MAPPING ILLEGAL DUMPING USING A HIGH RESOLUTION REMOTE SENSING IMAGE
CASE STUDY: SOWETO TOWNSHIP IN SOUTH AFRICA.

By

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DECLARATION

I, **Lungile Selani,** declare that this research report is my own unassisted 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

.... Day of......................**2017**......................in …..**Braamfontein**..................

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DEDICATION

In memory of my father and my mother, Toto and Teyase Selani respectively. To my children Lunathi, Lushay and Lumko and to my siblings for pestering me to finish my studies, without you all I wouldn't finish this project.

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ABBREVATIONS

C&D	Construction and Demolition
NSW	New South Wales
HCCREMS	Hunter and Central Coast Regional Environmental Management Strategy
GIS	Geographic Information Systems
RF and SVM	Random Forest and Support Vector Machine
GDPs	Gross Domestic Productions
DSDA	Developmental service delivery approach
LULC	Land Use Land Cover
NGO	Non-Governmental Organisation
IDL	Interactive Data Language
CoJ	City of Joburg

FLAASH Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes

Abstract

Although a vast number of illegal dumping investigations have been conducted in the City of Johannesburg by City of Johannesburg Municipality, Government, Corporates as well as NGOs previously, there has been a limited attempt to integrate available datasets from the different methods of illegal dumping monitoring (satellite, spatial data collection and ground-based observations) and GIS modelling. Most South African municipal administrations have had to acknowledge their incapability to cope with the difficulty of illegal dumping monitoring. Illegal dumping challenges often emanate from the incapacity of municipality administrations to meet the required assemblage and removal of wastes. Vacant or unoccupied land is the target of illegal dumping in most areas. This study compares modelled, satellite and collected data using GIS methods to determine the most accurate estimate of detecting illegal dumping. A comparison between Random Forest (RF) and Support Vector Machine (SVM) in mapping illegal dumping and to quantity the significance of Worldview-2 band in detecting and mapping illegal dumping was pursued. Two results were generated: multispectral imagery sorting production using machine-learning RF and SVM algorithms in a comparable land and definition of the significance of unrelated WorldView bands on sorting production. Precision of the derivative thematic maps was evaluated by calculating mix-up milieus of the classifiers' land use/ land cover maps with separate autonomous justification data sets. A complete classification accurateness of 84.07 % with a kappa value of 0.8116, and 85.16% with a kappa value of 0.8238 was attained using RF and SVM, respectively. An assessment of diverse WorldView-2 bands using the two classifiers indicated that the blend of the red-edge band had a vital consequence on the overall classification accurateness in mapping of illegal dumping.

Keywords: Illegal dumping, remote sensing, monitoring, vegetation, spatial datasets, image processing, image classification.

CHAPTER ONE: INTRODUCTION

1.1 Background of study

Illegal dumping is the disposition of waste in a prohibited area (Salleh et al, 2002). It comes in three forms: “open dumping,” “fly dumping,” and “midnight dumping”. This might is often due due to the fact that waste is often discarded in open, vacant and unoccupied land from automobiles, along kerbs, and late at night-time (Meares et al, 2011). Unlawfully discarded wastes are principally harmless materials that are discarded to avoid either dumping charges or the effort and time obligatory for appropriate dumping (Meares et al, 2011). Unlawful dumping of waste material could be as a result of construction rubble, demolition and domestic waste. (Salleh et al, 2002) Some can be from scrap tyres, bulky items and yard waste which is prohibited from landfills because their appropriate managing can be pricey (Salleh et al, 2002).

Illegal dumping has extensive environmental, health and social impacts. Unlawful discarding of construction and demolition (C&D) dump is the main cause of soil and underground water contamination (Seror et al, 2014). As construction dump frequently contains oil, diluents and fuel, these substances can seepage into underground aquifers, thereby contributing to underground water pollution (Seror et al, 2014). In addition, the coalition of dehydration and temperature can spark veld fires starting at illegal C&D waste spots leading to the discharge of noxious vapours into the air (Seror et al, 2014). According to Seror et al, (2014) the City of San Antonio in the USA devotes hundreds of millions of dollars yearly to alleviate ecological enormities of illegal waste discarding, such as dripping of harmful waste into underground water aquifers and forestry fires. Hence it is an expensive maintenance concern for municipal land managers, with councils often enduring the expenses related to clean up and removal of unlawfully discarded waste (Meares et al, 2011).

The need for managing and controlling the illegal dumping, in case of New South Wales (NSW), the Hunter and Central Coast Regional Environmental Management Strategy (HCCREMS) has been in engaging with member councils for the past three years to digitise, collect and plot evidence on illegal dumping occurrences. This is being prepared to detect tendencies and better notify councils of the pattern and degree of illegal dumping to warrant suitable resourcing to address the concern (Meares et al, 2011).

Illegal dumping management practices by municipalities or responsible authorities (e.g in Japan, US, some other African countries and in NSW) according to Meares et al, (2011) are creating and keeping Regional Illegal Dumping Databanks. The main purposes being: (i) to record hot-spot sites, (ii) to study developments in dumping formations across the regions, (iii) produce comprehensive reports on usual actions and behaviours as well as the type and quantity of materials discarded, and (iv) to offer insight to the imminent execution or pre-emption strategies of councils.

Due to the environmental complications of urban extents, it is not effectual to map the spreading of illegal dumping all over the area using straight field observation methods. Hence a need of spatial data for effective illegal dumping management and remote sensing would offer a suitable mapping substitute for illegal dumping (Aurelia et al, 2014).

1.2 Statement of the problem

Management of illegal dumping is one of the encounters fronting cosmopolitan areas in the world **(**Oyinloye, 2005). Illegal dumping has extensive environmental, health and social effects. It is also a pricy maintenance matter for public land overseers, with municipalities often bearing the expenses related with clean up and removal of unlawfully dumped waste (Meares et al, 2011). Like many urban areas, Soweto is not exempted from illegal dumping problems.

The factors that drive illegal dumping in Johannesburg, according to Meares et al, (2011) have been the emphasis of many social research studies over the past 20 years. Studies have shown people consciously discard waste illegally. The motives characteristically provided for why dumping happens include: waste management facilities opening hours being awkward; travel distances from the house to legal refuse facilities are long or deficiency of municipal refuse collections. Therefore it is easy to discard waste on existing loads of unlawfully discarded waste.

Continuous dumping of waste material may upsurge heavy metal absorption in soil, which could have damaging effects on human health, soils and crops (Chu et al, 2004). The ecological effects of illegal waste discarding, steer to the corrosion of land, contamination of surface and ground water as well as negatively impacting on air quality (Triassi et al, 2015).

Current management practices of illegal dumping in Johannesburg need spatial data for effective management. To regulate such illicit problem more successfully, there is a need to monitor illegal dumping technically. Therefore high resolution image can be used to monitor illegal dumping.

1.3 Aim (s)

The aim of this study is to map the status of illegal dumping in Soweto using earth observation techniques.

1.4 Objectives of the study

- To detect and map illegal dumping using WorldView-2 and advanced classification algorithm
- To compare between RF and SVM in mapping the illegal dumping
- To measure the importance of Worldview-2 band in detecting and mapping illegal dumping.

CHAPTER TWO – LITERATURE REVIEW

2.1. Introduction

This study is rested on the basis of previous and contemporary philosophies and conceptions of the use of Remote Sensing procedures to map illegal dumping and discriminating other land use/ land cover types. This section consists of succinct evaluation of the literature which is connected to this research. It takes evidences from those perceptions and philosophies that provision the research content and framework. These comprise a study of illegal dumping spots at City of Joburg township of Soweto and the role of Remote Sensing in mapping and discriminating dumping spots as well. The role of Remote Sensing in mapping and discriminating illegal dumping spots as well as discrimination of other land use and land cover types. It also lays bare the challenges of using Remote Sensing in illegal dumping mapping. Different understandings on the theme were also accepted and correlated with the research objectives as they functioned as a guide to the study.

2.2. Concept of illegal dumping

The concept of illegal waste dumping comprises of disposition of waste in areas not lawfully permitted as waste dump spots such as vacant land, cultivable spaces, roads, buildings and construction yards (Triassi et al, 2015). Illegal waste dumping is one of the chief contamination triggers of land degradation (Chu et al, 2004). Illegal dumping has come to be one of the severe environmental harms according to Chen, (2009). Seror et al, (2014) state that illegal waste dumping is also a challenge in other parts of the world, particularly in the United States with vigorously cumulative GDPs. Meares et al, (2011) emphasise that the unlawful dumping of waste is a common problem all over the world, and Soweto township is no exception. Salleh et al, (2002) state that the notion of dumping wastes illegally is done to evade either clearance fees or effort and the time needed for appropriate disposal. Places used for illegal dumping differ but may include abandoned industrial, housing, or commercial buildings; unoccupied lots on public or private property; and rarely used roadways or alleys (Salleh et al, 2002). It is noted that additional causes of illegal waste dumping are scarcity of authorised landfill sites, long conveyance hauls, excessive entry fees to authorised sites, absence of prosecution measures and slim information on recycling choices (Seror et al, 2014).

2.3. The impact of illegal Dumping

Constant dumping of waste material may upsurge heavy metal absorption in soil, which may have detrimental impact on soils, crops and human health (Chu et al, 2004). The environmental effects of illegal waste dumping are deteriorated land particles, poor surface and ground water as well as poor air quality (Triassi et al, 2015). Tasaki et al, (2006) state that illegal discarding causes severe environmental damage. Illegal disposition of construction and demolition (C&D) waste is a prime cause of underground water and soil pollution (Seror et al, 2014). It produces some substantial dangers and costs to the environment. Dumped substances produce physical (e.g. sharp edges or protruding nails) and chemical (dust or harmful fluids) exposures for anyone who visits the illegal dump area (Meares et al, 2011).

(Meares et al, (2011) emphasise that dumped substances can block the typical drainage sequence of overspill and make areas more vulnerable to overflowing and corrosion when waste blocks streams, storm water drains and trenches. Illegally dumped objects are a lost resource as many items can be recycled. These are predominantly garden carbon-based items, fridges, computers, beverage containers, car bodies and tyres (Meares et al, 2011). Ecological contamination of waste dumping contributes to poor health, both short and long-term. Instances of short-term results are congenital incongruities, respiratory infection and asthma. Overall indications such as dizziness, anxiety, nausea, stress, headache, eye and breathing exasperation have been also defined. Long-term health problems associated with waste exposure consist of cardiovascular and chronic respiratory diseases, brain and even cancer, nerves, liver, kidneys diseases or lymphohematopoietic (Triassi et al, 2015). Illegal dumping has elevated a lot of anxieties with regard to the life quality especially if one is close to the illegal dumping spot (Chen, 2009).

2.4. Illegal dumping management

According to Faisal et al, (2012) illegal dumping should be properly monitored by ground and physical visits on areas affected. Faisal et al, (2012) state that nonetheless, ground observing systems necessitate exhaustive energies and cost and additionally, ground monitoring may be tough to be accomplished in large geographic extent. Faisal et al, (2012) strongly emphasise that remote sensing machinery has been introduced for waste disposal monitoring and management of the effects of illegal dumping on the environment. In addition, it is alleged that several cases of domestic illegal discarding have been left unreported (Morita et al, 2005). Local municipalities challenging such illegal dumping concerns have been painstakingly working out counterplans and City of Johannesburg is no exception. Chu et al, (2004) state that, to deter waste dumping, environmental fortification establishments in many countries have executed various waste controlling methods.

To comprehend noticeable variations to the environment through activities such as illegal dumping, it is instantly required to craft a mechanism for monitoring close cooperation between the citizens and management (Morita et al, 2005). Remote sensing is anticipated to be useful in ameliorating this problem, especially in the monitoring of waste disposal sites. Effective illegal dumping recognised plans must be modified to regulate the problem (Chen, 2009). Yonezawa, (2008) argues that, remote sensing is anticipated to be useful in this problem, especially in the monitoring of illegal dumping spots.

2.5. Open or vacant land management

The common description of vacant land often refers to many different types of unutilised or underutilised plots - uncultivated or agricultural land; recently ruined land; rundown land; land with dilapidated buildings and uninterrupted open space to abandoned, contaminated brownfield structures (Michael et al., 2000). Michael et al., (2000) further state that vacant land is not basically damaged land; it can be irregularly or small shaped parcels left over from previous expansion. It can be plots with physical restrictions, practically unbuildable due to the topography of the area (Michael et al., 2000). The use of unoccupied land and abandoned buildings can signify an opening for the commercial development and retrieval of a varied assortment of metropolitan areas (Michael et al., 2000). For those working on nifty development matters, the tactical reprocess of metropolitan unoccupied land and abandoned buildings can signify a key prospect for encouraging bigger mass and decreasing the push to advance outlying green fields (Michael et al., 2000).

2.6. The use of Remote Sensing- GIS in mapping and monitoring illegal dumping

Mapping pollutants usually involves in-the-field sampling and laboratory examination of gathered trials followed by interpretation of the point results to define spatial dissemination maps; though, such tactics are energy and time consuming (Chu et al, 2004). Nonetheless, ground monitoring systems necessitate rigorous efforts and cost. Moreover, ground monitoring may be challenging to be accomplished in large geographic extent. Numerous studies have instead suggested the use of remote sensing (RS) for directly detecting minerals and pollutants contained in the soils and have measured metal absorptions using statistical estimate models (Chu et al, 2004). Remotely sensed sensors on airborne or satellite platforms deliver temporal and synoptic view to monitor and control land corrosion stimulated by pollution (Chu et al, 2004). Remote sensing technology has been introduced for waste disposal management and monitoring effects of the landfill sites on the environment.

2.7. Land use Land cover (LULC) mapping

Countless procedures have been established to evaluate distinctions in LULC types using satellite data on mapping and detecting illegal dumping. According to (Dewan et al, 2009) of these procedures, the pre and post cataloguing assessments have been comprehensively used. Dewan et al, (2009) state that in the pre cataloguing method, techniques such as image differencing, band controlling, direct multi-date classification, change vector investigation, and vegetation index differencing and belief element examination have been established. The rudimentary idea of these techniques is that variations in LULC outcome in transformations in the pixel reflectance values within the dates of interest are noted. Although these methods are actual precise for detecting alteration, they cannot recognise the nature of alteration (Dewan et al, 2009). Equally, post-classification assessments scrutinise variations over time amongst autonomously classified land cover information. Notwithstanding the complications affiliated with post cataloguing evaluations, this method is the best extensively used for classifying LULC variations (Dewan et al, 2009). In this case post-classification can be able to detect changes as a result of illegal dumping on the environment. Nonetheless, one of the drawbacks related with this tactic is that the precision of the resulting illegal dumping and LULC maps may hinge on the accurateness of the distinct cataloguing, meaning that such methods are prone to error proliferation.

Dewan et al, (2009) state that such post cataloguing methods are mostly valuable for creating 'from–to' maps, which can be used to simplify the place and extent or nature of the vicissitudes revealed. In addition, the method can be applied using data attained from sensors with dissimilar temporal, spectral and spatial resolutions (Dewan et al, 2009). For this study the spatial statistics were used to correct the inaccuracies and errors. The efficacious use of satellite remote sensing for illegal dumping spots and LULC detection hinged on a suitable understanding of imaging systems, landscape features and procedure employed in relation to the aim of examination (El-Kawy et al, 2011). Illegal dumping can influence the landscape of the affected area in different ways, it can change the land pattern; the environment may be depressed or can form a heap or furrow. In most theories variation discovery is described as the procedure of finding modifications in the state of a phenomenon or feature by perceiving it at distinct periods In addition, change discovery is valuable in several applications allied to land use and land cover variations, such as landscape changes and shifting dumping occurrences and territory disintegration and other cumulative changes (El-Kawy et al, 2011). Mostly change detection can happen in areas where the illegal dumping has taken place and it can be used for analysis of impact in the surrounding area. Historical and continual collection of accurate data on the LULC variations of the Globe is very imperative for any kind of supportable advance on an illegal dumping management programme. Therefore, mapping and analysing the existent illegal dumping and LULC condition, as well as the deviations in illegal dumping and LULC over time is recognised as significant to better comprehend and offer resolutions for commercial, environmental and social problems (El-Kawy et al, 2011).

According to Ayebare et al, (2011) ground referencing of land-cover classes is a vital element to any mapping application. Land cover maps attained from low- and medium resolution satellite imagery offer broad landscape data. Nevertheless, ground referencing information is essential for confirmation of illegal dumping, and land-cover classes. This will be used as point of reference in this study in classifying illegal dumping and the land cover types and image classification to detect changes on the surface. Furthermore, GIS can be pragmatic to an environment monitoring system by getting data captured such as images and location data gathered by portable terminals (PDAs) and digital cameras. A system that gathers environment data via the Internet and uploads it onto a GIS can be projected to serve as a robust support for citizens or an NGO in starting events for environmental protection and of all governmental measures against illegal dumping, patrolling and illegal dumping database management investigation seems to be reinforced efficiently by the use of GIS (Morita et al, 2006).

Yonezawa, (2009) states that researches have shown that the usefulness of remote sensing data in waste management depends on sensor parameters, including the spectral, spatial, and temporal resolutions. However, ambiguity in the results by image spatial and spectral dimensions has been pointed out. The possibility of using remote sensing data to detect illegal dumping has also been discussed. Yonezawa, (2009) assessed the capability of detecting illegal waste dumping sites using airborne SAR data. A method that uses IKONOS satellite data and GIS (Geographic Information System) data to identify illegal dumping over large areas was validated. Dool et al, (2014) state that, in order to notice substances in an image with image dispensation procedures it is essential to first create a model that defines the common characteristics of concern like illegal dumping spots. Automated feature removal necessitates that the model be precise in a way that is implementable in a computer. The feature model defines the limitations and interactions of a variety of characteristics such as texture, context, shape and intensity.

CHAPTER THREE - RESEARCH METHODOLOGY

3.1. Study area

The study was piloted in an area of Soweto (Figure 2) and is located on latitude of 26.1625° S, 27.8725° E in the south western side of Johannesburg. According to Statistics SA, (2013). The past of South African township south west of Johannesburg that later formed Soweto was driven by the removal of black South Africans by municipal and state-run institutions (Statistics SA, 2014). It has been projected that 40% of Johannesburg's population live in Soweto. The 2008 Census places its populace at 1.3 million which is about one-third of the city's total population (Statistics SA, 2014). Several parts of Soweto rank the most underprivileged in Johannesburg, though specific townships tend to have a mixture of better-off and poorer households. The economic growth of Soweto (Figure 2) was harshly reduced by the apartheid government, which delivered very inadequate resources and forbade citizens from generating their own companies.

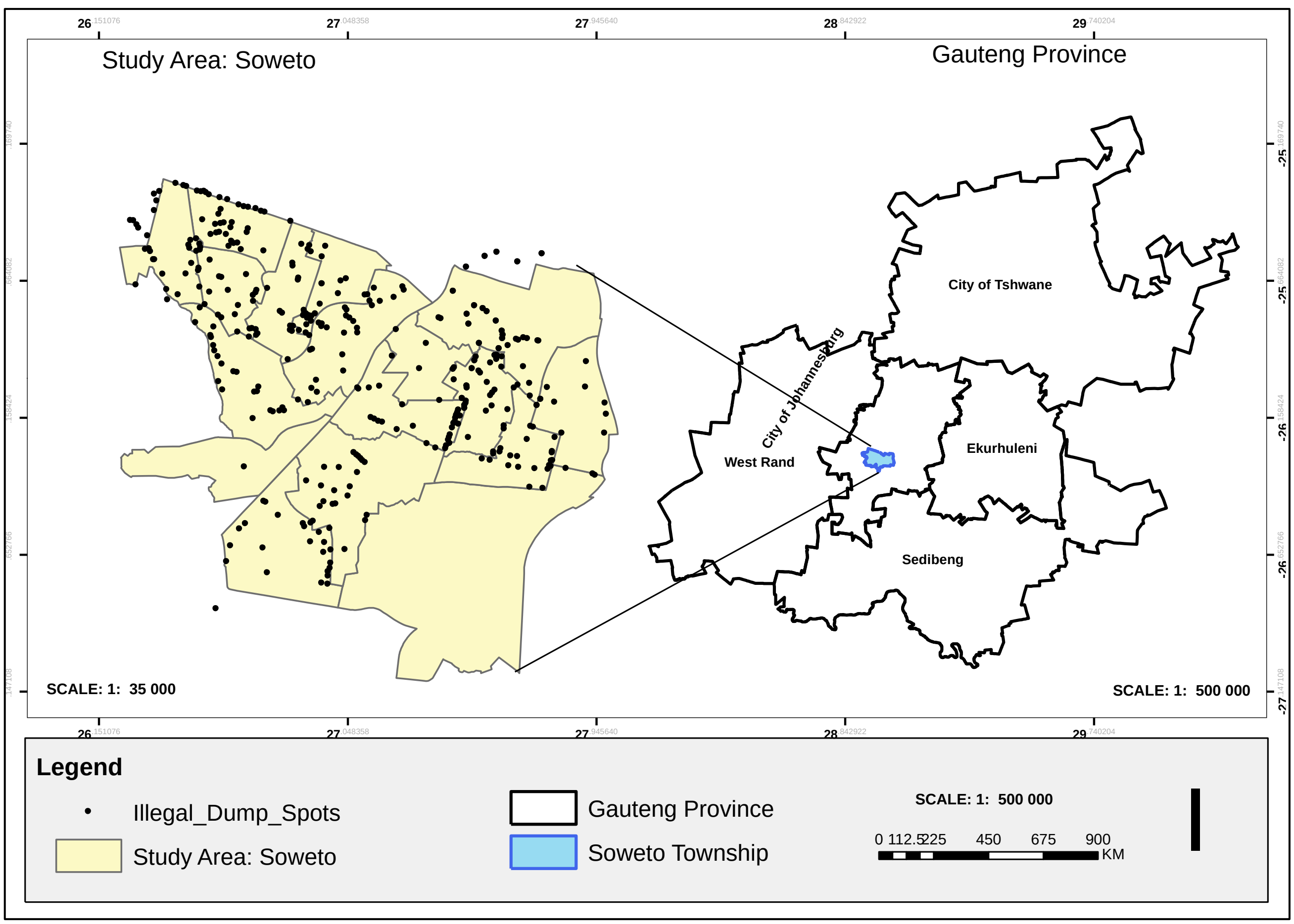


Figure 1. Location of study area of Soweto and City of Johannesburg

3.2. City of Johannesburg collection waste strategy

City of Johannesburg collects 4 500 tonnes of illegally dumped waste per week. On yearly basis this closes into 1.56 million tonnes of waste produced (The Star, 2015) quoting Pikitup waste statistics. It is projected that if the tenants of Johannesburg do not change the way in which they dispose of waste, there won't be space to discharge such waste by the year 2022 as Pikitup cited by (The Star, 2015). Its waste department has a plan that is embedded into a Developmental Service Delivery Approach (DSDA) to ensure active participation from local communities. Pikitup, as quoted from The Star (2015) states that there is a mechanisms in place for the improvement of their waste collection services and provision of the required tools and equipment such as refuse bags, bins and storage receptacles. The refuse collection strategy deployed for the Soweto area is distributed into five days collection points. Below (Figure. 2) is the Soweto refuse collection schedule.

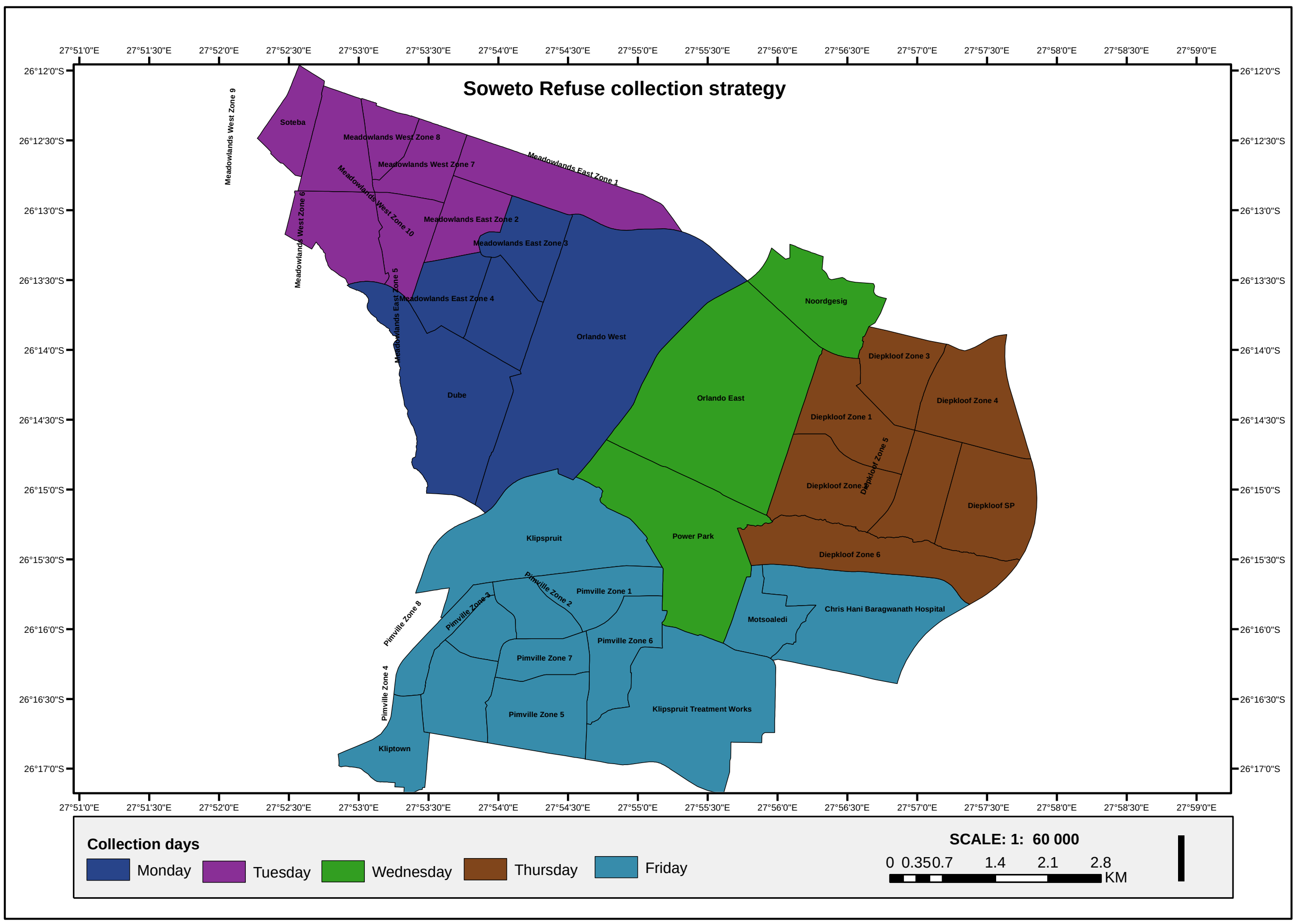


Figure 2. A refuse collection schedule for Soweto area depicting days of refuse collection

3.2.1 Dataset

The Study involves primary and secondary data collection. Data used in this study are WorldView-2 (secondary data) and ground reference point (primary data).

3.2.2 Field data collection and ground reference data

The position data for validation and training was collected in December 2015 through ground-based field work on two of Illegal dumping types: domestic dump and building rubble. On this data collection exercise, other data points collected were bare soil, Built-Up, Grassland, Woody Vegetation and Wetlands which all fall under the land –use land-cover types. For each illegal dumping type and other land cover/use classes, about 45 of building rubble and 90 of bare soil, built-up, grassland, wetland and 115 Domestic points were collected and totaled to 610 points as shown in (Table 1). The total reference data for each class was then arbitrarily fragmented into 70% for training and 30 % for validation as shown in (Table 1).

Table 1. Training and validation data set for the LULC classes

SAMPLE POINTS	CODE	TRAINING	VALIDATION	TOTAL
BARE SOIL	BS	63	27	90
BUILDING RUBBLE	BR	32	13	45
BUILT UP	BU	63	27	90
DOMESTIC	DM	35	80	115
GRASSLAND	GL	63	27	90
WOODY VEGETATION	WV	63	27	90
WETLAND	WL	63	27	90

3.3 Remote sensing data acquirement and pre-processing

Worldview-2 was used in this study to map illegal dumping as well as land. Image acquirement and pre-processing WorldView-2 images masked the study were acquired on the 1st of December 2015 from Digital Globe. For this study the images were ortho-rectified and geometrically corrected using ENVI 5.2. Radiance images were atmospherically modified and converted to canopy reflectance using the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) system assembled in ENVI 5.2 platform. The procedure assumed for this study took into deliberation numerous image pre-processing procedures, comprising of gap filling, geometric correction, image interpretation and enhancement. The pre-processing of the attained image was orthorectified under a pixel and symmetrically rectified by WorldView-2 (Adam et al, 2014). To recover surface reflectance, the image was atmospherically improved and converted to canopy reflectance by means of the atmospheric and topographic correction (ATCOR2) algorithm component in ENVI 5.2 platform (Adam et al, 2014).

Individual sensor were closely concentrated on a specific array of the electromagnetic spectrum that was delicate to a specific piece on the surface, or a chattels of the atmosphere (www.digitalglobe.com). Altogether they were intended to enhance the subdivision and sorting of aquatic and land topographies beyond any other space-based remote sensing arena (www.digitalglobe.com).

Worldview 2 had high resolution (Table 2) and was able to detect illegal dumping types and was easy to analyse. El-Kawy et al, (2011) state that pre-processing of satellite images before modification recognition is crucial and has the distinctive objective of creating a more straight relationship amid the data and biophysical occurrences. WorldView-2 is the first commercial high-resolution satellite to deliver eight spectral sensors in the visible to near-infrared array (www.digitalglobe.com) as shown below in table 2. Furthermore, it is also the foremost commercial satellite adept to offer 8-band multispectral images at 1.84 m spatial resolution and panchromatic images at 46 cm of spatial resolution (Tarantino et al, 2012).

Table 2. WorldView-2 Spectral properties with important bands for this study

Bands	**Band name**	**Spectral range**
B1	Coastal Blue	400 – 450nm
B2	Blue	450–510 nm
B3	Green	510–581 nm
B4	Yellow	585–625 nm
B5	Red	630–690 nm
B6	Red Edge	705–745 nm
B7	Near Infra-Red -1	770–895 nm
B8	Near Infra-Red -2	860–1040 nm

3.4 Extraction of image bands

A point map of illegal dumping and other LULC was created using the field data and GPS interpretations. This map was then overlapped on the WorldVeiw-2 images to construct a LULC plot region-of-interest (ROI) map using the centroid GPS point for each scheme (n = 610). An 8 × 8 pixels window (i.e. 16 m × 16 m) was used to gather illegal dumping type and LULC image spectra from each band (n = 8) using ENVI 5.2 platform. An 8×8 pixels window was used in order to evade counting pixels positioned outside the plot. Therefore, only pixels that fall fully inside the ROIs were incorporated in the spectral dataset, whereas the pixels that partly fall in or outside the ROIs were rejected (Wang *et al*., 2006). The bands were extracted and averaged for each illegal dumping and LULC type, and saved on a Microsoft Excel Spreadsheet for further analysis.

3.5 Image classification

Image classification is a procedure that operates in the feature space. It is centred on the diverse spectral features of different materials on the Earth's surface (Bakker et al, 2001). In this process the human as an operative instructs the computer to execute a reading according to certain order, often defined by the operator (Bakker et al, 2001). Image classification is one of the techniques in the arena of digital image interpretation. Other techniques include automatic object recognition (for example, road detection) and scene reconstruction (for example, generation of 3D object models). Image classification, however, is the most frequently applied technique in the ITC context (Bakker et al, 2001).

For this study, the Support Vector Machine and Random Forest classifier was used to categorise the illegal dumping and LULC categories. Images were classified using supervised classification technique and random forest algorithm in EnMAP software. In the next sections, a transitory description of the two classification algorithms is delivered.

3.6.1 Random Forest classifier

Random Forest is a collaborative learning method established by Breiman (2001) to advance the classification and regression of trees (CART) by joining a big set of decision trees (Adam et al., 2014). Particular tree underwrites a solitary vote for the consignment of the utmost common class to the contribution data. The procedure profits from two powerful systems: random and bagging subspace selection (Lin et al. 2011).While the presentation of classification processes such as SVM and RF has been extensively used in land-use and land cover organisation using regularly used multi-spectral imagery, there is a rarity of familiarity on the presentation of these systems on high-resolution WorldView images (Adam et al, 2014). The RF system has been used in various data mining performances, yet, its credibility is not fully reconnoitred for analysing remotely sensed images. RF is originated on tree classifiers and develops many classification trees (Kulkarni et al., 2016). RF can also quantity mutable prominence using Out-Of-Bag data (OOB). Individually, variable *m* is arbitrarily permuted and the latter OOB instances are sent down the tree again (Kulkarni et al., 2016). According to Breiman, (2001) the easiest random forest with random items is moulded by choosing at random, at each nodule, a small set of contribution variables to divide on. The tree should be produced using CART method to full size and not be pruned. Breiman, (2001) further states that for RF, a better bound can be copied for the generalisation error in terms of two bounds that are estimates of how accurate the individual classifiers are and of the dependency between them.

3.6.2 Support Vector Machine classifier

The Support Vector Machine classifier (SVM) is a machine learning controlled classifier capable of discovering a best classification hyper-plane for complete lessening of the upper bound of the classification inaccuracy (Adam et al, 2014). SVM is a supervised nonparametric statistical learning method which targets finding a hyper-plane that parts training samples into predefined number of classes (Kulkarni et al., 2016). In a twofold classification test, SVM makes the most of the length from the information points of each class to the optimum unravelling linear hyperplane axes shaped from each mutable (Adam et al, 2014). In the easiest form, SVMs are dual classifiers that assign the agreed test sample to one of the two likely classes (Kulkarni et al., 2016). According to Kulkarni et al., (2016) the SVM algorithm is extended to nonlinearly separable classes by mapping samples in the feature space to an upper dimensional feature space using a kernel function. Kulkarni et al., (2016) state that SVMs are mostly attractive in remote sensing field due to their capacity to effectively handle small training datasets, often delivering higher classification precision than common methods. Similar to RF, SVM is a delivery-free system and does not come across any over-fitting challenge. In a binary sorting trial, SVM capitalises on the space from the information points of distinctly class to the optimum unravelling linear hyper-plane axes shaped from each mutable (Adam et al, 2014). However, the applications of SVM and RF procedures have not been extensively accepted by the remote-sensing society for reproducing map-based spatial exhibitions due to the absence of suitable software and intricate workaround (Adam et al, 2014). Lately, this restraint has been effectively hindered by the employment of ImageRF and ImageSVM, comprehensible tools for RF and SVM systems, correspondingly (Adam et al, 2014). The tools can also be applied as a supplementary to the EnMAP-Box, a freely accessible and standalone handling background for remote-sensing imagery.

3.7 Accuracy assessment and Statistical Methods used to analyse the data

Accuracy calculations were made for both SVM and RF classifiers to measure the likelihood presentation of the qualified models by means of an autonomous test data set. The assessment showed exhaustive mix-up matrices of cataloguing precisions for SVM and RF, individually. An autonomous test data set was used to assess the thematic maps obtained from the application of respective cataloguing procedure (SVM and RF) to WorldView 2 images (Adam et al, 2014). A mix-up matrix was then assembled to calculate the users, overall, producer's accuracies, and kappa statistic. The effectiveness of SVM and RF classifiers were used to map illegal dumping and the land use/cover classes. Both classifiers were trained on 70% (n=427) and 30 % (n=183) of dataset. Spectral signatures were created for seven land use/ cover classes (Table 2) of study area. Both RF and SVM were used to classify WorldView-2 images. Both classifiers were optimized and loaded on ENVI 5.3 to map all the land use/cover on WorldView-2 images.

The remaining 30% (n=183) dataset was used to test accuracy and to assess the land cover map by SVM and RF classifiers of WorldView-2. A mix-up matrix was created to equate the right class apportioned by classifiers by computing kappa statistic, user's, overall and producer's accuracies. Overall accurateness, which is displayed as a fraction, signified the chance that arbitrarily chosen point would be categorized properly on the map. The kappa coefficient provided a quantity of the variance among the definite arrangement. Location data and the classifier accustomed executed the grouping against the probability of covenant amongst unsystematic classifier and the reference data.

3.8 Kappa Statistics

Kappa statistics were used to regulate the performance variation between the two classifiers. The Kappa statistics, and a non-parametric test computed from error milieus of the two classifiers, were implemented (Adam et al, 2014). Accuracy assessment of illegal dumping and other land cover or land use categorisations acquired by satellite remote sensing was vital to appraise the eminence of maps produced from remotely sensed data (Stehman, 1996). A distinctive plan for accurateness valuation was to use a numerically rigorous specimen design to select a trial of locations (pixels) in the study place, and to define if the land cover or land use arrangement allocated to that pixel tied the factual sorting of the ground location signified by that pixel (Stehman, 1996). Apiece cell value in the background had been well-adjusted by the other values in its conforming column and row. This matching had the effect of combining producer's and user's accuracies together. As each row and column added to 1, a distinct cell value could swiftly be transformed to a percentage by increasing by 100. Consequently, the regularisation procedure offered a useful way of associating singular cell values between error matrices irrespective of the number of samples used to develop the matrix.

3.9 Vacant land mapping

As most of the illegal dumping occurred on vacant or unused lands, there was a need to map the vacant lands and overlay them with illegal dumping points in order to test or validate the statement that illegal dumping occurs on vacant or unused land. The mapping of vacant land was done using ArcGIS 10.3 and a Zoning data from the City of Joburg. Out of all this, definition query was performed to select among open, public and private vacant land in the area of Soweto. The illegal dumping types were overlaid against vacant land to check intersects of illegal dumping from the vacant land (Figure. 3). The comparison found that 85 illegal dumping spots out of 160 illegal dumping were found on 85 vacant land. 54 percent of illegal dumping was done on vacant land. Below are the pictures of illegal dumping sites (domestic and building rubble) captured from vacant land (figures 3 and 4).

$^{Illegal\ dump}/_{vacant\ land}$ X 100 = 54% on vacant land.

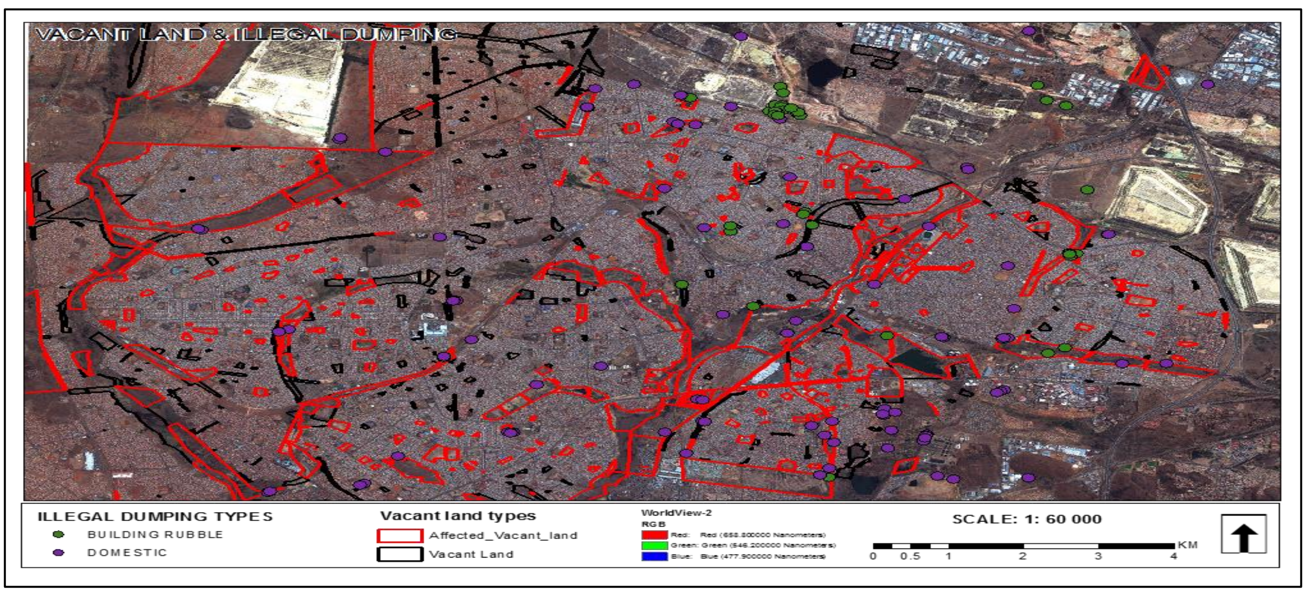


Figure 1. A map of illegal dumping and vacant land showing types of illegal dumping and vacant land types in Soweto area

Figure 2. Building rubble waste in a vacant land in Soweto area

Figure 3. Black bags containing domestic waste in Soweto area surrounded by woody vegetation

CHAPTER FOUR - RESULTS AND DISCUSSION

This chapter embodies the results and discussion of this study. The analysis of WorldView 2 data gave quantification and prognosis results of two classifiers of RF and SVM which delivered a comprehensive understanding of illegal dumping and other LULC in Soweto area.

4.1. Tuning of RF parameters

Random forest parameters were augmented in order to get the best parameters and to train the algorithm for classifying of seven land use/cover classes. As the outcomes from the frame search shows/showed, the default *mtry* value of 2 joint with ntree value of 500 formed the bottom OOB error ratio that is lower than (0.210). The maximum OOB error ratio (0.235) on the supplementary side was formed by the alliance of mtry value of 4 with ntree value of 1500 (Figure 6). Subsequently, an mtry value of 2 with ntree value of 1500 and alliance of 6 were nominated as participating limitations to sequence the Random Forest procedure to categorise the land-use/ land cover classes.

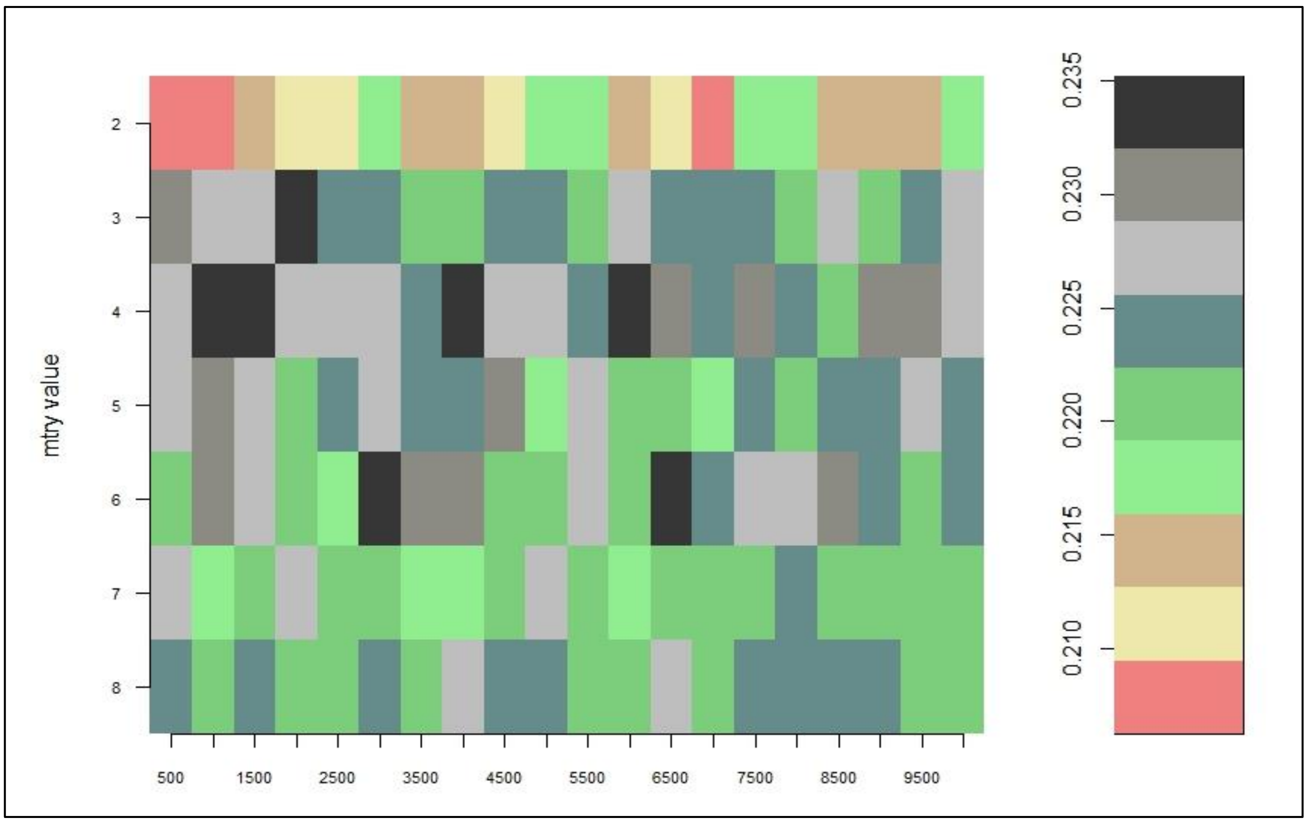


Figure 4. The RF parameters optimisation (mtry and ntree) using the grid search system using the Out-Of-Bag (OOB) sample

4.2 Tuning of SVM parameters

Support Vector Machine parameters for grouping via a circular basis kernel role were enhanced to outline the best contributing parameters to sequence the process to categorise the seven land-cover classes. Using a 10-fold cross validation, the lowest error was formed from the grouping of gamma (γ) value of 0.1 and cost (C) value of 100 (Figure 7).

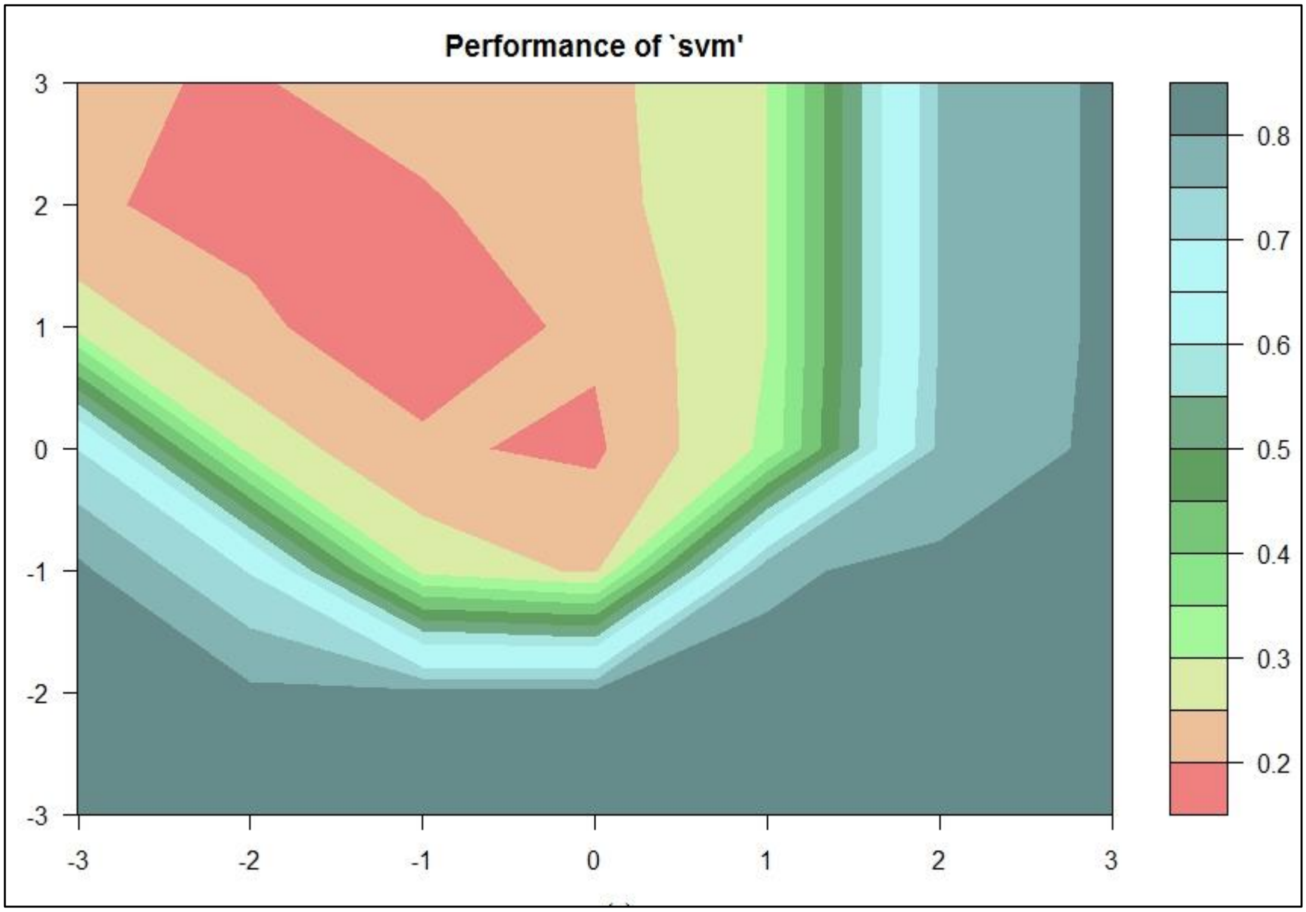


Figure 5. Graph of SVM algorithm optimisation parameter for (C and y using 10 fold graph search performance

The results from the performance of SVM shows that the default value of 3, 2 and 1 combined with a value of -3, -2 and -1 produced the lowest error rate that is less than (0.2). The uppermost error rate (0.8) on the other hand was formed by the mixture value of -1 up to 3 (Figure 7).

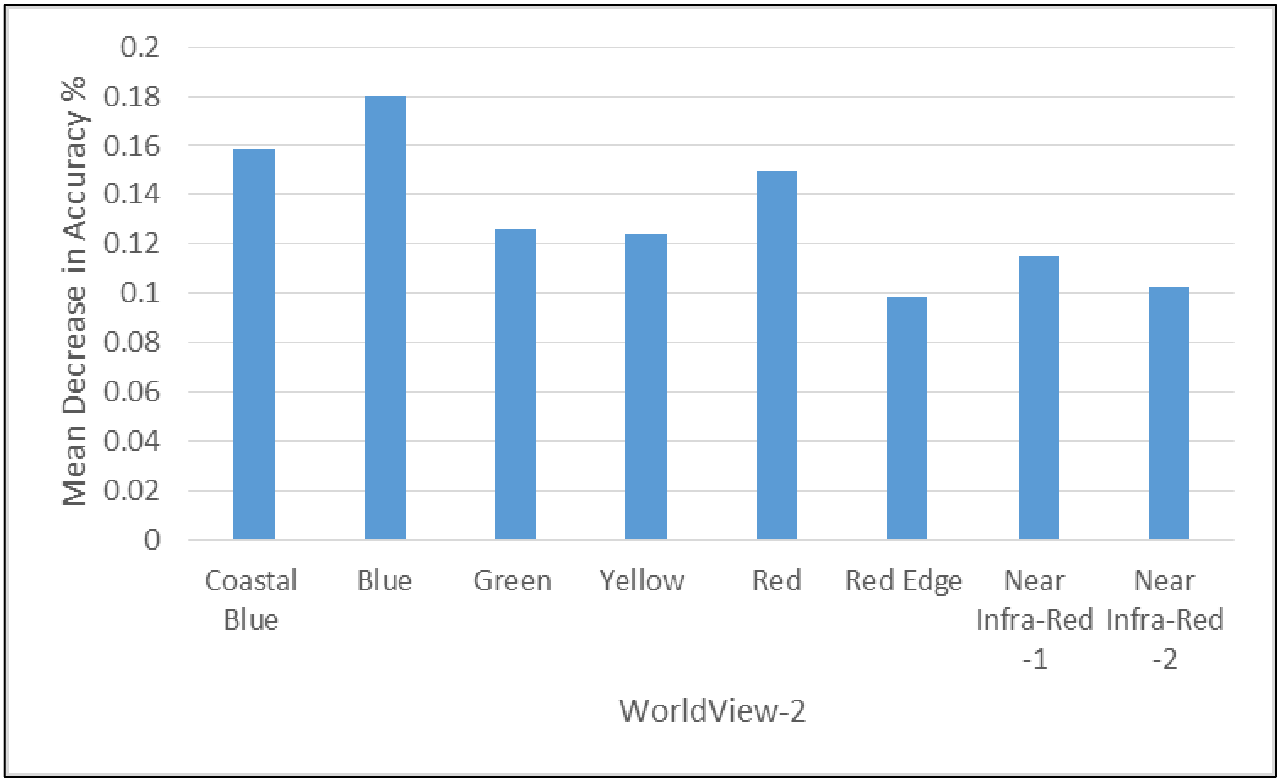


Figure 6. Rating of critical band of WorldView-2 using Random Forest. The critical band has the highest mean decrease in accuracy

RF also provided a variable importance measurement to indicate the role of each band in the classification process. The most critical bands were those with the highest mean decrease in accuracy (Figure 8) which in this classification, are allocated at the blue and costal blue bands respectively. Blue and Coastal Blue are the ones that played a bigger role compared to other bands of the Random Forest.

4.3 Results of RF and SVM in land-use/cover classification for Building Rubble

Land-use/ land cover maps of building rubble dumping produced by means of SVM and RF. There was a small alteration in the coastal blue pixels northerly part of the maps (Figure 9).

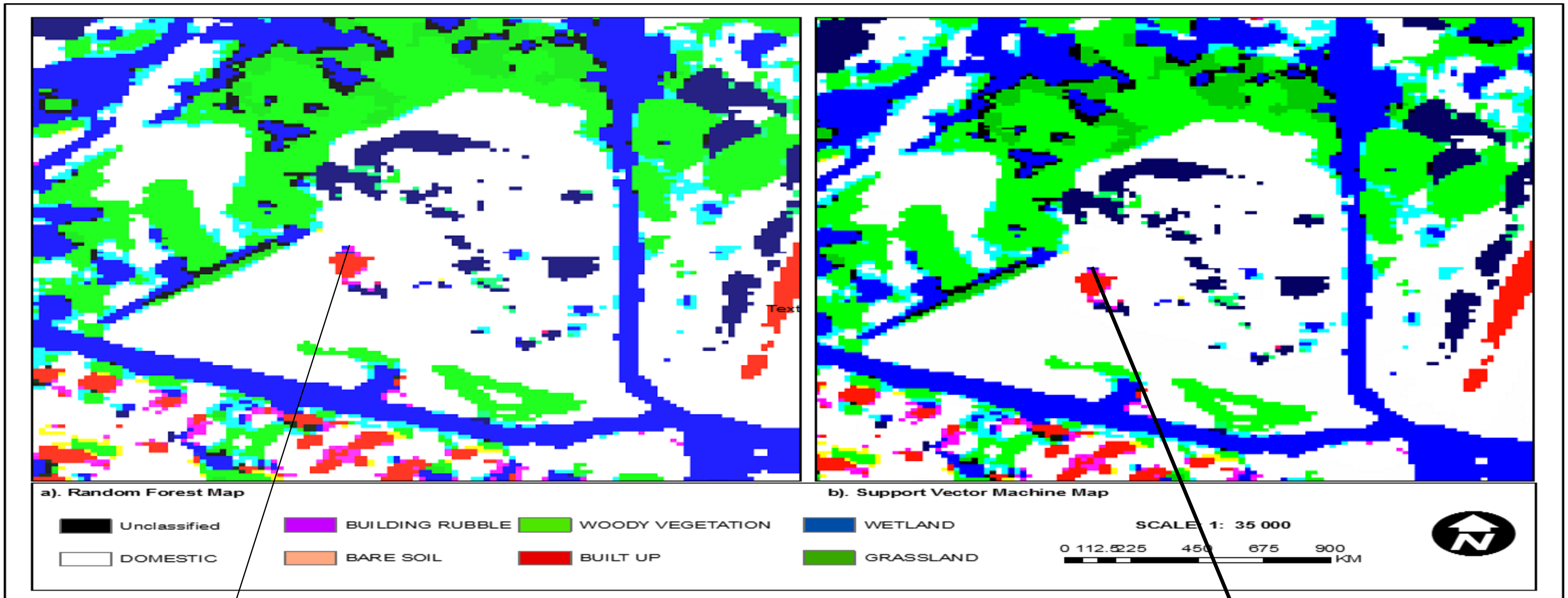


Figure 7. Random Forest (a) and Support Vector Machine (b) classification for Building rubble.

Building Rubble

Building Rubble

4.4 Results of RF and SVM in land-use/cover classification for Domestic

Land-use/ land cover maps of domestic dumping produced by means of SVM and RF. There was a noticeable modification in the coastal blue pixels northerly part of the maps (Figure 10).

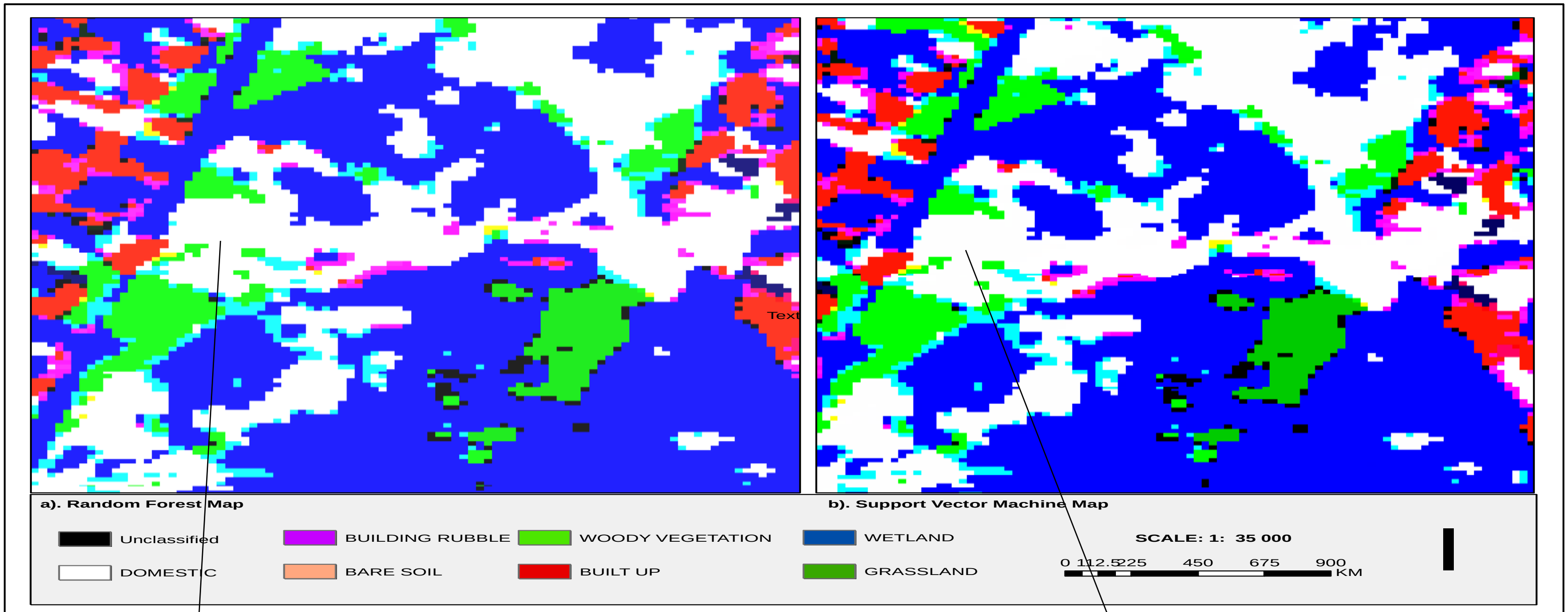
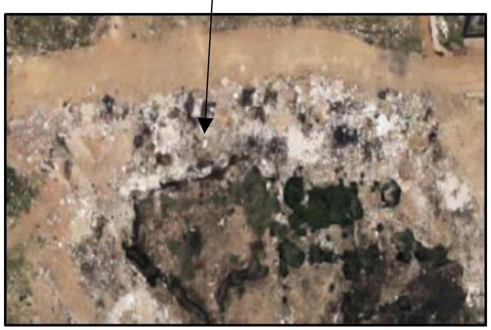
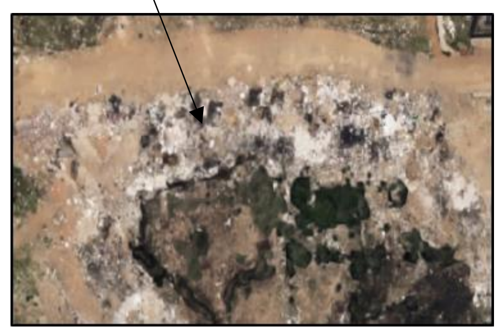


Figure 8. Random Forest (a) and Support Vector Machine (b) classification for Domestic



Domestic



Domestic

4.5 WorldView-2 individual bands for classification of LULC class

Resolution of variables' prominent in this research were permissible for discovery of the significance of each of WorldView bands (n = 8) in the land-use/ land cover categorisation (Figure 11). A valuation of altogether WorldView 2 bands (n = 8) displayed the B2 or Blue band to be the greatest influence in the sorting procedure and shaping accurateness. Figure 11 shows the overall accuracy of land-use/ land cover sorting drops by 5.1% when the Blue band is taken out from the model.

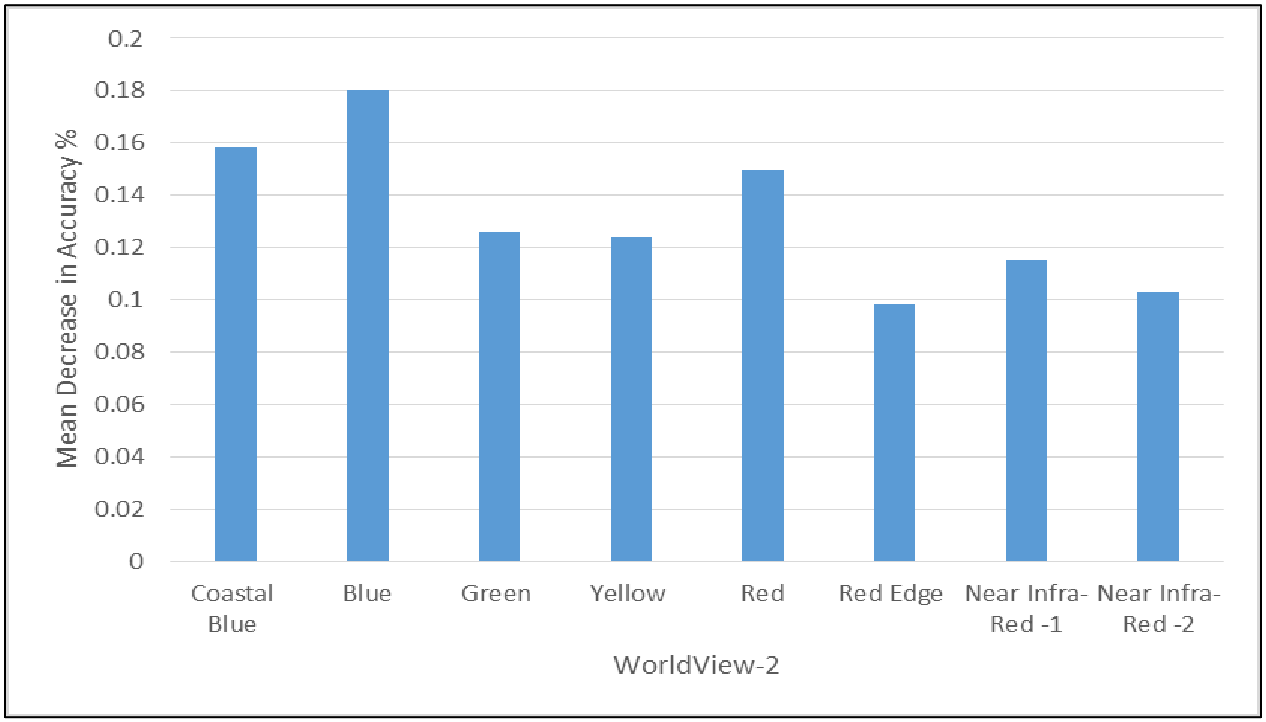


Figure 9. WorldView-2 individual bands for classification of LULC class

The most important band is always indicated by highest mean decrease in accuracy. When the efficacy of each band for a specific land-use/ land cover category is examined, the NIR-2 band demonstrates to be the greatest valued for defining woody vegetation while the costal blue band and near-infrared 2 is the least important for delineating building rubble and woody vegetation (Figure 12).

Conclusions derived from figure 12 are that areas that are partially or completely enclosed by flora are mainly in NIR1, Red Edge, Red, Yellow and Green WorldView 2 bands while areas without vegetation such as bare soil, building rubble and Built-Up lie on the Coastal Blue, Blue and Green bands of the WorldView 2.

4.6 WorldView-2 bands of all the LULC classes and their importance

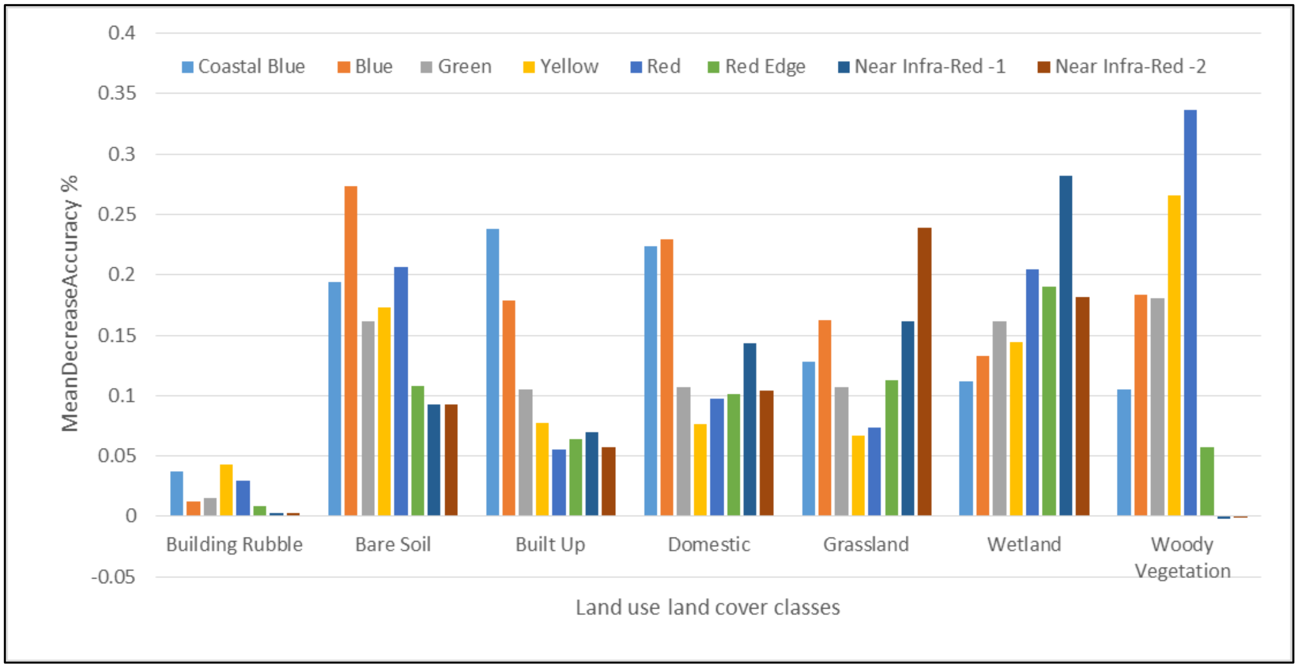


Figure 10. WorldView-2 bands of all the LULC classes and their importance

The highest mean decrease in accuracy indicates the highest significant band. When the usefulness of each band for a particular land-use/ land cover class is scrutinised, the red band shows the greatest importance for defining woody vegetation and wetland while the Near Infra-Red band is the slightest significant for defining woody vegetation and building rubble (Figure 12).

In addition to the above, it can also be interpreted thus: areas that are partially masked by vegetation are principally in blue, coastal blue, green and yellow WorldView-2 bands while areas with vegetation such as grassland, wetland are mostly on the NIR-1 and NIR-2 bands (Figure 12).

4.7.1 Accuracy assessment for RF

The accuracy assessment tests were done for land cover/ land use types for the RF and an independent examination dataset was used to evaluate the calculation presentation of RF as a classifier. Table 3 below shows the confusion matrix for random forest. The Random Forest classifier produced an overall accuracy of 84.07% with a Kappa value of 0.8116. For this RF the Spectral confusion was noted between Building Rubble (BR) and Domestic material (DM) and therefore the lowest user accuracy for Domestic of 73% and a low producer's accuracy of 94% whilst Building Rubble obtained a user's accuracy of 50% and a producer's accuracy of 54% (Table 3). The class separation of the seven land-cover types (Table 2) shows a reasonable overlap between classes. There main classes that are noticeably separable and are Built Up and Grass land. The producer's accuracy (PA); user's accuracy (UA); overall accuracy (OA) were developed on the test dataset using the EnMAP-Box ImageRF Accuracy Assessment tool.

Table 3. Table showing confusion matrix for Random Forest

	BR	**BS**	**BU**	**DM**	**GL**	**WL**	**WV**	**Totals**	**UA %**
BR	**4**	1	1	2	0	0	0	**8**	50
BS	2	**25**	1	0	0	1	0	**29**	86
BU	0	0	**19**	0	0	0	0	**19**	100
DM	7	0	5	**32**	0	0	0	**44**	73
GL	0	0	0	0	**24**	0	0	**24**	100
WL	0	1	1	0	3	**25**	3	**33**	76
WV	0	0	0	0	0	1	**24**	**25**	96
Total	**13**	**27**	**27**	**34**	**27**	**27**	**27**	**182**	
P A: %	54	93	70	94	89	93	89		**84.07**
OverallAccuracy:	**84.07**								
Kappa: 0.8116									

BR – Building Rubble, **BS** - Bare Soil, **BU** - Built-Up, **GL** - Grassland, **WL** - Wetlands and **WV** - Woody Vegetation

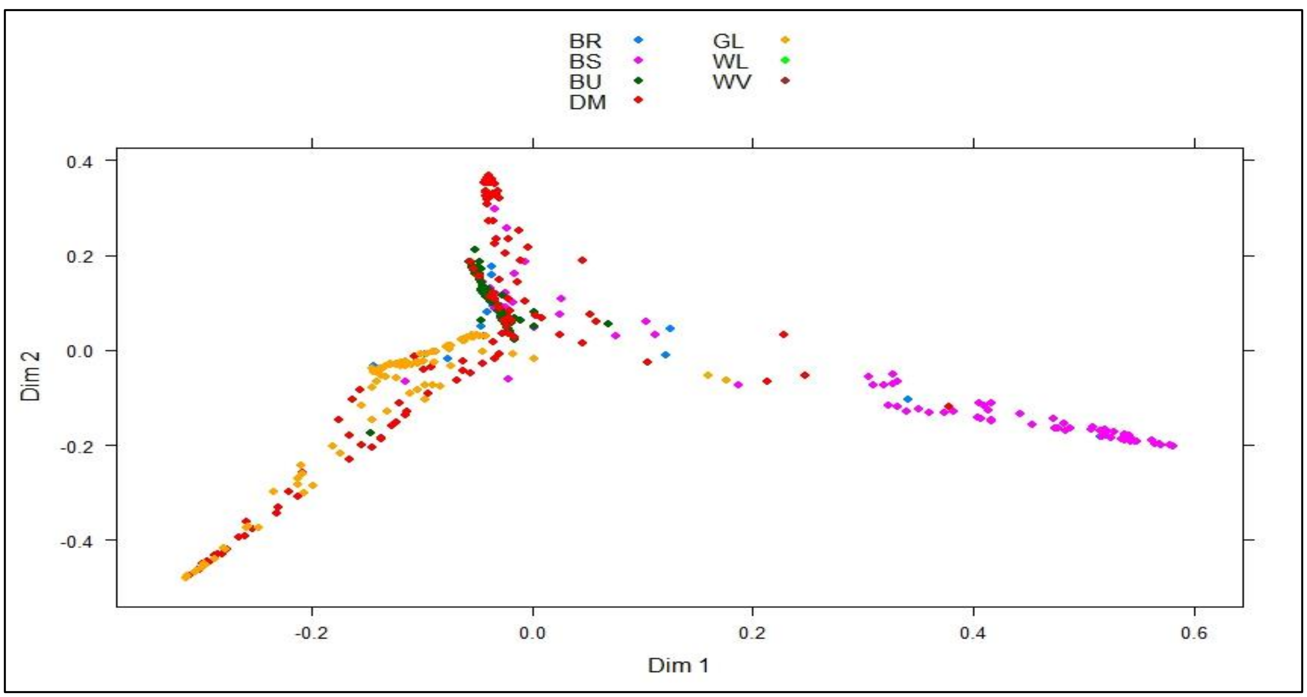


Figure 11. Class separation using Random Forest classification

4.7.2 Accuracy assessment for SVM

The (table 4) below is showing the support vector machines confusion matrix and unlike RF, the SVM classifier generated a higher overall accuracy of 85.16% with a Kappa value of 0.8238 respectively. In the same way as the Random Forest classifier, due to spectral confusion done, the SVM classifier obtained lower user accuracies for Domestic (68%) and Wetland (81%) and producer's accuracies of 78% and 85% for Building Rubble (Table 4).

As indicated on figure 10, there is a class separation that further authenticates the vast or major confusion occurring on almost all the species in this classification method. There are two classes that are significantly confused with almost every other class (Figure 10) that is, domestic and building rubble hence the lowest user and producer accuracies as is indicated on (Table 4).

The producer's accuracy (PA); overall accuracy (OA); user's accuracy (UA) and were developed on the test dataset using the ENVI-5.3 Confusion Matrix Workflow.

Table 4. Confusion matrix using the Support Vector Machine classifier

	BR	**BS**	**BU**	**DM**	**GL**	**WL**	**WV**	**Total**	**UA %**
BR	**11**	0	0	1	0	0	0	13	**100**
BS	2	**27**	1	0	0	0	0	30	**90**
BU	0	0	**21**	0	0	0	0	21	**100**
DM	0	0	4	**32**	0	0	0	47	**68**
GL	0	0	0	1	**24**	0	0	25	**96**
WL	0	0	1	0	3	**26**	2	32	**81**
WV	0	0	0	0	0	1	**25**	26	**96**
Total	13	27	27	34	27	27	27	**166**	
PA %	**85**	**100**	**78**	**94**	**89**	**96**	**93**		**85.2**
Overall Accuracy : 0.8516									
Kappa : **0.8238**									

BR – Building Rubble, **BS** - Bare Soil, **BU** - Built-Up, **GL** - Grassland, **WL** - Wetlands and **WV** - Woody Vegetation

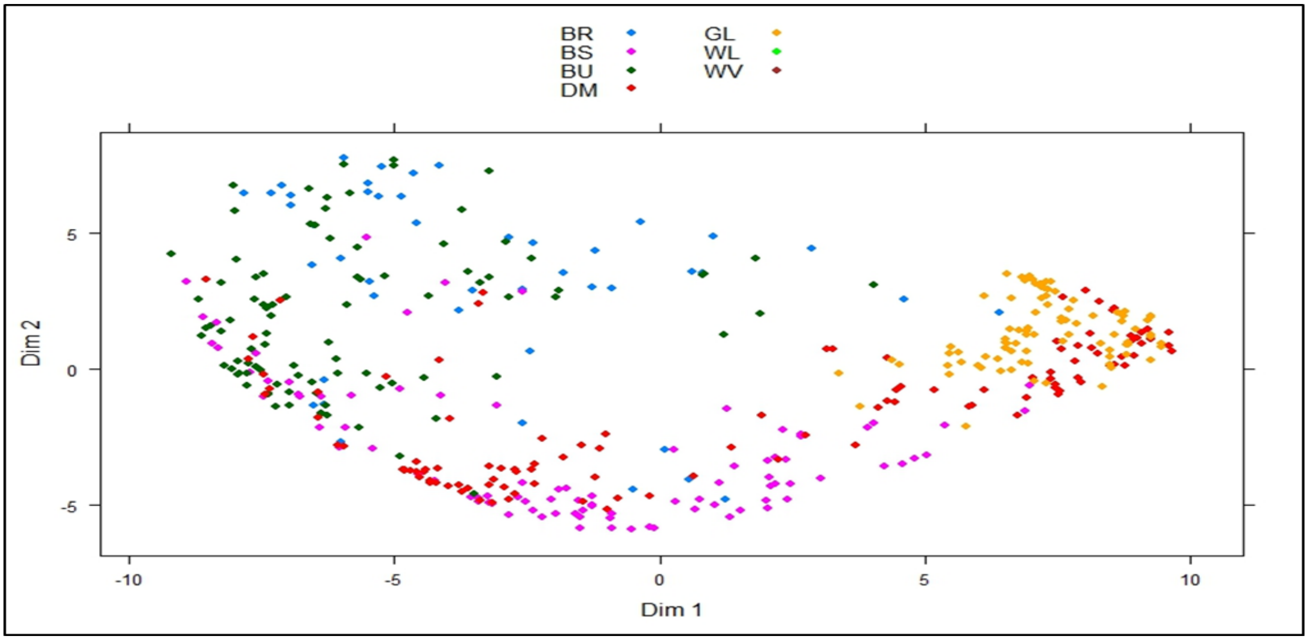


Figure 12. Class separation using Support Vector Machine classification

A mapping of vacant land (Figure 3) was done showing all types of vacant land in area of Soweto and its periphery. The dominant types of vacant land recorded were public and private vacant lands. It showed that above fifty (50 %) percent illegal dumping occurred on vacant land and the rest on pavements and on alley ways. As shown on (Table 1), 115 sites of domestic waste and 45 of building rubble were captured along other land use/ land cover types.

4.8 DISCUSSION

According to Seror et al, (2014) the state of San Antonio in the USA devotes hundreds of millions of dollars every year to alleviate ecological costs on , for example leaking of harmful elements into underground water aquifers and vegetation fires as a result of illegal waste disposals. Illegal waste presents municipalities with an extensive array of dangers that have encouraged burdens for cost-effective, effectual mapping and monitoring resolutions to upkeep enhanced management results (Glanville et al., 2015). Remote sensing has the prospective to deliver useful data on the position of illegal dumping to alert directed active surveillance procedures and cost-effective remedial happenings (Glanville et al., 2015). Remote Sensing data can provide real-time waste dumping proportion, which implies the spectrally suspected illegal area with higher probability of waste dumping (Chu et al., 2015). Multispectral image classification has extensively involved the courtesy of the remote-sensing society because classification grades are the origin for various ecological and socio-economic submissions (Kulkarni et al., 2016).

Researchers and experts have achieved great results in evolving cutting-edge classification methods and systems for refining classification accuracy (Kulkarni et al., 2016). Recently, the usage of diverse categories of spatial and spectral resolutions of visual sensors has attained diverse grades of accomplishment in land-use/ land cover mapping. Nevertheless, worries over accuracy levels still continue (Adam el al., 2014).

It is against this context that this research pursued to: decide the accomplishment of the WorldView-2 in mapping and detecting the vacant land where illegal dumping occurred using high resolution image; to map the illegal dumping using advanced classification algorithm; to compare SVM and RF in mapping the illegal waste dumping and to discriminate between the domestic waste and building rubble. Classification outcomes in this research substantiated that WorldView-2 images using SVM and RF classification are more appreciated in mapping and understanding intricate illegal dumping and land-use/ land cover types. High classification accuracies were attained. The diverse technique, in comparison to a classifier confusion matrix method, was employed to improve the accurateness of the subsequent mapping of illegal dumping and other land-use/ land cover types. The valuation was carried out to compute the enhancement in accuracy mapping between a RF and SVM. Table 5 shows the RF and SVM algorithm user accuracy and overall accuracy performance of the two classifiers for the different land use land cover types.

Table 5. Land cover classes showing Random Forest and Support Vector Machine percentage

	User Accuracy in Percentage %	
Land-cover class	**Random forest (RF)**	**Support vector machines (SVM)**
BR	50	100
BS	86	90
BU	100	100
DM	73	68
GL	100	96
WL	76	81
WV	96	96
Overall Accuracy	**84.07**	**85.16**

The capability of SVM and RF to quantify and categorise the abovementioned land-use/ land cover classes (Table 5) was equated. Both SVM and RF classifiers moulded equivalent overall accuracies. As is displayed above (Table 5), SVM achieved a slightly higher classification accuracy compared to RF by a marginal 1%. To further compare RF and SVM algorithm, the producer accuracy was used. An average producer accuracy for SVM of 90.71 was obtained as compared to 83.14 of RF. SVMs are highly precise in remote sensing arena owing to their capability to effectively handle small training datasets. Hence frequently producing advanced classification accuracy than ordinary systems (Kulkarni et al., 2016). Among many benefits of RF the more significant ones are: unsurpassed accuracy amongst present algorithms, effective application on large data sets, and an effortlessly kept structure for future usage of pre-generated trees (Kulkarni et al., 2016).

For this study a mapping of vacant land was done using a high resolution image to detect vacant land in an area of Soweto and its periphery. The study found that above 50% of illegal dumping occurred on the vacant land which was categorised into private and public unused land.

To cover the other objectives of the study, discriminations between domestic waste and building rubble using SVM and RF algorithm were done in order to classify results. The study proved that WorldView-2 images using SVM and RF classification are more applicable in mapping and complimenting complicated land-use/ land cover types. Extraordinary classification precisions were accomplished for domestic waste and building rubble. Building rubble classifier accuracy for RF is 50% slightly lesser than SVM with 100% accuracy rate. Domestic accuracy rate was 73% for RF classifier as compared to 68% of SVM for domestic. As the most published papers suggest the arrival of new-generation sensors such as WorldView-2, with improved spectral and spatial resolution, delivers new prospects for plotting parts that are very difficult to map like the mixed waste of domestic and building rubble.

CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS

5.1. Conclusions

This comprises of the conclusions and recommendations of this study. The scrutiny of WorldView 2 data gave quantification and prognosis results which delivered a comprehensive understanding of illegal dumping and other LULC in Soweto area. The research conducted was aimed at assessing the utility of the advanced classification algorithms which are RF and SVM on a new-generation WorldView-2 image to outline illegal dumping sites in Soweto area. In terms of classification the SVM classification outperformed the RF classification method as it was more flexible for parameter and kernel function selection of specific data sets like building rubble and domestic waste. GIS data used for vacant land mapping achieved the objective of mapping and detecting the illegal dumping that occurred on vacant land using the high resolution image. It also produced the overall accuracy of 90 % on mapping vacant land where illegal dumping occurred. It is noted that comparing the two classifiers, outcomes confirmed both the uniqueness and the resemblance of the performance of RF and SVM. There are however, many uncertainties associated with mapping the building rubble and built-up types using RF and SVM. These uncertainties can be due to the complexity of the material used for the study, that is building rubble. It requires reliable mapping for better management. It was also noted that due to the often high similarity of building rubble and built-up types, there was a bit of confusion in their delineation using traditional classification techniques and broadband multispectral images.

5.2 Recommendations

Remote sensing is a field that is not much exploited in mapping and monitoring illegal dumping. Inadequate studies into evolving and testing techniques on mapping and monitoring illegal dumping have been done over the past 15 years (Glanville et al., 2015). There are a few published studies on mapping and monitoring of illegal dumping spots. It is recommended that more studies be executed for the benefit of collecting more datasets containing test and training samples of high quality. This would ensure assessment on the presentation of the RF and SVM algorithms on similar fields of illegal dumpsite mapping and monitoring. Weih Jr. et al, (2010) suggest that an object-based classification would be the best method in comparison to the traditional algorithms. It outperforms both unsupervised and supervised pixel-based methods. This supports the outcomes of comparable investigations that have been piloted in the last few years. Scientific progresses and the growing accessibility of high-spatial resolution imagery has fixated consideration on the restrictions of normal pixel-based sorting procedures and triggered the need for additional innovative systems such as Object-based sorting methods, that recognise the improvement of both the contextual information and spectral in remotely sensed imagery (Weih Jr. et al, 2010).

The researches published in remote sensing have identified a growing unhappiness in pixel-by-pixel image analysis done by traditional algorithms classifiers hence the introduction of Object based methods. Yu et al. (2006) produced a complete flora catalogue for an investigation area in Northern California and practically revealed that the OBIA method outwits the unruly salt-and-pepper properties found in cataloguing outcomes from normal per pixel methodologies. With traditional algorithms classifiers it is difficult to map and classify the built up and building rubble due to its composition. This method of OBIA can be successfully applied to map and classify building rubble and built up. IKONOS remote sensor have very high resolution panchromatic (panchromatic what- it feels like you left out a word) and are the most appropriate of the trialled remote sensors to be of usage in observing and plotting illegal dumping. Consequently, the spatial determination of the remote sensor is principally significant for any upcoming plotting of illegal dumping spots (Glanville et al., 2015).

Spectral characteristics of some waste supplies had similar appearances to bare soil and replicated the constraints of multispectral images which were used; advanced spectral resolution images could be critical to resolve the spectral problem (Glanville et al., 2015). A future research can look at integrating the best methods of predictive models to curb the scourge of illegal dumping. If Remote Sensing studies can design preventative measures to predict the hotspot areas that prone to illegal dumping. (Glanville et al., 2015).

5.3 Limitations of the Study

This study is limited to mapping of illegal dumping spots for 2016 in Soweto area and not the whole of City of Joburg (CoJ). Monitoring of illegal dumping is not covered by this study because it needs gathering of data for different years to monitor changes and that is quite expensive to undertake. Spectral-based analysis of illegal dumping and other land-user/ land cover is another aspect that could not be intensively assessed in this current study. If done comprehensively, it could potentially have increased the accuracy of the training samples.

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