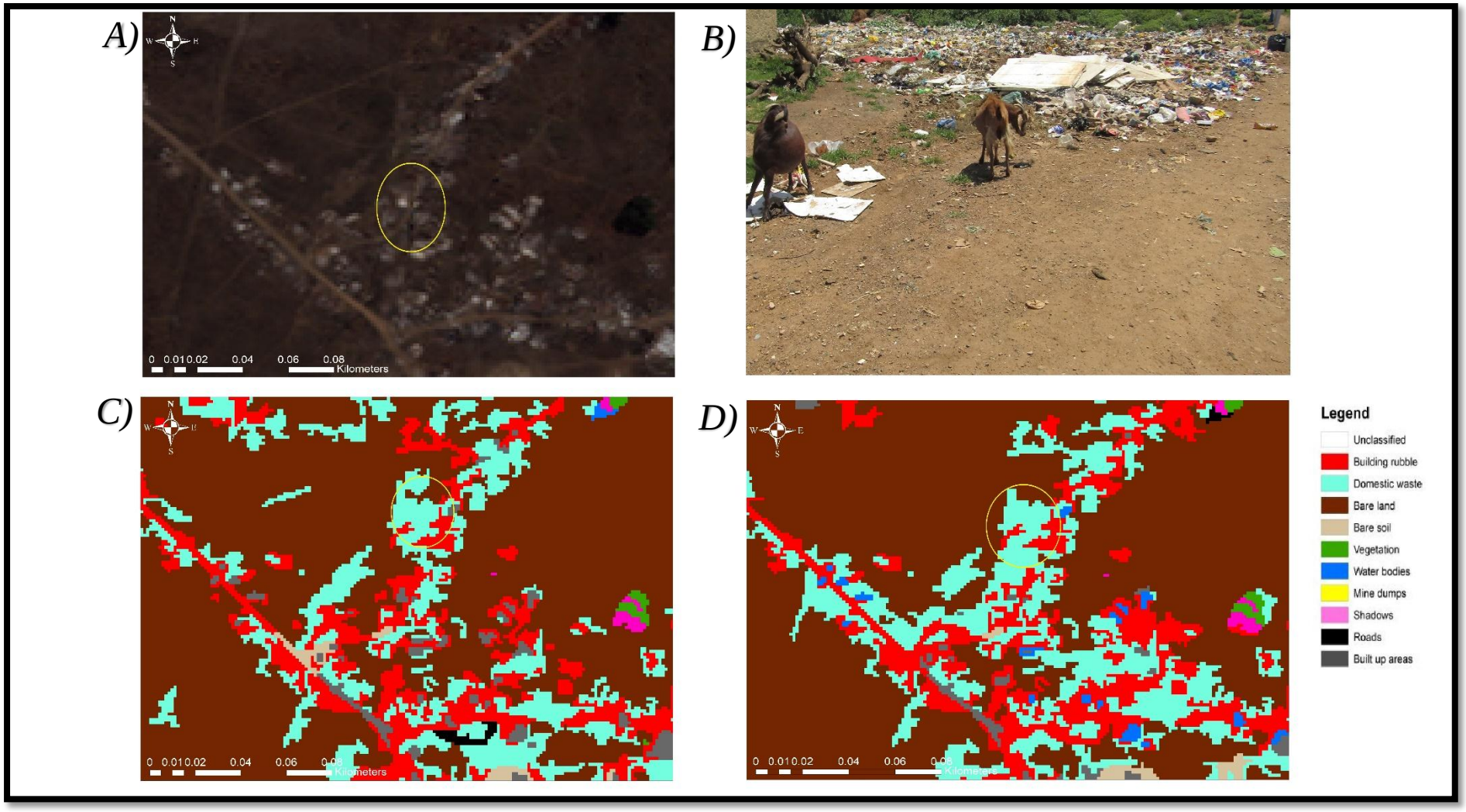

Figure 11: The zoomed-in classification of domestic waste using Random Forest and Support Vector Machine models. (A: original WorldView-4 image) (B: photograph showing the map insert in the yellow colour) (C: RF classification result) (D: SVM classification result).

4.4 Accuracy Assessment

A set of data, commonly referred to as test data, was used for assessing the classification accuracies for both the RF and SVM classifiers by employing an error matrix based on samples as shown in Table 6 and 7. When comparing the two classification algorithms, the SVM classifier had a higher overall accuracy than the RF classifier.

An accuracy assessment for the RF classifier using the test data achieved an overall accuracy of 93.98% with a kappa coefficient value of 0.9325. Building rubble had the highest producer's accuracy value of 100% when compared to that of domestic waste which achieved a producer's accuracy value of 92.3 %. Domestic waste had one confusion with roads in one of the sites, whilst building rubble had no confusion with other classes. The other land-cover classes that produced the highest producer's accuracy value of 100% were mine dumps and shadows, with water bodies producing the lowest producer's accuracy value of 83.3%.

The user's accuracy for the individual land-cover classes shows that domestic waste achieved the highest accuracy value of 85.7% when comparing it to that of building rubble which achieved a user's accuracy value of 76.5% for the two illegal dumps. Green vegetation, bare soil, mine dump, and water bodies achieved the highest user's accuracy with a value of 100%. Building rubble was the land-cover class that produced the lowest user's accuracy with the value of 76.5%.

Table 6: The confusion matrix of different LULC types using the Random Forest model accuracies based on the test data set. Accuracies include User's accuracy (**UA**), Producer's accuracy (**PA**), Overall accuracy (**OA**), and Kappa statistic.

	BS	**BL**	**BR**	**BUA**	**DW**	**GV**	**MD**	**RD**	**SHDW**	**WB**	Total	UA%
BS	28	0	0	0	0	0	0	0	0	0	28	100
BL	0	24	0	1	0	0	0	0	0	0	25	96
BR	0	2	13	2	0	0	0	0	0	0	17	76.5
BUA	1	0	0	21	0	0	0	0	0	0	22	95.5
DW	0	0	0	1	12	0	0	0	0	1	14	85.7
GV	0	0	0	0	0	23	0	0	0	0	23	100
MD	0	0	0	0	0	0	13	0	0	0	13	100
RD	0	0	0	0	1	0	0	26	0	0	27	96.3
SHDW	0	0	0	0	0	1	0	1	28	2	32	87.5
WB	0	0	0	0	0	0	0	0	0	15	15	100
Total	29	26	13	25	13	24	13	27	28	18	216	
PA%	96.6	92.3	100	84	92.3	95.8	100	96.3	100	83.3		
OA%:				93.98								
Kappa:				0.9325								

The support vector machine algorithm yielded an overall accuracy of 94.91% and a kappa coefficient of 0.9429 when using the test data for accuracy assessment (Table 7). Building rubble produced the highest producer's accuracy of 100% together with shadows, roads and mine dumps with no confusion between them and other classes. Domestic waste achieved a producer's accuracy of 92.3%, 7.7% less than that of building rubble with one RD site confused as domestic waste. Green vegetation achieved the lowest producer's accuracy value of 87.5%.

The user's accuracy for the different land-cover classes shows that bare soil, bare land, mine dumps and green vegetation achieved a user's accuracy of 100% for each class. However, looking at the two land-cover classes that the study is interested in, building rubble achieved a user's accuracy of 81.2% with three confusions two at bare land and one at the built-up area. Domestic waste achieved a user's accuracy of 85.7% with two confusions each at green

vegetation and water bodies. Both building rubble and domestic waste produce the least percentage of user's accuracy.

Table 7: The confusion matrix of different LULC types using the Support Vector Machine model accuracies based on the test data set. Accuracies include User's accuracy (**UA**), Producer's accuracy (**PA**), Overall accuracy (**OA**), and Kappa statistic.

	BS	**BL**	**BR**	**BUA**	**DW**	**GV**	**MD**	**RD**	**SHDW**	**WB**	Total	UA%
BS	28	0	0	0	0	0	0	0	0	0	28	100
BL	0	24	0	0	0	0	0	0	0	0	24	100
BR	0	2	13	1	0	0	0	0	0	0	16	81.2
BUA	1	0	0	23	0	1	0	0	0	0	25	92
DW	0	0	0	0	12	1	0	0	0	1	14	85.7
GV	0	0	0	0	0	21	0	0	0	0	21	100
MD	0	0	0	0	0	0	13	0	0	0	13	100
RD	0	0	0	0	1	0	0	27	0	0	28	96.4
SHDW	0	0	0	0	0	1	0	0	28	1	30	93.3
WB	0	0	0	1	0	0	0	0	0	16	17	94.1
Total	29	26	13	25	13	24	13	27	28	18	216	
PA%	96.6	92.3	100	92	92.3	87.5	100	100	100	88.9		
OA%:				94.91								
Kappa:				0.9429								

There are some differences in the users and producers' accuracies achieved by both classifiers in predicting building rubble and domestic waste. Looking at the user's accuracy, SVM achieved 81.2 % and RF achieved 76.5% for the building rubble class Table 6 and 7. For the domestic waste class both the classifiers achieved an accuracy of 85.75%. The SVM algorithm showed better performances between the two dumps and other LULC classes.

When looking at the producers' accuracies for both classifiers, Both RF and SVM achieved the same in terms of predicting building rubble and domestic waste classes. For building rubble each classifier achieved an accuracy of 100% and an accuracy of 92.3% for domestic waste Table 6 and 7. The SVM classifier managed to out-perform the RF classifier by

achieving a producers' accuracy of 100% for four LULC classes whilst the RF classifier only managed to get three 100% producers' accuracy.

4.5 Factors associated with the spatial distribution of illegal dumps

There are a lot of socio-economic factors that influence the spatial distribution of illegal dumps as discussed in chapter 2. This study only focused on four factors which are 1) population density, 2) household size, 3) level of education and 4) household income. Soweto is a highly populous township with an estimated population of 1 271 628 that is not evenly distributed (Statistics South Africa, 2011). Referring to (Figure 12 **A**), there are more illegal dumps in highly populated areas of Soweto than those in less populated areas. Suburbs with a population density of more than 20029 people have a lot of illegal dumps in and around the suburbs. The same can also be said about the household size (Figure 12 **B**) and the number of illegal dumps in the respective suburbs. Suburbs with a high number of household size with 10+ people also have a huge number of illegal dumps in the suburbs. Suburbs associated with high population density and high household size have a lot of domestic waste type of dump in their surroundings.

Furthermore, suburbs situated next to the Marie Louise Landfill site and Goudkoppies Landfill site tend to have the least populated areas with less illegal dumps. Due to a number of environmental and health concerns, people tend to live far away from these landfill sites.

When looking at the level of education particularly grade 12 (Figure 12 **C**), surprisingly there are a high number of people who have completed grade 12 at areas where illegal dumping occurs the most. People are settled at more developed areas of the township which is where the illegal dumping is most likely to occur. When looking at the household income map (Figure 12 **D**), areas that illegally dump their waste have high levels of no income. Majority of the people in these areas are unemployed meaning that they cannot afford to dispose of their waste legally since doing so might be expensive for them.

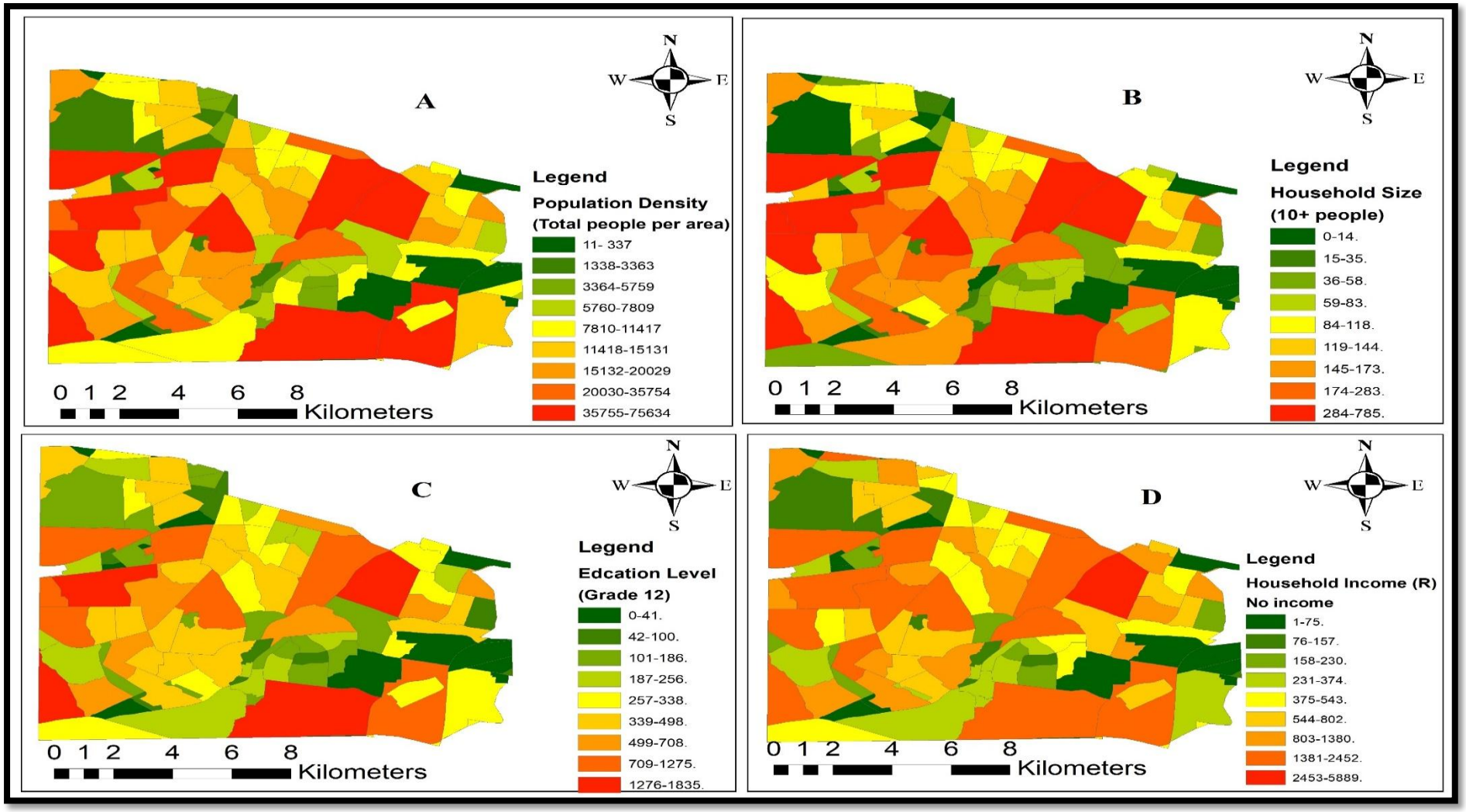

Figure 12: The socio-economic factors associated with the spatial distribution of illegal dumps in Soweto, data provided by STATSSA. (A: Population density, B: Household size, C: Educational level, and D: Household income).

Chapter Five: Discussion and Conclusion

5.1 Introduction

The illegal disposal of waste accumulating to 1.6-1.8 million tons per annum in the City of Johannesburg is a detrimental issue (City of Johannesburg, 2014). With the city failing to have effective and efficient illegal dumping strategies in place as identified by Polasi (2018). This meant that a huge amount of illegal waste in the City and particularly Soweto was unaccounted for especially in remote areas and vacant spaces. The traditional and conventional pixel-based methods of identifying illegal dumps have the shortfall of being costly, labour-intensive and time-consuming, and the spectral mixture between similar objects when using very high resolution (Romeo *et al.*, 2003; Chang, 2015; Jawak *et al.*, 2015).

This study employed a remote sensing-based model to detect and map illegal dumping in Soweto. Object-based image analysis was utilized on a very high spatial resolution image (WorldView-4). Multi-resolution segmentation approach was used to produce image segments. Machine learning algorithms such as Random Forest and Support Vector Machine were used for classifying the image and to see whether the classified maps would produce significantly different results.

5.1.1 The detection and differentiating of domestic waste and building rubble

The importance of each WorldView-4 band was assessed using the random forest model in R version 3.6.1 for differentiating between building rubble and domestic waste. The four bands contributed differently to the detection of the two dumps. This was likely caused by the different densities, overall sizes, chemical composition, and reflective ability of the materials found in the dumps (Domanska & Bondar, 2013)

The use of WorldView-4 imagery and OBIA proved to be a success in achieving the second objective of the study. According to Chu (2015), remote sensing data with very high-resolution probabilities can provide real-time dumping proportions and the spectral difference between image objects. This can be seen from achieving high overall accuracy and kappa coefficient for RF and SVM classifiers.

The use of the very high-resolution image with a panchromatic resolution of 31cm and a multispectral band image of 1.24 m meant that the detection of the illegal dumps as possible. All the dumps which were identified during the fieldwork were correctly classified by the

model, approving the ability of remote sensing satellite sensors to detect both domestic waste and building rubble.

Selani (2017) used Worldview-2 which offers 8-band multispectral images at 1.84m spatial resolution and a panchromatic image at 46cm spatial resolution. The satellite imagery was able to detect illegal dumping types as well (Selani, 2017). However, the additional bands of WorldView-2 (Coastal, Yellow, Red Edge, NIR2) compared to those of WorldView-4 had no impact on the classification accuracy. The study also employed machine learning algorithms such as RF and SVM. However, the classification accuracy of the algorithms were 84.16% for RF and 85.16 for SVM were low when compared to that of this research. Selani (2017) used pixel-based approaches on a high-resolution image which produced a "salt-and-pepper" effect which subsequently affected the overall accuracy of the classification algorithms. On the other hand, this study used the object-based approach which considers object characteristics such as spectral, shape, texture, area, and content (Jawak *et al.,* 2015). This approach enabled the study to try several different object features such as the mean and standard deviation of the layer values, geometry, extent, shape, and NDVI using the OOB as an estimate error method which optimized the models for RF and SVM.

Silvestri and Omri (2007) used IKONOS satellite data to identify unknown landfill sites in NE Italy (part of the Venice Lagoon watershed). The authors managed to detect unknown landfill sites through calibrating the spectral signatures of stressed vegetation resulting from soil contamination effects from known illegal landfill sites (Silvestri & Omri, 2007). The study employed the pixel-based approach and the Maximum Likelihood classification algorithm. The classification algorithm achieved an overall accuracy of 74%, which is low when compared to that of this research study.

Firstly, the results are different because the study employed pixel-based approaches on a high-resolution image. Pixel-based approaches have limitation regarding context, relative scale, fuzzy or smooth transitions (Blaschke, 2010). Remote sensing images with low-to-medium spatial resolutions, where pixels are larger than or the same size with objects, sub-pixel and per-pixel techniques are appropriate; but for high spatial resolution images, where pixels are smaller than objects, there is a need for grouping pixels into objects (Estoque *et al.,* 2015).

Secondly, the was a significant difference between the two results because Maximum Likelihood classifier is excellent when dealing with unimodal data; and have a limitation

when dealing with multi-modal input data, because it assumes a normal distribution data (Liu *et al.,* 2011). RF and SVM are non-parametric supervised classifiers which do not make any assumption regarding the distribution of the data and have become increasingly popular (Liu *et al.,* 2011; Mountrakis *et al.,* 2011). Furthermore, non-parametric classifiers have achieved efficient classification results in various remote sensing studies (Belgiu & Dragut, 2016).

This achievement can aid the City of Johannesburg, Pikitup, and land management practitioners for the development in identifying and managing illegal dumps at a low cost and less time-consuming rate.

5.1.2 Comparison of random forest and support vector machines algorithm

The RF and SVM classifiers achieved high overall classification accuracies of 93.98 % and 94.91 %, respectively. According to Foody (2002), a commonly suggested accuracy for land cover classification is 85%. Both the classifiers surpassed the commonly suggested accuracy. This was because both classifiers are non-parametric algorithms with the ability to handle complex and high dimensional data (Adam *et al.,* 2014; Wang *et al.,* 2016).

A comparative analysis of the classification results obtained by both RF and SVM was done and both classifiers show that they can differentiate between domestic waste and building rubble. Selani (2017) tested both the classification algorithms and attained an overall accuracy of 84.07% for RF and 85.16% for SVM. The overall accuracies between the two algorithms were not significantly different, with the SVM classifier outperforming RF. The same results were achieved in this study. The SVM classifier outperformed the RF classifier because it is often reported to achieve better results than other classifiers with a limited amount of reference data (Adam *et al.,* 2014). Mountrakis *et al.,* (2011) and Belgiu and Dragut (2016) agree that the SVM classifier is highly precise in remote sensing owing to its ability to effectively handle small training datasets. On the other hand, the RF classifier is reported to perform best on large datasets (Yu *et al.,* 2017).

However, this study achieved high overall accuracies for both the RF and SVM classification algorithms compared to that in the study by (Selani, 2017). Selani (2017) utilized pixel-based classification techniques on a very high-resolution image, which come with the limitation of not being effective on very high-resolution image and produce a “salt-and-pepper” effect (Nassbaum & Menz, 2008; Blaschke, 2010). On the other hand, the use of object-based image classification techniques proved to be vital by achieving a difference of 9.91% for RF and 9.75% for SVM overall accuracies between the two studies. Object-based techniques are

effective for 1) urban land-cover classification than pixel-based, 2) suited to the increased complexity of very high-resolution imagery, 3) allow the imaged reality using topological features, contextual, textural, spectral, and spatial in a multi-scalar and integrated fashion (Lang, 2008; Lichtblau & Oswald, 2019).

5.1.3 Factors associated with the spatial distribution of illegal dumping

The spatial distribution of illegal dumps in Soweto is not random. There are several research studies conducted globally which are consistent with the statement (Liu *et al.,* 2016; Polasi, 2018; Sotamenou *et al.,* 2019; Yang *et al.,* 2019). This study chose to analyze four socio-economic factors associated with the spatial distribution of illegal dumps identified by (Oyekale, 2015) in South Africa. The Author identified that several factors that influence the spatial distribution of illegal dumps to be: 1) the willingness of waste disposal and recycling (education), 2) landfill cost (the cost of disposing waste legally), and 3) the number of people in the given area (population density and household size).

The relationship between the illegal disposal of waste and income is the most studied field in waste management (Liu *et al.,* 2015). Illegal dumping frequently occurs in low-income areas. According to Rea (2005), the legal route of disposing of the waste is not always affordable and convenient. Liu *et al.,* (2015) concur and further add that the cost of waste landfill becomes more and more expensive, making residents dump waste illegally. Soweto is no different from other areas, as seen in this study, a high number of illegal dumps were observed in low-income areas (no income). Residents residing in these areas choose to dispose of their waste illegally, because they are not able to afford pickup services and disposal fees.

Soweto has only two waste disposal centers which are located far away from highly populous residential areas. Illegal dumping is more frequent in urban areas due to the inaccessibility of recycling or waste disposal centers (Rea, 2005). As seen from the classification results of this study, huge amounts of domestic waste are found near residential areas (built-up areas) along roadsides and pavements, whilst building rubble is located near vacant/open spaces. Oyekale (2015) also found that due to the inaccessibility and costs associated to these disposal centers, residents prefer to dispose of their waste in open vacant land, along roadsides, bushes, railway lines, and in wooded areas which is much more convenient for them.

More waste is generated in households who have more people living in it. As can be seen in this study, areas with a household size of 10+ individuals are areas with high levels of illegal

dumping as well. Conversely, areas with individuals who are more educated have fewer illegal dumps in their areas. Oyekale (2015) and Sotamenou *et al.,* (2019) state that household characteristics such as family size, available income, and education can be associated with the spatial distribution of illegal dumps.

5.2 Conclusion

This research study aimed at developing a remote sensing-based approach to detect and map illegal dumping in Soweto. The aim was achieved by mapping and differentiating between illegal domestic waste and building rubble using a very high-resolution remote sensing imagery (Worldview-4) and object-based image analysis. Using a multi-resolution segmentation approach, a comparison between random forest and support vector machine classification algorithms were tested for classifying illegal dumping sites in the study area. The classifiers produced an overall accuracy of 93.98% for random forest and 94.91% for support vector machines. The high accuracy of both classifiers showed the effectiveness of using remote sensing-based tools and methods for the detection and mapping of illegal dumps.

The study revealed that factors such as high population density, household size, education, and household income do influence the spatial distribution of illegal dumps in Soweto. Communities that are unemployed, populated, and less educated tend to have a lot of illegal dumps in their areas compared to their employed, less populated, and educated counterparts. Reasons such as not being able to afford waste disposal fees and the cost of landfills are why people dispose of their waste illegally.

This study has demonstrated that very high-resolution remote sensing data and advanced non-parametric classifiers (RF and SVM) can detect and map illegal dumps. This achievement will aid the City of Johannesburg, Pikitup, land management practitioners, and environmentalists in using an easy, reliable, and cost-effective approach for detecting and mapping illegal dumps and their spatial distribution and growth. Remote sensing approaches and methods, like the ones implemented in this research study, are reliable and do not require a lot of resources.

5.2.1 Key findings

The key findings of the study were:

1. The capability of WorldView-4 in identifying illegal dumps and how it can be used as a tool for collecting reference data.
2. The efficiency and high accuracy of non-parametric supervised classifiers Random Forest and Support Vector Machines in differentiating between domestic wastes and building rubble.
3. The effectiveness of contemporary object-based image classification methods compared to traditional pixel-based approaches in classifying satellite images.
4. The capability of multi-resolution segmentation approach in detecting illegal dumps and other LULC classes from the WorldView-4 image.
5. Socio-economic factors do affect the spatial distribution of illegal dumps in Soweto.

5.2.3 Challenges

Even though the study proved to be a success, there were some challenges. The first challenge was the similar spectral characteristics between building rubble and built-up areas. The materials found in illegal building rubble dump are the same material that is used to construct residential, industrial, commercial structures, and factories. So, detecting and differentiating between the two classes proved to be a difficult challenge. Shadows and water bodies also provided uncertainties, because both classes appeared blackish on the satellite image. The shadow class was included in this study because the study area is in an urban area with a high variety of tall trees and buildings. Nevertheless, these challenges were alleviated by using different object features and improving the classification results.

5.2.4 Recommendations

The author recommends the remote sensing tools and techniques such as the ones implemented in this study to be tested for reliability in the greater City of Johannesburg region and other parts of the world as well. The spectral mixture between similar objects limitation can be alleviated by fusing different remote sensing data such as (LiDAR and high resolution images) and using ancillary vector data.

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