A remote sensing based delineation of the areal extent of smallholder sugarcane fields of South Africa

By

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Abstract

The areal extent delineation of smallholder sugarcane fields in fragmented landscapes is a challenge due to their complex spatial configuration (i.e. patchy field sizes) and timeless planting and harvesting dates. Nevertheless, delineating and estimating areas of such farming systems is essential in crop yield estimation as well as food supply inventorying to enhance food security planning for the country. Moreover, estimating the areal extent of fragmented smallholder fields can provide insights into their natural resource uses as well as their contribution to carbon pool. However, the challenge is the lack of robust, applicable methods and platforms that could be used to accurately map these farming systems in a quick, efficient and cost-effective manner. Based on that premise, this study sought to evaluate the utility of remotely sensed data coupled with advanced machine-learning classification algorithms for estimating the areal extent of smallholder sugarcane fields. The scope of this study was limited to (1) evaluating the performance of support vector machine (SVM) at pixel-based image analysis (PBIA) and object-based image analysis (OBIA) platforms in delineating areas of fragmented smallholder sugarcane fields using Landsat 8 Operational Land Imager (OLI) imagery (2) Comparing support vector machine and random forest (RF) in delineating the areal extent of smallholder sugarcane fields based on Landsat 8 OLI imagery.

The performance of the two algorithms was determined based on accuracies derived using confusion matrices. Based on objective 1, the findings show no statistical significant difference ($p \geq 0.05$) between PBIA and OBIA when using support vector machine (SVM). Furthermore, when comparing SVM with RF an increase of 6% was observed in overall accuracy. Nevertheless, results from the McNemar's showed that the 6% difference was not significant.

From the findings on this study, it was concluded that (1) Support vector machine can reduce the accuracy gap between PBIA and OBIA in delineating areas of smallholder sugarcane fields based on Landsat 8 OLI imagery, (2) Despite observing no statistical significance difference in accuracy, SVM outperformed RF by a margin of 7%. Meanwhile, both RF and SVM have great potential in delineating areas of the fragmented smallholder sugarcane fields.

Declaration

This study was undertaken in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from February 2015 to December 2016, under the supervision of Prof Onisimo Mutanga and Dr. George Chirima to fulfil the requirements of Master in Science.

I declare that the current work represents my own thoughts and has never been submitted to any other academic institutions. Acknowledgement has been duly made for statements originating from other authors.

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Plagiarism declaration

I Reneilwe Maake, declare that:

1. The research reported in this thesis, except where otherwise indicated is my original research.
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CHAPTER 1

General introduction

1.1 Background

Approximately 325000 hectares of sugarcane is harvested yearly worldwide (FAO 2011). In South Africa (SA), sugarcane cultivation is of great agricultural and economic value and it is a major source of employment for rural communities (SASA 2012). Sugarcane is a C4 crop with a relatively high carbon fixation rate (Lara and Andreo 2011). As such, it plays a significant role in combating global warming. In SA, sugarcane crop farming traverses from large scale commercial to smallholder farming in local communities. Although large scale sugarcane farming forms the hub of the sugar industry in the country, the commercial, environmental as well as the socio-economic role of smallholder sugarcane farms is often neglected and hence remains largely unknown despite contributing about 12% to the country's total cane production. Moreover, they are drivers of rural economic growth and serve as a source of community livelihood.

Despite their vital role, the spatial distribution and areal extent of these smallholder sugarcane farms is largely unknown. This is mainly due to the lack of access to data, which is often costly. In addition, the contribution of smallholder sugarcane farms to the carbon pool also remains unknown when compared with the large commercial farms. Most studies have focused on delineating areas of large commercial farms than in smallholder farms (Abdel-Rahman 2010). The lack of interest in delineating parcels in small-scale farms could be attributed to their spatial configuration. Most plots in smallholder farms are highly fragmented as compared with the large, mono-cropping and regular shaped commercial farms (Debats *et al.* 2016). Moreover, crops in smallholder farms are frequently diversified without specific planting dates, resulting in spatial heterogeneity (Padoch *et al.* 2007). This presents a challenge when delineating these parcels and therefore necessitate the need for specialized yet currently lacking approaches. As such, diverting more attention to these highly fragmented smallholdings will improve decision maker's understanding of their role in offsetting global warming. This lack of knowledge on smallholder sugarcane farms hinders accurate forecasts on food availability, government interventions, and efficient agricultural policy enforcement.

Given that smallholder farming systems heavily practise crop rotation, frequently delineating their spatial distribution could be useful for tracking changes in crop rotation and cultivated areas. This will also help us understand their level of natural resource usage (e.g. water and land). Sugarcane area statistics are needed by policy developers nationally for marketing, pricing, and import-export decisions (Schmidt *et al.* 2000). Sugarcane farmers also use these statistics for irrigation, cash flow and harvest planning (Schmidt *et al.* 2000). Customary field surveys have been used for recording sugarcane areal extent. However, besides lacking spatial reference linked to the crop fields, field surveys are often time consuming, labour-intensive and costly (Tsiligirides 1998). For example, the South African Sugar Association (SASA) routinely collects sugarcane statistics through telephone from selected fields. Nevertheless, limited access, poor communication between farmers and government agencies renders these methods unreliable (Grace *et al.* 2014). As such, other cost-effective methods that will offer timely and reliable crop area statistics are required.

Due to its succinct scope, recapitulation, and cost-viability, remote sensing (RS) can offer a feasible approach for acquiring crop area statistics, particularly in smallholder farming landscapes (Tsiligirides 1998, Mulianga *et al.* 2013). A vast group of literary works investigated the utilization of RS in crop area estimation (Schmidt *et al.* 2000, Gers and Schmidt 2001, Doraiswamy *et al.* 2003, Carfagna and Gallego 2005, Verma *et al.* 2011, Atzberger and Rembold 2013, Gallego *et al.* 2014). Some took advantage of the coarse freely available sensors (e.g. National Oceanic and Atmospheric Administration‑Advanced Very High Resolution Radiometer (NOAA-AVHRR) or Moderate Resolution Imaging Spectroradiometer (MODIS)) to quantify crop area (Xavier *et al.* 2006, Dheeravath *et al.* 2010, Atzberger and Rembold 2012). For example, Xavier et al (2006) used multi-temporal Enhanced Vegetation Index (EVI) derived from MODIS data to classify sugarcane crop in Sa˜o Paulo State. However, the significant obstacle of these studies is the coarse resolution (i.e. 1 km or 250 km) which makes it difficult to detect the highly fragmented smallholder fields which are usually characterized by mixed farming practices (Mulianga *et al.* 2013).

Conversely, improvements in sensor technology and data availability at limited cost should overcome the challenge of mapping smallholder fields in fragmented areas. For instance, the recently propelled Landsat 8 sensor offers a promising free source of data for mapping areas occupied by smallholder sugarcane fields, especially in resource-restricted regions (e.g. Sub-Saharan Africa). Landsat 8 consists of the Thermal Infrared Sensor (TIRS) and the Operational

Land Imager (OLI), with a refined spectral range that can improve the discrimination of crops. When compared to its predecessor (i.e. Landsat 7 Enhanced Thematic Mapper Plus (ETM^+)), Landsat 8 OLI has an improved signal-to-noise (SNR) radiometric performance approximated at a 12-bit dynamic range (Irons *et al.* 2012). Landsat 8 OLI has large swath width of 185 km and a 16-day temporal resolution with a great potential for quantifying sugarcane area in smallholder farming systems.

Pixel-based image analysis (PBIA) and Object-based image analysis (OBIA) domains are commonly used for analysing Earth Observation (EO) data (Duro *et al.* 2012). OBIA domain has been favoured over the customary PBIA domain due to their ability to incorporate features such as spatial, spectral and texture into a classification (Aplin and Smith 2008), a strength lacking in PBIA domain. The ability of OBIA to combine several attributes for classification offers improved methods for overcoming the complexities associated with mapping smallholder farming systems. However, OBIA operates on expensive software which hinders its application in most research institutions, especially in resource-scarce nations such as South Africa. Hence, the use of PBIA associated with limited costs persists in such areas.

Nevertheless, PBIA were reliant on parametric algorithms such Maximum likelihood techniques have been criticised for accuracies (Duro *et al.* 2012, Wu and Li 2012). Probability-based classifiers assume that data follows a normal distribution and hence fail to characterize fields with small plot sizes. The limiting factors encountered when classifying using PBIA techniques further necessitated the need for development of advanced classification approaches (Hay *et al.* 2005). Advanced machine-learning classifiers such as SVM and RF stimulated enhanced and reliable classifications. To the best of my knowledge, the performance of the newly launched Landsat 8 OLI dataset coupled with advanced classification algorithms has not yet been tested for delineating areas under sugarcane, especially in the highly fragmented smallholder fields. Therefore, this study explored the utility of advanced machine-learning algorithms coupled with Landsat 8 OLI imagery in estimating areas of smallholder sugarcane fields in Nkomazi, South Africa.

1.2. Research Questions

- ⇨ Can SVM reduce the accuracy gap between OBIA and PBIA classification platforms
- ⇨ What is the performance of SVM compared to other machine-learning classifiers?

1.3. Objectives

The overall goal of this study was accomplished through the following objectives:

1. To evaluate the performance of SVM in delineating fragmented smallholder sugarcane fields at object-based and pixel-based image analysis platforms using Landsat 8 OLI imagery.
2. What is the performance of SVM compared to its competitive advanced machine-learning algorithms in estimating the areal extent of smallholder sugarcane fields using Landsat 8 OLI imagery?

1.4. Summary of chapters

The thesis is composed into four sections. The first main section (chapter 1) presents the background of the study and blueprints the research questions and objectives. Chapter two and three are composed in an article layout for publication in peer reviewed journals (both in preparation). Chapter two investigates the performance of support vector machines at pixel and object-based image analysis platforms in delineating smallholder sugarcane farming systems. Chapter three compares between SVM and RF in estimating areas of fragmented smallholder sugarcane fields. The fourth chapter is a synthesis, providing an overview all imperative research findings highlighted in connection to the objectives of the study. Conclusions and recommendations for further research are also highlighted.

1.5. General Methodology

The first part of the study investigated the performance of SVM at PBIA and OBIA classification platformS for delineating smallholder sugarcane fields using Landsat 8 OLI image captured during winter (August 2015) at a tillering stage of the crop. The second part compared SVM and RF based on Landsat 8 OLI in delineating areas of fragmented smallholder sugarcane fields. A schematic representation of the research methods is presented in **Figure 1.1**

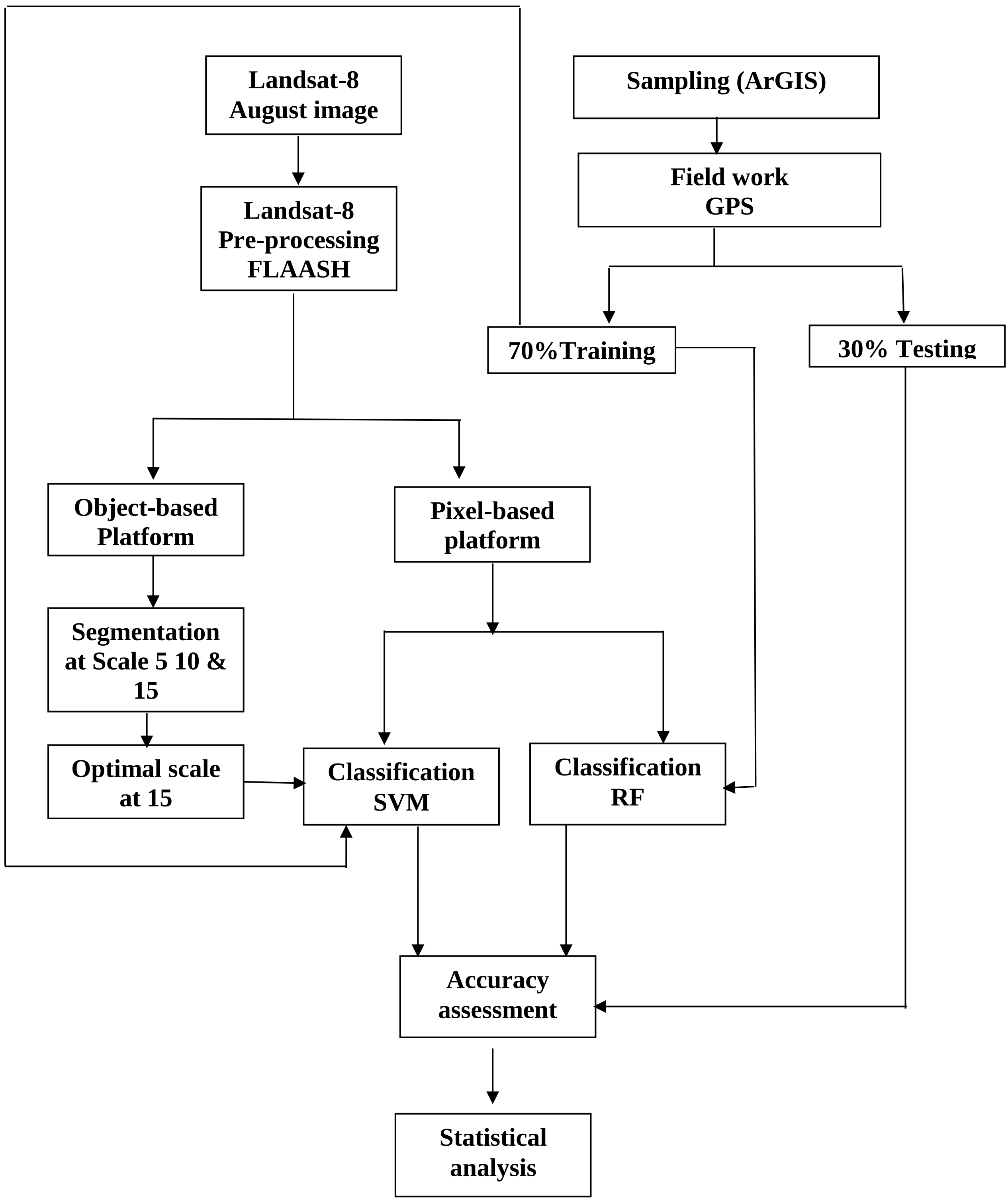

Figure 1.1. Schematic depiction of the data and research methods utilised.

CHAPTER 2

Evaluating the performance of support vector machine at pixel and object-based image analysis platforms in delineating areas of fragmented smallholder sugarcane fields using Landsat 8 OLI imagery

This chapter is based on:

Maake, R., Mutanga, O., Chirima J.G. and Kganyago, M. (In preparation). Evaluating the performance of support vector machine at pixel and object-based image analysis platforms in delineating areas of fragmented smallholder sugarcane fields using Landsat 8 OLI imagery.

Abstract

Delineation of the areal extent of smallholder sugarcane fields in fragmented landscapes can be a challenge due to their complex spatial configuration (i.e. patchy field sizes) and non-uniform planting and harvesting dates. However, delineation and area estimation of such farming systems is essential in crop yield estimation for food security. Moreover, estimating the areal extent of fragmented smallholder sugarcane fields can provide an insight of their water use as well as their contribution to the carbon pool. Exploring different classification platforms could aid in finding the optimal classifier to overcome the challenges of delineating fragmented smallholder fields. This study sought to evaluate the performance of support vector machine (SVM) at object-based image analysis (OBIA) and pixel-based image analysis (PBIA) platforms in delineating the areal extent of fragmented smallholder fields using Landsat 8 Operational Land Imager (OLI) imagery. The SVM classifier at both classification platforms was evaluated based on overall accuracy and statistical significance. Findings of this study showed overall classification accuracies of 79.79% and 77.97% for OBIA SVM and PBIA SVM respectively. Results from the McNemar's test indicated an insignificant statistical difference ($p \geq 0.05$) in overall classification accuracies obtained by the SVM between the two classification platforms. This study demonstrates that SVM can be utilised to improve the accuracy in delineating fragmented smallholder sugarcane fields while reducing the accuracy gap between OBIA and PBIA.

Key words: Support vector machines, Landsat 8 OLI, sugarcane, smallholder fields

2.1. INTRODUCTION

Lately, there has been a developing interest in delineating smallholder sugarcane operations in South Africa (SA). This was triggered by the need for rural development and economic growth stimulation. Sugarcane is a C4 crop with an accelerated rate of fixing carbon (Lara and Andreo 2011). Such a characteristic enables it to play a critical role in balancing global warming. Sugarcane has the ability to store high levels of sucrose (Grof and Campbell 2001). It is principally cultivated for sugar production. Approximately 50% of the world's sugar supply is from sugarcane (Abdel-Rahman 2010). The crop also forms part of the calorie component of the human diet. Furthermore, sugarcane produces several by-products such as bagasse and molasses used in ethanol production and animal feed respectively (Xavier *et al.* 2006). In SA, the crop is cultivated for food and income generation. In areas such as Nkomazi in Mpumalanga Province, sugarcane is a strategic crop, providing employment to farm workers as well as to factory workers in the mills.

The SA sugar industry has approximately 22 500 registered sugarcane farms of which 21 110 are emerging smallholder sugarcane growers (SSG) (SASA 2015). This implies that there are more emerging SSG compared to the large scale sugarcane growers (LSG) in the country. These emerging SSG contribute approximately 12% to SA's total cane production (SASA 2016). Regardless of their contribution, SSG experience reduced support from government or banks and marginalisation in the markets and in policy developments compared to the large scale farms (IFAD 2013). Much of the commercial, environmental as well as the socio-economic roles of LSG have been documented, but little is known concerning the emerging SSG. Despite their crucial role, their spatial distribution, areal extent and contribution to the carbon pool remains largely unknown. Smallholder sugarcane farmers lack the capacity to delineate their parcels because they lack access to data and skills, which are often characterised by high costs (Abdel-Rahman 2010).

In order to comprehend the contribution of SSG to commercial markets and socio-economic factors, there is a need for mapping the spatial distribution as well as accurately estimating the areal extent of these operations. This information is important for formulating strategies on sugarcane marketing and export-import decisions. At mill level, cash flow budgeting as well as opening and closing operations are formulated based on these estimates, while at farm level, such estimates inform decisions on irrigation arrangements, planting and harvest plans as well as decisions concerning transport schedules (Schmidt *et al.* 2004). Annual sugarcane areal extents may vary due to abandonment of the fields or other commitments beyond cultivation.

As such, timely sugarcane area estimates are required for accurate sugarcane production statistics (Wu and Li 2012).

Given that traditional methods of surveying SSG such as questionnaires used by the South African Sugar Association (SASA) are time consuming and expensive, earth observation systems offer spatial data, which could be utilised to accurately delineate the spatial distribution and areal extent of sugarcane fields fairly quickly.

Earth observation technology provides spatially continuous and frequent observations, which allows the retrieval of large data volumes at different spatial and temporal resolutions (Mulianga *et al.* 2013). Coarse resolution sensors such as Moderate Resolution Spectrometer (MODIS) and Advance Very High Resolution Radiometer (AVHRR) are suitable for daily monitoring in large scale farms due to their higher temporal resolutions. For example, (Zhang *et al.* 2014) used MODIS derived multitemporal enhanced vegetation index for mapping maize over large scale farms using support vector machines. They obtained an overall accuracy of 79% for maize cultivated area. However, spatial resolutions of 250m - 1km are insufficient to delineate crop boundaries and area in smallholder farms, i.e. approximately 5ha. Padoch *et al.* (2007) noted that intercropping and non-uniform planting and harvesting dates exacerbate the difficulty of mapping smallholder fields. High (i.e. 10m - 2.5m) to very high resolution (2.5m - 0.5m) sensors such as Satellite Pour l'Observation de la Terre (SPOT 6/7), RapidEye and WorldView are characterised by improved spatial and spectral imaging capabilities, thus offer better prospects for mapping smallholder fields (Atzberger 2013, Gallego *et al.* 2014). For insatnce, Worldview-2 has bands in the yellow and red edge spectral region at 2m spatial resolution.This charcateristics are valuable for species discrimination and mapping at a more detailed local scale, especially at smallholder farm level (Cho *et al.* 2011). However, the wider adoption of such sensors has been limited by their associated high costs (Rembold and Maselli 2004) and computational costs. Therefore, medium resolution (20m - 30m) sensors such as Landsat remain the most suitable due to their global coverage, high revisits, larger swath width and free availability.

For years, pixel-based image analysis (PBIA) has been the core platform for image classification, especially in developing countries with limited access to expensive data and software. However, their reliance on spectral attributes while ignoring other attributes such as texture, geometry (i.e. extent and shape) during classification is a constraining factor on the reliability and accuracy of maps derived using PBIA (Blaschke *et al.* 2000, Hay *et al.* 2005).

During the past decade, object-based image analysis (OBIA) platform has gained a wider audience in the remote sensing research community, due to its ability to incorporate spectral, spatial, textural and contextual information, which increases classification accuracies (Whiteside *et al.* 2011, Duro *et al.* 2012, Petropoulos *et al.* 2012). Even though OBIA has shown slight supremacy in mapping fragmented landscapes (Nitze *et al.* 2012), PBIA classifiers remains popular due to their wider availability in most open-source and proprietary software compared to OBIA classifiers. Moreover, the accuracy gap between the two platforms is closely related to a wide adaptation of traditional classifiers such Maxim-likelihood at PBIA platform for classification. This classifiers have been criticised for their deficiency in handling unbalanced and training data, therefore providing lower accuracies (Wu and Li 2012).

Recently, researchers have resorted to machine-learning classifiers such as support vector machine (SVM) for classification (Oommen *et al.* 2008, Kumar *et al.* 2016). SVM. This classifier has been demonstrated to provide better accuracies compared to the traditional probability-based classifiers (Kumar *et al.* 2016) and other machine-learning algorithms (Duro *et al.* 2012, Feyisa *et al.* 2016). For instance, Feyisa *et al.* (2016) found that SVM with radial kernel function (RBF) performs better than Random Forest (RF) and a rule-based model (C5.0) for mapping cropping patterns in complex agro-ecosystems using MODIS. Given its successful application, this study aimed to exploit SVM classifier within two platforms of image classification, *viz*. PBIA and OBIA, for crop boundary delineation and area estimation within smallholder fields at Nkomazi in Mpumalanga Province, South Africa. Specifically, the study compared the performance of PBIA and OBIA SVM in delineating the areal extent of smallholder sugarcane fields. It was hypothesised that, SVM's improved capabilities will reduce the accuracy gap between OBIA and PBIA.

2.2. DATA AND METHODS

2.2.1. Study area

The study was conducted in the rural Nkomazi Local Municipality, near the towns of Malelane and Komatipoort in Mpumalanga Province, South Africa (-25°42′E, 31°43′S) (Figure 1). There are seven administrative Tribal Authorities in Nkomazi, namely Mlabo, Ka-Hloyi, Kwa-Lugedlane, Soboswa, Matsamo, Mawewe and Mlaba. The area experiences cool, frost-free winters with average minimum temperatures of around 8^{o}C, and hot and humid summers with maximum temperatures averaging 33^{o}C, which is a suitable climate for sugarcane cultivation. Annually, rainfall ranges from approximately 750mm -860mm, and occurs from October to

March. In these rural communal lands, sugarcane is a strategic crop maintained through irrigation systems. There are two main sugarcane planting windows: August - November and February - April. Moreover, the crop is harvested at an average age of 12 months. There are two main planting cycles. The first is a planting-cane cycle, which begins after planting a sugarcane stem and completes with the first harvest. This cycle typically lasts between 12 - 18 months. The second is a ratoon cycle, which occurs after the first harvest where a portion of the sugarcane plant is cut and the stem with roots and a bud is left in the soil to allow re-growth. The ratoon cycle repeats on a yearly basis to a maximum of 5 years. The sugarcane crop consists of the following growth stages: pre-emergence, emergence, tiller emergence and flowering(Gers 2004).

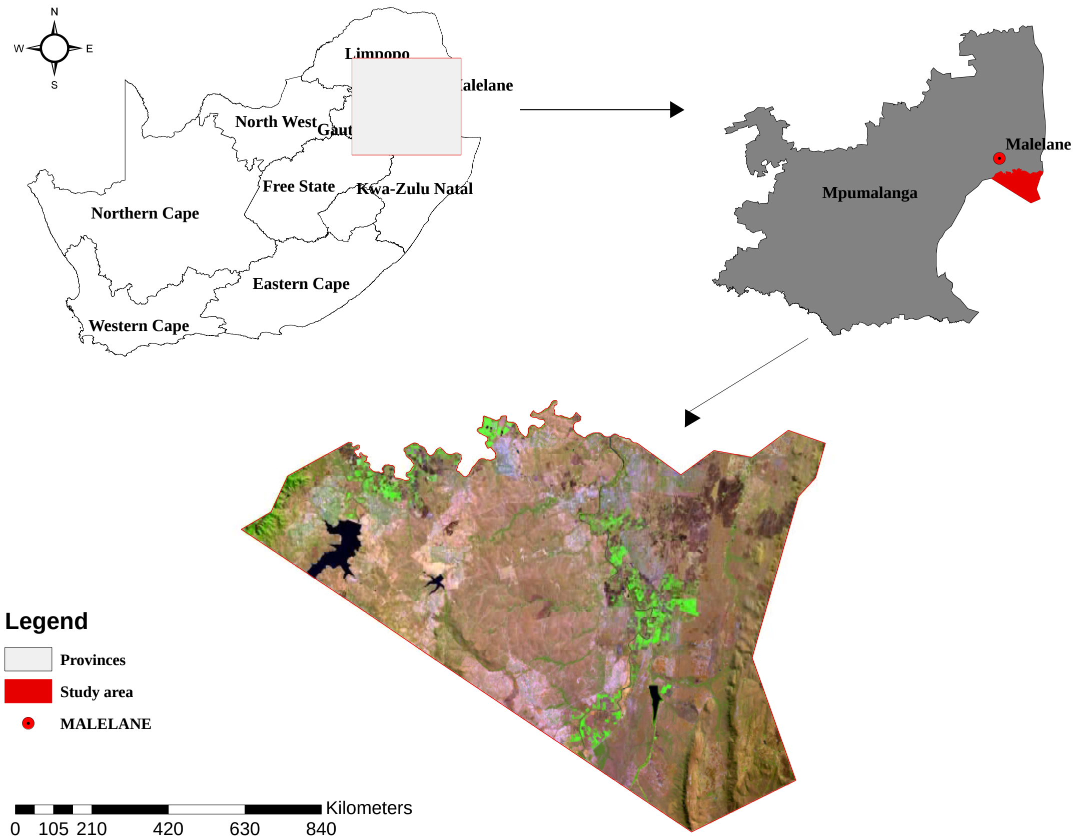

Figure 2.1. Location of the study area. An insert of a Landsat 8 OLI (RGB=543) satellite image is attached.

2.2.2. Data acquisition

2.2.2.1. *Satellite data & pre-processing*

A cloudless Landsat 8 OLI multispectral image captured on the 1st of August 2015 (Path 168 and Row 78) covering the study territory was extracted from the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre (http://www.edc.usgs.gov). The image capture date was chosen to coincide with the tillering stage, since it is when sugarcane population stalk and leaves start developing. Landsat 8 OLI sensor captures images in two modes: spectral and panchromatic. Landsat 8 OLI image has seven spectral bands, namely: Coastal blue (430-450nm), blue (450-510nm), green (510-590nm), red (640-670nm), Near Infrared (NIR) (680-880nm), Short Infrared (SWIR 1) (1570-1650nm), Short Infrared (SWIR 2) (2110-2290nm) at 30m spatial resolution. The sensor has a swath width of 170 by 183 km and a maximum revisit resolution of 16 days. For this study, all seven spectral bands were utilised, namely: Coastal Blue; Blue; Green; Red; NIR; SWIR 1, and SWIR 2 given their previous successful application.

The Landsat 8 OLI scene was obtained as standard L1t files (geo-registered & ortho-rectified) to Universal Transverse Mercator (36 North) projection using World Geodetic Datum (WGS 84) coordinates system from the USGS EROS Data Centre. In order to delineate smallholder sugarcane fields from the Landsat 8 OLI image, the digital number (DN) values of the multispectral bands were converted to Top-of-Atmosphere (TOA) spectral radiance and then to at-sensor surface reflectance using the rescaling coefficients provided within the image's metadata file (Chander *et al.* 2009) using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module in Environment for Visualizing Images (ENVI) software (Cooley *et al.* 2002). This enabled the retrieval of accurate reflectance spectra. The image was re-projected to a Universal Transverse Mercator (UTM zone 36 South) using World Geodetic Datum (WGS-84) so that it can overlay with other datasets, e.g. study area boundary layer. A subset covering the study area was then extracted in a Geographic Information System (GIS) environment.

2.2.2.2. *Field data collection*

A vector file for the administrative tribal authorities taken from the Agricultural Research Council - Institute for Soil, Climate and Water (ARC-ISCW) was used to delimit the boundary of the study area. A sugarcane boundary map was used as a base for selecting sugarcane fields and for generating sampling points in a GIS environment. High spatial resolution SPOT 6/7 embedded on Google Earth™ and a National Land-Cover (NLC) map obtained from the ARC-ISCW aided the identification and on-screen digitisation of additional land-cover classes useful for discriminating sugarcane. The field samples were collected from the 1st to 5th of September 2015. A total of 399 points were produced following a stratified random sampling technique with the assistance of high resolution data from SPOT 6/7 and Google Earth™ as well as the NLC map (Congalton and Green 1999). The sampling was restricted to homogenous areas where land-cover was consistent with the image acquisition date. The points were then uploaded into a Garmin Montana 650 Global Positioning System (GPS) for locating them in the field where they were identified and assigned to one of the classes found within the study area (Table 1). Points located in a rugged terrain and inaccessible areas were manually obtained by visual interpretation of SPOT 6/7 and Google Earth™ imagery. The samples were split into 70% training (n = 281) and 30% validation (n = 118) for subsequent classification (Omer *et al.* 2015).

Table 2.1. Training and validation data used for OBIA and PBIA platforms.

Class name	**Code**	**Training (*n*)**	**Testing (*n*)**
Sugarcane	S	42	18
Fallow	F	42	14
Dense vegetation	DV	34	18
Sparse vegetation	SV	42	18
Burnt areas	BA	42	18
Bare-surfaces	BS	23	9
Water bodies	WB	25	10
Communal residence	CR	45	11
Total		281	118

2.2.3. Methods

2.2.3.1. *Support vector machine classifier*

SVM is a supervised machine-learning algorithm that groups classes based on the statistical learning theory (Vapnik 1998). It functions by maximising the margin (i.e. the distance between points of each land-cover relative to the best separating hyperplane) (Petropoulos *et al.* 2012). It consists of numerous hyperplanes that discriminates varying number of classes (Oommen *et al.* 2008). However, only a single hyperplane (i.e. optimal hyperplane) with a maximum margin best separates between the classes (Petropoulos *et al.* 2012). The training points that lie closer to the optimal hyperplane are called support vectors. Hence, the larger the margin, the lower the generalisation error of the classifier. In the process, only support vectors (points) construct the optimal hyperplane while the validation dataset validates the performance of the developed hyperplane (Oommen *et al.* 2008). However, in scenarios where classes are not linearly separable, a kernel function is used, which allows points to scatter such that a linear hyperplane can be fitted (Foody and Mathur 2004). Examples of common kernels include polynomial, sigmoid and radial basis function (RBF) (Oommen *et al.* 2008), with RBF being popular in remote sensing due to its optimal performance (Pal and Mather 2005). The accuracy of SVM classifier depends on optimising key parameters namely: Gamma and Cost (γ & C) (Oommen *et al.* 2008). In this study, parameters of SVM classifier were tuned in R statistical software (Team 2014) using e1071 package (Duro *et al.* 2012). The optimal parameter was determined by grid search on values ranging from 1.001 to 1000 using a 10-fold cross-validation (Huang *et al.* 2002, Duro *et al.* 2012). Optimised SVM parameter values were used in subsequent image classification.

2.2.3.2. *Segmentation & object feature selection*

Image segmentation serves as the building block from which object-based image classification can be performed (Castilla and Hay 2008). As such, Landsat 8 OLI image was first partitioned into image objects (IO) using the multi-resolution (MRS) algorithm within the commercial eCognition Developer software version 9.2 (Tremble 2016). This algorithm utilises a bottom-up approach that begins with one pixel and fuses similar neighbouring pixels to form image objects based on a number of user-defined factors such as scale, shape and compactness (Baatz and Schäpe 2000). Literature suggests that, the average size of IOs is determined by the scale parameter, which determines the maximum spectral heterogeneity allowed within an object (Gao and Mas 2008, Zhang *et al.* 2012).The choice of the scale parameter is critical as it can result in an over or under-segmentation (Espindola *et al.* 2006).

In this study, optimal values for parameters and input layers useful for MRS algorithm were selected following a technique by (Dingle Robertson and King 2011). Image segmentation was undertaken at three multi-scale levels (Table 2.2) using all seven spectral bands with equal weighting. Different scale parameters (5, 10, 15, Figure 2.2) were used as different levels of segmentation starting with the smallest to the largest objects, following a successful application by (Castilla and Hay (2008), Duro *et al.* (2012)). This was done to allow the selection of the best scale in which optimal segments can be sampled for classification. Segmentation was considered optimal once IO were meaningful and representative of features within the study area by visual inspection (Duro *et al.* 2012).

Prior to classification, object attributes considered the most representative of the eight classes (Table 2.1) were extracted for implementation in the classification stage. A variety of object attributes exist within the eCognition software. For this study, the same features used in PBIA were used for OBIA to allow for an unbiased comparison (Table 2.3). Description and meaning of the equations can be accessed in Tremble (2016). Information based on the seven spectral bands, optimal segmentation level (Figure 2.2D) and the three object features were utilised for OBIA classification. Sample objects for all the classes were selected from the lowest scale level (Table 2.2) and were used for the SVM classifier.

Table 2.2. Summary of parameters used in multi-resolution segmentation (MRS) algorithm

Scale level	Scale parameter	Shape factor	Compactness
1	5	0.7	0.3
2	10	0.8	0.2
3	15	0.9	0.4

Table 2.3. Object features used for OBIA classification (adopted from Trimble 2016)

Type	Name	Feature value range
Spectral	Mean	[Ckmin,Ckmax]
	Standard deviation	0; 1/2Ckrange
Customised	NDVI	[−1, 1]

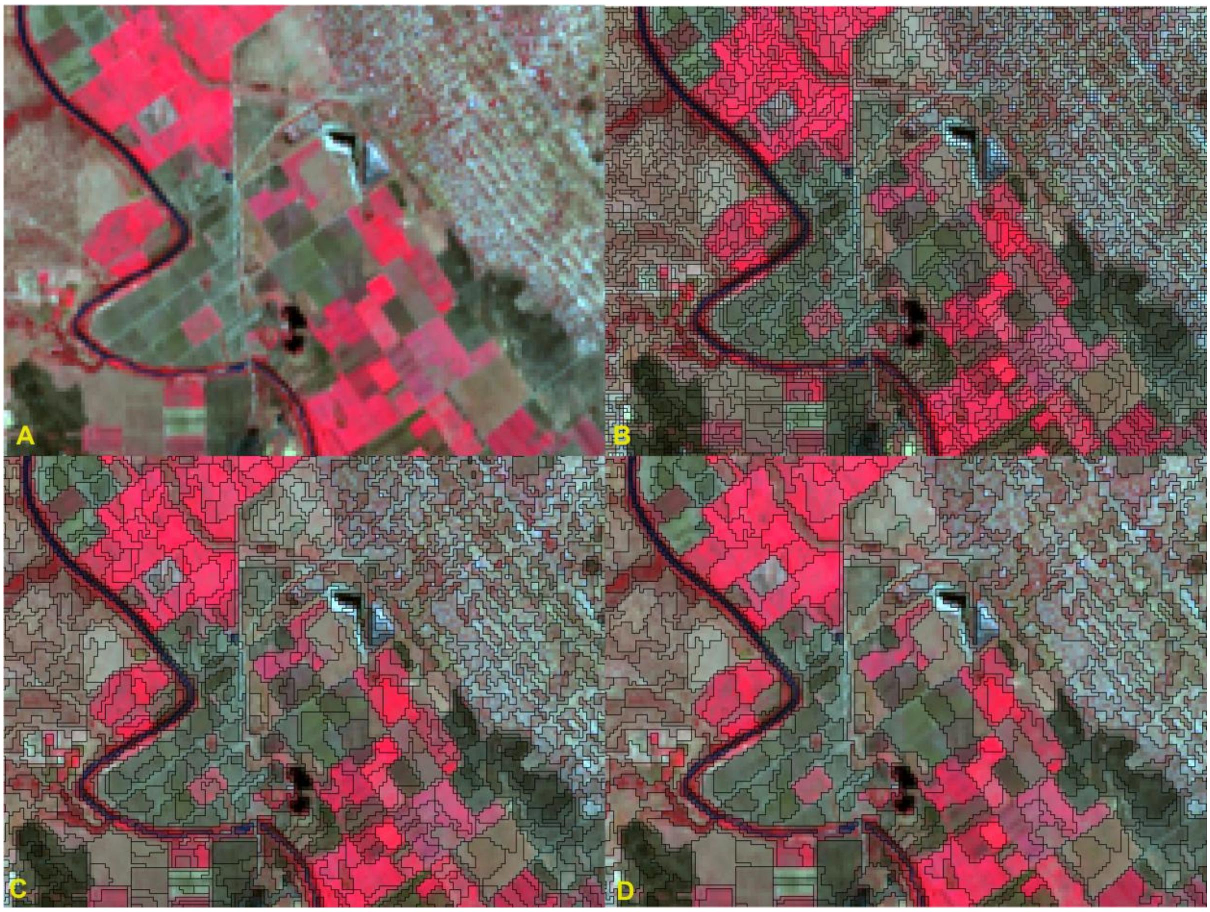

Figure 2.2. Illustration of MRS Segmentation result: (A) Landsat 8 OLI false colour composite (RGB, = 653) (B) level-1 Scale = 5, (C) Level-2 Scale = 10 & (D) Level-3 Scale = 15.

2.3.4. ***Accuracy assessment & map comparison***

Accuracy assessment was executed on all thematic maps resulting from OBIA SVM and PBIA SVM using the 30% validation data (n = 118). Error matrices were computed for each thematic map in EnMap-box software (Adelabu *et al.* 2013). For comparison purposes, error matrices for each thematic map were computed using the independent validation samples (n=118). For SVM at each classification platform, users accuracies (UA) and producers accuracies (PA) were computed and reported for each class (Congalton and Green 1999, Petropoulos *et al.* 2012). The performance of PBIA SVM and OBIA SVM were then compared using the McNemar's test. The McNemar's is a non-parametric test speculating that the quantity of correctly and incorrectly grouped samples is equivalent for both classifications using the validation data (Dingle Robertson and King 2011, Whiteside *et al.* 2011). Given that the two algorithms $A_{OBIA\text{-}SVM}$ and $A_{PBIA\text{-}SVM}$ have a similar deviation rate, McNemar's test compares the number of instances incorrectly allocated by $A_{PBIA\text{-}SVM}$, but correctly allocated by $A_{OBIA\text{-}SVM}$ (f_{12}) with the number of instances incorrectly allocated by $A_{OBIA\text{-}SVM}$ but not by $A_{PBIA\text{-}SVM}$

(f_{21}) (Bostanci and Bostanci 2013). The test utilizes a *z score* (Equation 1) to evaluate the dissimilarities between the two classifications methods.

$$z = \frac{(f_{12} - f_{21} - 1)}{\sqrt{(f_{12} + f_{21})}} \quad (1)$$

The null hypothesis that the classification accuracy of OBIA SVM is not significantly different from that of PBIA SVM in delineating the areal extent smallholder sugarcane fields among other land-covers was tested at 95% confidence level. Two classification accuracies can be considered significantly different if ***z*** is above 1.96 at 5% significant level. Furthermore, f_{11} and f_{22} were incorporated for instances that were wrongly grouped at both platforms and the number of instances that were correctly grouped at both PBIA and OBIA correspondingly.

2.3. RESULTS

2.3.1. *Areal extent delineation & visual comparison*

Figure 2.3 shows the resulting thematic maps derived from the SVM at PBIA and OBIA. Visual inspection of SVM at both classification platforms (Figure 2.3B & C) portrays similarities in terms of the sugarcane spatial coverage and other classes in relation to the Landsat 8 OLI image. However, a slight deviation in spatial coverage of sugarcane can be observed on the north-western part of the map (Figure 2.4B). Moreover, traces of the salt and pepper are present in PBIA-SVM, while OBIA depicts a relatively smooth classification.

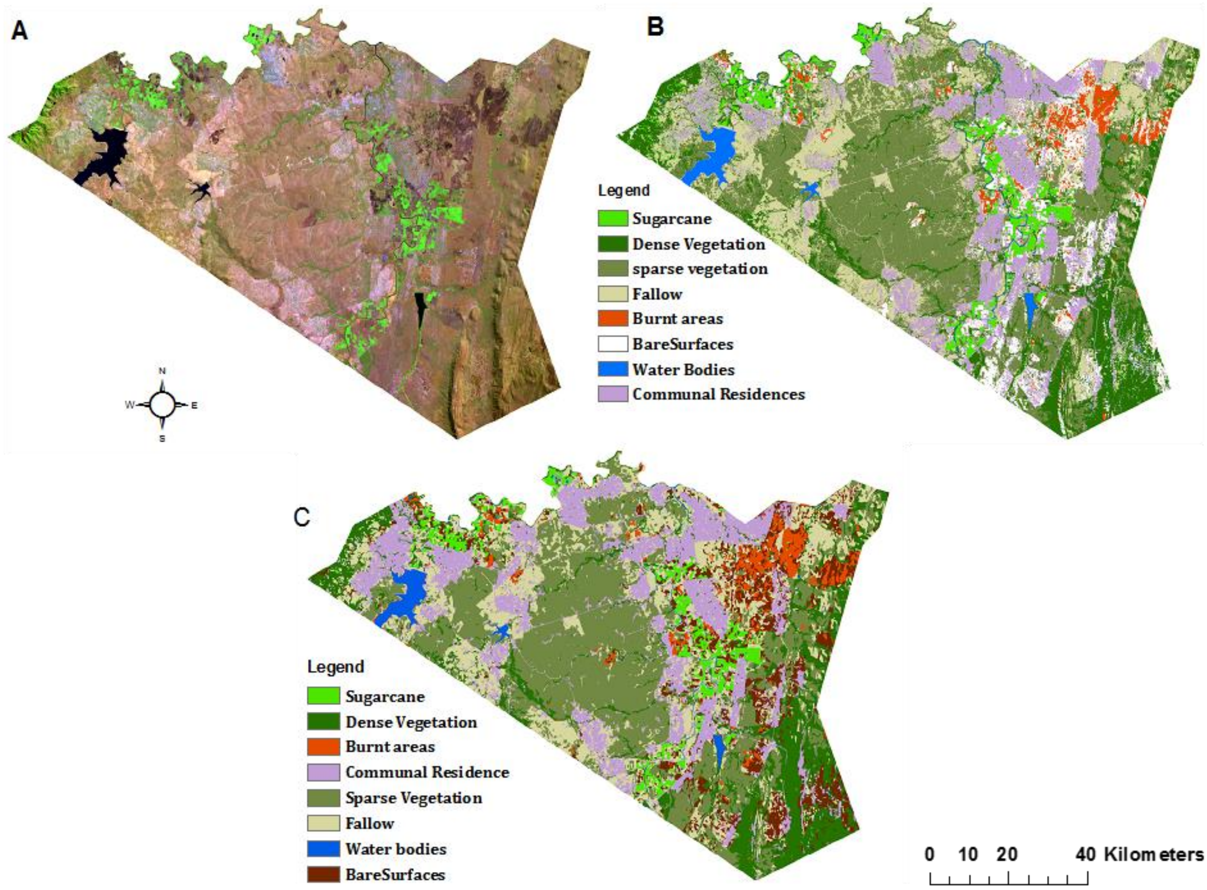

Figure 2.3. Thematic maps derived from classifying Landsat 8 OLI image: A) Landsat 8 OLI false colour composite, B) PBIA SVM C) OBIA SVM thematic map.

Table 2.4 summarises areas (hectares) derived from the thematic maps resulting from classifying Landsat 8 OLI data using SVM at both classification platforms. From the findings, areal extents of 3155.01ha and 2675.22ha were observed for PBIA SVM and OBIA SVM respectively. Figure 2.4 further illustrates observed difference in the areal extent of sugarcane from the two classification platforms using SVM. The 479.97ha difference in sugarcane areal extent is mostly centered on the northwestern and the central portion of the study area. Generally, SVM at both classification platforms assigned almost similar areal extents to all observed classes in the study territory, with the lowest being water and highest being sparse vegetation respectively.

Table 2.4: Area of each land-cover type in the study site assigned by PBIA & OBIA SVM classifier coupled with Landsat 8 OLI imagery.

Class code	OBIA (ha)	(%)	PBIA (ha)	(%)	Relative Difference	% Difference
S	2675.22	3.4	3155.01	4.1	479.97	0.7
DV	10234.49	13.9	12558.53	16.32	324.04	2.42
SV	24406.35	31.7	25093.50	32.6	687.15	0.9
F	15533.81	20.2	*14821*	19.3	712.81	0.9
BA	2368.92	3.1	2298.06	2.9	70.86	0.2
BS	6467.15	8.4	6271	18.16	196.15	9.76
WB	1169.86	1.5	2391.75	1.61	221.89	0.12
CR	13432.51	17.4	11299.29	14.72	221.89	2.68

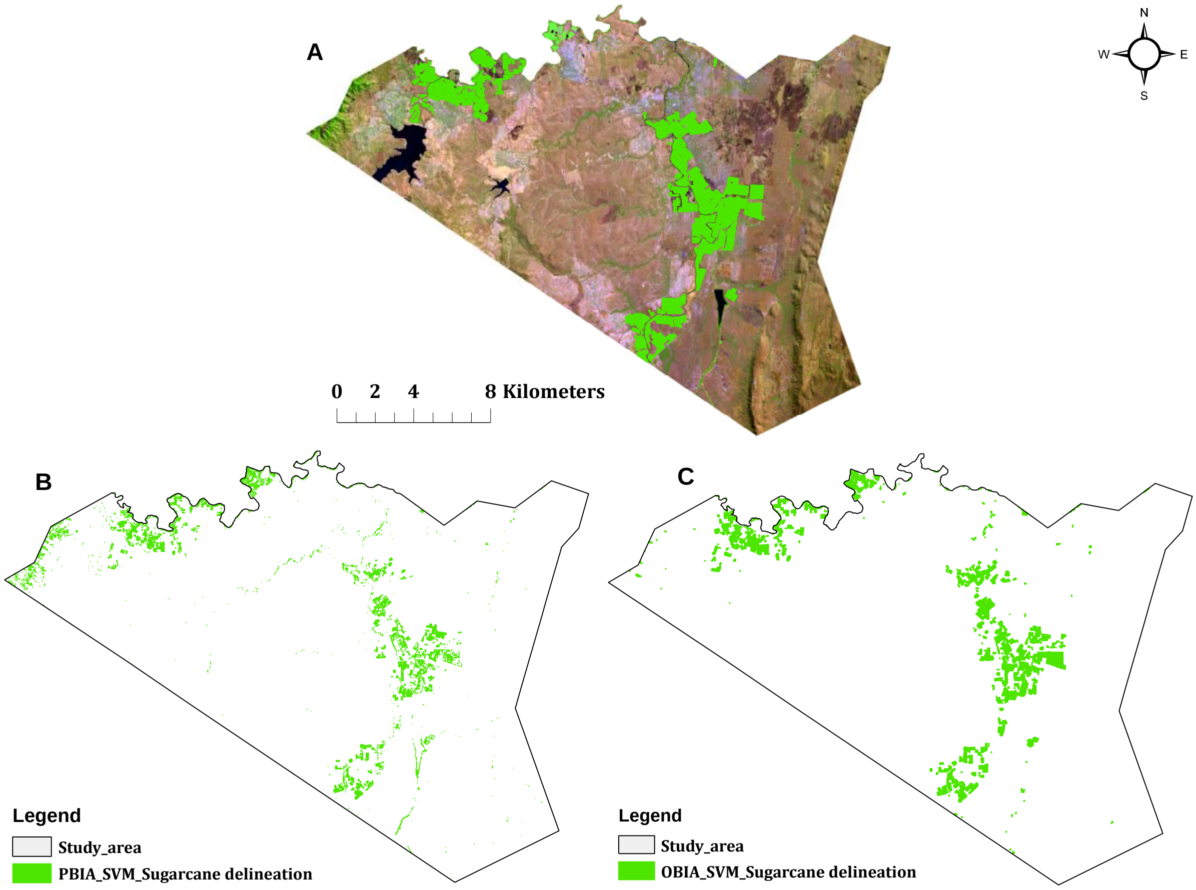

Figure 2.4. Distribution of sugarcane area delineated by SVM at PBIA & OBIA platforms; A) Landsat 8 OLI false colour composite B) PBIA SVM C) OBIA SVM.

2.3.2. *Accuracy and statistical assessment*

Overall, SVM classifier at both PBIA and OBIA classification platforms was almost similar regarding overall classification accuracy (78 & 79.7% respectively) (Table 2.5 & 2.6). Similarly, Kappa coefficient obtained from SVM was within the same range for both PBIA and OBIA platforms (0.74 & 0.76) respectively. Sugarcane obtained high producers (94.44%) and user (94.44%) accuracies for OBIA SVM compared to PBIA SVM (93.75 & 83.33). From a user's perspective, OBIA SVM increased the accuracy of delineating sugarcane by 11% compared to PBIA SVM. Collectively, SVM at both classification platforms had five classes with producers and user accuracies above 70%. Individually, bare surfaces (BS) scored the lowest producers (61.11%) while communal residence (CR) the lowest users (46.15%) accuracies for OBIA SVM. while fallow (F) scored the lowest for PBIA SVM (66.67 & 44%). From a user's perspective, water bodies (WB) have been accurately classified (100%) at OBIA while the same was observed from a producer's perspective at PBIA compared to other classes.

Table 2.7. shows a comparison of PBIA SVM and OBIA SVM using McNemar test. When comparing the performance of the tuned SVM using the validation dataset, McNemar's test showed that the observed differences in accuracies between PBIA and OBIA were statistically insignificant ($p \geq 0.05$) (Table 2.7). The McNemar's test score of 1.000 was below 1.96, which is a prerequisite to considered two classifiers statistically significantly different at 5% error rate. As such, the assumption that SVM can reduce the accuracy gap between PBIA and OBIA performance was achieved.

Table 2.5. Confusion matrix from PBIA classification using SVM based on Landsat 8 OLI image.

				PBIA SVM						
Reference	1	2	3	4	5	6	7	8	Total	PA **(%)**
(1) S	15	0	0	1	0	0	0	1	16	**93.75**
(2) DV	1	12	2	0	0	0	1	1	17	**70.59**
(3) SV	0	1	14	0	0	0	0		15	**93.33**
(4) Fallow	1	0	0	8	0	1	0	5	12	**66.67**
(5) BA	0	0	1	3	11	0	0		15	**73.33**
(6) BS	0	0	1	1	1	7	0	1	10	**70.00**
(7) WB	0	0	0	0	0	0	9		9	**100.00**
(8) CR	1	1	0	5	0	1	0	16	24	**66.67**
Total	18	14	18	18	12	9	10	19	118	
UA (%)	83.33	85.71	77.78	44.44	91.67	77.78	90.00	84.21		
OA (%)	**78**									
Kappa	**0.75**									

Table 2.6. Confusion matrix from OBIA classification using SVM based on Landsat 8 OLI image.

	OBIA SVM									
Reference	1	2	3	4	5	6	7	8	Total	PA **(%)**
(1) S	17	1							18	**94.44**
(2) DV		10		1	1	1		1	14	**71.43**
(3) SV			9					3	12	**75.00**
(4) Fallow				16		2		1	19	**84.21**
(5) BA			1		17				18	**94.44**
(6) BS	1		3		1	11		2	18	**61.11**
(7) WB		1		1			8		10	**80.00**
(8) CR					2	1		6	9	**66.67**
Total	18	12	13	18	21	15	8	13	118	
UA (%)	**94.44**	**83.33**	**69.23**	**88.89**	**80.95**	**73.33**	**100.00**	**46.15**		
OA (%)	**79,7**									
Kappa	**0.76**									

Table 2.7. Comparison of PBIA SVM and OBIA SVM using McNemar test.

		PBIA SVM		
		Correctly classified	Misclassified	Total
OBIA SVM	Correctly classified	101	0	101
	Misclassified	1	16	17
	Total	102	16	118

NB: McNemars *z* score = 1.000

2.4. DISCUSSION

This study investigated the performance of SVM at PBIA and OBIA platforms in delineating the areal extent of the fragmented smallholder sugarcane fields based on Landsat 8 OLI. Comparisons were made based on overall classification accuracy and the McNemar's test. Particularly, this study assessed the effect of two classification platforms (i.e. PBIA and OBIA) on the accuracy of SVM in delineating the areal extent of fragmented smallholder sugarcane fields. The results indicated that SVM at both classification platforms resulted in similar sugarcane area estimation and accuracy with only 2% difference.

2.4.1. *Areal extent delineation and map comparisons*

PBIA and OBIA SVM characterised the spatial pattern of sugarcane and other associated land-cover. Nevertheless, a slight 479.22ha areal extent difference resulting mostly from PBIA SVM was observed on the north-western and the central portion of the thematic maps for sugarcane, and were not statistically different. No reference data on sugarcane area was available for direct comparison with estimates obtained in this study. However, Chemura and Mutanga (2016), using an advanced classifier (RF), obtained coffee areas that were consistent with farm records. A possible reason for the area disaggregation in this study could be the association between the spectral signatures of other vegetation classes and sugarcane. Generally, discriminating between classes with similar spectral signatures is challenging (Xavier *et al.* 2006), particularly at PBIA platform. The spatial resolution (30m) of Landsat 8 OLI could have contributed to this confusion due to its insufficient resolution to characterise smallholder fields. Meanwhile, OBIA SVM seems to handled the confusion between sugarcane and other natural dense vegetation better. OBIA's ability to exploit objects instead of individual pixels and using a combination of the spatial and spectral information of such objects in a classification process could have contributed to the minimisation of the spectral confusion between sugarcane and other vegetation classes (Table 2.2). Nevertheless, the similarities in areal extents of sugarcane and its associated classes (Figure 2.3) in both PBIA and OBIA suggests a good general spatial agreement between PBIA and OBIA. He *et al.* (2015) noted that the accuracy of a classification relies on the classifier used during classification. As such, this study demonstrated that the selection of SVM had a positive impact on the overall accuracy of delineating fragmented smallholder fields using Landsat 8 OLI image.

2.4.2. ***Accuracy and statistical assessments***

With regards to overall classification accuracy, both PBIA and OBIA SVM show similar accuracy frequencies (Figure 2.4). However, OBIA SVM enhanced the overall classification accuracy marginally by 2% compared to PBIA SVM. Nevertheless, the 2% accuracy difference observed between PBIA-SVM and OBIA SVM showed no statistical significance. This implies that the areas of fragmented smallholder sugarcane fields based on Landsat 8 OLI data can be delineated accurately at either PBIA or OBIA platform, using SVM classifier. The results obtained support the hypothesis that SVM reduces the accuracy gap between PBIA and OBIA. The use of the same classifier (SVM) at both classification platforms could have contributed to the similar accuracies observed. SVM has the ability to optimally separate hyperplanes for classes, a characteristic lacking in customary techniques (e.g. Maximum likelihood) (Licciardi *et al.* 2009). The algorithm can tolerate high volume of input data as well as limited training sample data (Devadas *et al.* 2012).

The results from the user's accuracies showed that, OBIASVM improved the accuracy of sugarcane compared to PBIA. It seems that OBIA minimises confusion of classes with similar spectral signatures such as dense and sparse vegetation. This could be attributed to its ability to classify using objects instead of pixels.

The higher PA and UA accuracies obtained for sugarcane compared to other spectrally related classes such as sparse and dense vegetation noted in this study could be attributed to the image acquisition date (i.e. during the dry season) and the irrigation state of sugarcane. During the dry season, most of the vegetation exhibits lower spectral reflectance due to senescence while irrigated sugarcane had higher reflectance peaks making it easily detectable with Landsat 8 OLI imagery. Findings of this study imply that SVM can accurately delineate the fragmented smallholder sugarcane fields irrespective of the classification platform used, therefore reducing the accuracy gap between the two platforms.

Overall, the outcomes of this study concur with other studies which revealed that when utilizing similar machine-learning algorithm, there is no statistical distinction between PBIA and OBIA (Dingle Robertson and King 2011, Duro *et al.* 2012, Goodin *et al.* 2015). For example, Duro *et al.* (2012) compared PBIA and OBIA for mapping agricultural areas using Decision Tree (DT), RF and SVM. They obtained no statistical significance between PBIA and OBIA when using RF and SVM.

In contrast, others found that OBIA outperformed PBIA and noted a statistical difference in terms of classification accuracies between the two platforms (Yan *et al.* 2006, Araya and Hergarten 2008, Gao and Mas 2008, Whiteside *et al.* 2011). For example, Araya & Hergarten (2008) compared PBIA Maximum likelihood (MLC) and OBIA Bhattacharyya distance (BD) using Landsat Enhanced Thematic Mapper (ETM)+ for land-cover in urban and peri-urban landscapes. Their results indicate that OBIA BD (85%) outperformed PBIA MLC (78%). Tehrany *et al.* (2014) compared PBIA Decision Tree (DT) and OBIA Nearest Neighbour (NN) with SVM for land-cover mapping. Using a SPOT 5 image for the years 2003 and 2010, they discovered that OBIA NN performed better (90.5% & 91%) than PBIA DT (68.6% & 68.4%) and OBIA SVM (80.6% & 78.15%) for the two respective years. Regardless of their higher accuracies, these studies focused on different algorithms between the two classification platforms. Generally, different classifiers have different classification properties and therefore give different outputs for the same spatial land-cover. This renders direct comparisons difficult. In this study, we compared the same algorithm (SVM vs SVM) at both PBIA and OBIA platform. As such, results drawn by our study allow direct comparison to be made.

Altogether, this study contributes towards the utility of advanced classification algorithms, i.e. SVM in delineating the fragmented smallholder farming systems. The almost similar accuracies obtained at both PBIA and OBIA platforms suggest that SVM bridges the accuracy gap between the two platforms, and therefore provides a cheap and reliable method, especially in developing countries such as South Africa with limited access to expensive data and software. The findings of this study form a baseline against which future estimates could be compared for effective and informed decision making in sugarcane farming. Nevertheless, it will also be of interest to compare the competence of SVM with other advanced machine-learning algorithms in delineating the areal extent of the fragmented smallholder farming systems. This will provide a basis for drawing concrete conclusions as to which classification algorithm and platform accurately delineates such complex farming systems.

2.5. CONCLUSIONS

From the outcome of this study, it was concluded that:

i) SVM has great potential in delineating the areal extent of the fragmented smallholder sugarcane fields.
ii) When advanced SVM was applied at PBIA and OBIA classification platforms, no statistical significant difference in overall classification accuracies was observed.
iii) Overall, the advanced SVM classifier reduces the accuracy gap between OBIA and PBIA classification platforms.

CHAPTER 3

Comparing Support Vector Machines and Random Forest in estimating the areal extent of smallholder sugarcane fields using Landsat 8 OLI imagery

This chapter is based on:

Maake, R., Mutanga, O., Chirima, J.G., and Sibanda, S. (in preparation). Comparing Support Vector Machines and Random Forest in estimating the areal extent of smallholder sugarcane fields using Landsat 8 OLI imagery.

Abstract

Smallholder agricultural areas are the mainstay of developing regions such as southern Africa. These farming systems consist of highly fragmented plot sizes and irregular sowing and harvesting schedules. This makes it difficult for policymakers and scientists to develop effective management strategies for these smallholder farmers. As such, tailored techniques are requisite for accurately delineating their areas. The goal of this study was to compare the performance of support vector machines (SVM) and random forest (RF) in delineating the areal extent of smallholder sugarcane fields using Landsat 8 Operational Land Imager (OLI) imagery, in South Africa. The findings of this study indicated that SVM outperformed (overall accuracy = 77.97 %, and Kappa = 0.74) RF (overall accuracy 71.2%, kappa = 0.68). Furthermore, the McNemar's test indicated a statistically insignificant difference ($p \geq 0.05$) in the accuracies of the two algorithms. The outcomes of this study emphasises the efficacy of the newly launched Landsat 8 OLI satellite imagery in characterising smallholder sugarcane areas.

Key words: Support vector machines, random forest, Landsat 8 OLI, sugarcane, smallholder fields

3.1. INTRODUCTION

Smallholder farmers, growing crops using low-intensity practices on small parcels of land (typically ≤ 2 ha), comprise approximately 50% of rural populations in developing nations and contribute up to 90% of developing nations' staple food production (Singh *et al.* 2002, Morton *et al.* 2006). In South Africa (SA), smallholder sugarcane growers (SSG) dominate in most sugarcane growing regions (Hurly *et al.* 2014). They cover approximatively 371 662 hectares (ha) of land and produce an average of 19.9 million tons of sugarcane yearly (SASA, 2015). Smallholder sugarcane farms stimulate economic growth in rural communities and alleviate poverty through income generation from cane sales. In addition, these smallholder farms play a critical role in the biogeochemical processes such as carbon cycling. To this end, little is known about the contribution of these smallholder farms to the carbon storage/sinks. The long-term sustainability of the basic livelihood provided by these smallholder farms is currently under threat (Sibiya and Hurly 2011). For example, in the year 2000 there were about 50000 registered smallholder sugarcane farms (Dubb 2015) compared to the current estimate of 21110 (SASA 2016). Considering the critical roles played by these smallholder farmers, there is need for accurate and robust methods of identifying and mapping the cropping patterns. Understanding their areal extent would aide in prolonging the services and roles played by these farms.

Earth observation (EO) data offers a quick, accurate and efficient method of feasibly characterising smallholder fields (Nitze *et al.* 2012, Ok *et al.* 2012, Chemura and Mutanga 2016). This is because EO instruments are frequently observing these croplands at various spatial extents (Markley *et al.* 2003). Furthermore, EO such as Landsat 8 Operational Land Imager (OLI) offers such data at limited costs (Duro *et al.* 2012, Maguranyanga *et al.* 2015). Specifically, Landsat 8 OLI is purported to offer numerous invaluable opportunities for applications such as understanding the spatial distribution of smallholder famers. Landsat boasts of a long record of accomplishment of freely availing archived spatial digital data from a swath width of 185 km and a 16-day revisit resolution suitable for timely characterising smallholder farms at a larger geographical area. Landsat 8 OLI provides a refined spectral collection of specific wavebands that are essential in improving crop area monitoring. The sensor also contains an improved radiometric resolution of 12 bits relative to its predecessors, which is critical in characterising croplands. A vast group of literary works attests the utility of Landsat 8 OLI in vegetation mapping (Dube and Mutanga 2015, Ahmadian *et al.* 2016, Dong *et al.* 2016, Roy *et al.* 2016). Dong et al (2016) characterised the spatial distribution and area occupied by paddy rice fields using Landsat 8 OLI and obtained producer and user accuracies of 73% and 92%, respectively. It is hypothesised that the combined use of Landsat 8 OLI satellite with robust classification algorithms could accurately characterise the areal extent and spatial distribution of sugarcane fields.

Pixel-based image analysis (PBIA) and Object-based image analysis (OBIA) domains are commonly used for analysing EO data (Duro *et al.* 2012). Despite it being criticised for accuracies, PBIA is the most widely utilised image analysis platform. Because it ready available at low cost compared to OBIA. Several classification algorithms have been utilised for mapping sugarcane areas using EO data. Examples include maximum likelihood classifier (MLC) & minimum distance (MD) with MLC being the most widely used (Narciso and Schmidt 1999, Markley *et al.* 2003, Xavier *et al.* 2006). The se classifiers have been executed at pixel-based image analysis However, the usefulness of such customary classifiers in smallholder sugarcane landscapes is limited by the fragmented small plot sizes and irregular sowing as well as harvesting schedules (Padoch *et al.* 2007, Debats *et al.* 2016). The major challenge with these algorithms is that they are parametric in nature assuming that the input data should be normally distributed which is not generally the situation in applied EO studies (He *et al.* 2015). Furthermore, mixed pixels remain a challenge when using such algorithms (Walton 2008). As such, these farming systems require robust classification techniques, which can surpass the challenge of smallholder field fragmentation.

In an effort to reduce such difficulties, advanced classifiers (i.e. non-parametric classifiers) that do not require data to be normally distributed have been revolutionized and favoured over the traditional classifiers (He *et al.* 2015). Furthermore, these advanced classification algorithms have the ability to deal with large quantities of data in heterogonous settings (Devadas *et al.* 2012). The most widely utilised robust machine-learning algorithms include Support vector machines (SVM) and random forest (RF). RF works by producing numerous classification decision trees (He *et al.* 2015) where each tree is trained on a bootstrapped sample of the original training data. Contrarily, SVM utilizes an optimization principle to find the optimal boundary between object of interest (Petropoulos *et al.* 2012). A number of scholars have compared SVM and RF (Nitze *et al.* 2012, Adelabu *et al.* 2013, Adam *et al.* 2014). For instance, Nitze *et al.* (2012) compared SVM, RF and Nearest Neighbour (NN) to MLC for crop type mapping using Landsat Thematic Mapper ™. Akar and Güngör (2013), compared MLC, RF and SVM for classifying land-cover using Quick-bird and IKONOS imagery. They discovered that RF outperformed SVM and MLC.

However, the majority of the aforementioned studies compared ordinary classifiers with advanced machine-learning algorithms, hence the biased results (Mountrakis *et al.* 2011, He *et al.* 2015). Others diverted their attention to the large regular-shaped commercial farms where fragmentation is not a problem (Chemura & Mutanga 2016). To the best of our knowledge, no study evaluated the relative performance of SVM in relation to RF for mapping the areal extent of fragmented smallholder sugarcane fields in South Africa. As such, the goal of this study was therefore to compare the performance of SVM and RF for delineating areas of fragmented smallholder sugarcane fields.

3.2. DATA AND METHODS

3.2.1. Study area

The study was conducted in the rural Nkomazi Local Municipality, Mpumalanga Province, South Africa (-25°42′E, 31°43′S) (Figure 3.1) near Malelane and Komaatipoort towns. The area experiences cold, frost-free winters with average minimum temperatures of around 8^{o}C, and extremely hot and humid summers with maximum temperatures averaging 33^{o}C, which is suitable for sugarcane cultivation. Annually, rainfall ranges from approximately 750 and 860mm, and occurs from October to March. In these rural communal lands, sugarcane is a strategic crop that is mainly under irrigation. There are two main cane-planting windows, namely: August - November and February – April. Moreover, the crop is harvested at an average age of 12 months. There are two main planting cycles; the first is a planting-cane cycle, which begins after planting a sugarcane stem and completes with the first harvest. This cycle typically lasts between 12 and 18 months. The second is a ratoon cycle, which occurs after the first harvest where a portion of the sugarcane plant is cut and the stem with roots and a bud is left to allow re-growth. The ratoon cycle repeats on a yearly basis to a maximum of 5 years. The sugarcane crop consists of the following growth stages: pre-emergence, emergence; tiller emergence and flowering stage (Gers 2004).

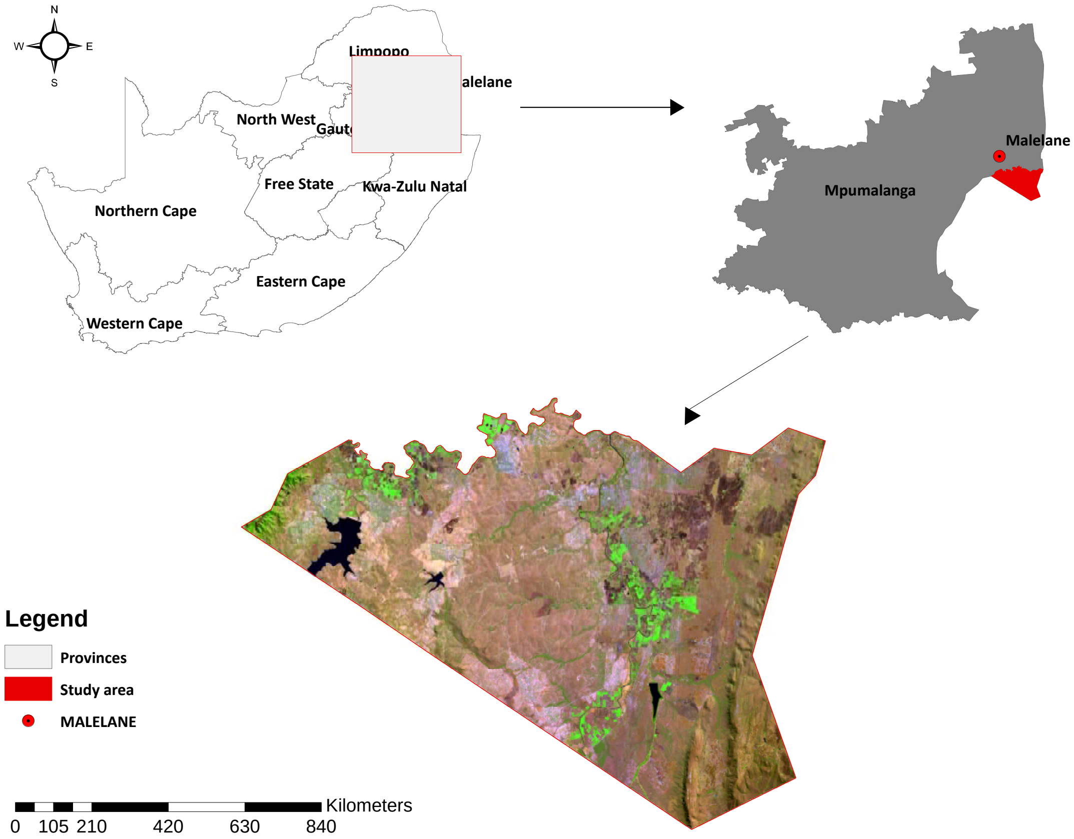

Figure 3.1. Location of the study area. An insert of a Landsat 8 OLI (RGB=543) satellite image is attached.

3.2.2. Data acquisition

3.2.2.1. *Satellite data & pre-processing*

A cloudless Landsat 8 OLI multispectral image captured on the 1st of August 2015 (Path 168 and Row 78) covering the study boundary was extracted from the U.S Geological Survey (USGS) Earth Resource Observation and Science (EROS) Centre (http://www.edc.usgs.gov). The image capture date was chosen to coincide with the tillering stage, since it is when sugarcane population stalk and leaves start developing. Landsat 8 sensor captures images in two modes: spectral and panchromatic. Landsat 8 Operational Land Imager (OLI) yields seven spectral bands, namely: Coastal blue (430-450nm), blue (450-510nm), green (510-590nm), red (640-670nm), Near Infrared (NIR) (680-880nm), Short Infrared 1 (SWIR) 1 (1570-1650nm), Short Infrared 2 (SWIR 2) (2110-2290nm) at 30m spatial resolution. The sensor has a swath width of 170 by 183 km and a maximum revisit resolution of 16 days. This study utilised all seven spectral bands namely: Coastal Blue; Blue; Green; Red; NIR; SWIR 1, and SWIR 2 given their previous successful application.

The Landsat 8 OLI scene was obtained as standard L1t files (geo-registered & ortho-rectified) to Universal Transverse Mercator (36 North) projection based on the World Geodetic Datum (WGS 84) coordinates system from the USGS EROS Data Centre. In order to delineate smallholder sugarcane fields from the Landsat 8 OLI image, the digital number (DN) values of the multispectral bands were converted to Top-of-Atmosphere (TOA) spectral radiance and then to at-sensor surface reflectance using the rescaling coefficients provided within the image's metadata file (Chander *et al.* 2009) using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module in Environment for Visualizing Images (ENVI) version 5.2 software (Cooley *et al.* 2002). This enabled the retrieval of accurate reflectance spectra. The image was re-projected to a Universal Transverse Mercator (UTM zone 36 South) based on the World Geodetic Datum (WGS-84) so that it can overlay with other datasets, e.g. study area boundary layer. A subset covering the study area was extracted in a GIS environment.

3.2.2.2. *Field data collection*

A vector file for the administrative tribal authorities acquired from the Agricultural Research Council's Institute for Soil, climate & Water (ARC-ISCW) was used to delimit the boundary of the study area. A sugarcane boundary map was used as a base for selecting sugarcane fields and for generating sampling points in a Geographic Information Systems (GIS) environment. High spatial resolution SPOT 6/7 satellite images embedded on Google Earth and a National Land-cover map obtained from the ARC-ISCW aided the identification and on-screen selection and digitization of additional land-cover classes useful for discriminating sugarcane. The field samples were collected from 1 to 5 September 2015. A total of 399 points were produced following a stratified random sampling technique with the assistance of high resolution data from Satellite Pour l'Observation de la Terre (SPOT 6/7) emended on the Google Earth domain as well as National Land Cover map (Congalton and Green 1999). The sampling was restricted to homogenous areas where land-cover was consistent with the image acquisition date. The sampling points were then uploaded into a Garmin Montana 650 Global Positioning System (GPS) for navigation in the field where they were identified and assigned to one of the classes found within the study site (Table 3.1). Sampling points located in a rugged terrain and inaccessible areas were manually obtained by visual interpretation of SPOT 6/7 and Google Earth™ imagery. The samples were split into 70% training (n = 281) and 30% validation (n = 118) for subsequent classification (Omer *et al.* 2015).

Table 3.1. Training and validation data used for both OBIA and PBIA platforms

Class name	**Code**	**Training (*n*)**	**Testing (*n*)**
Sugarcane	S	42	18
Fallow	F	42	14
Dense vegetation	DV	34	18
Sparse vegetation	SV	42	18
Burnt areas	BA	42	18
Bare-surfaces	BS	23	9
Water bodies	WB	25	10
Communal residence	CR	45	11
Total		281	118

3.2.3. Methods

3.2.3.1. *Support vector machines and random forest classifiers*

SVM is a supervised machine-learning algorithm that groups classes based on the statistical learning theory (Vapnik 1998). It functions by maximising the margin (i.e. the distance between points of each land-cover relative to the best separating hyperplane) (Petropoulos *et al.* 2012). It consists of numerous hyperplanes that discriminates varying numbers of classes (Oommen *et al.* 2008). However, only a single hyperplane (i.e. optimal hyperplane) with a maximum margin best separates between the classes (Petropoulos *et al.* 2012). The training points that lie closer to the optimal hyperplane are called support vectors. Hence, the wider the margin, the lesser the generalisation error of the classifier. In the process, only support vectors (points) construct the optimal hyperplane while the validation dataset validates the performance of the developed hyperplane (Oommen *et al.* 2008). However, in scenarios where classes are not linearly separable, a kernel function is used, which allows points to scatter such that a linear hyperplane can be fitted (Foody and Mathur 2004). Examples of common kernels include polynomial, sigmoid and radial basis function (RBF) (Oommen *et al.* 2008), with RBF being popular in remote sensing due to its optimal performance (Pal and Mather 2005). The accuracy of SVM classifier depends on optimising key parameters namely: Gamma and Cost (γ & C) (Oommen *et al.* 2008). In this study, parameters of SVM classifier were tuned in R statistical software (Team 2014) using e1071 package (Duro *et al.* 2012). The optimal parameter values were determined by grid search on values ranging from 1.001 to 1000 using a 10-fold cross-validation (Huang *et al.* 2002, Duro *et al.* 2012). Optimised SVM parameter values were utilised for subsequent image classification at PBIA platform.

Random Forest (RF) is also a machine-learning algorithm used for classification and regressions (Ok *et al.* 2012). It is an ensemble algorithm and runs by creating several classification decision trees (He *et al.* 2015). Each tree is trained on a bootstrapped sample of the genuine training data (Loosvelt *et al.* 2012). The individual trees formed undergo a voting process, and ultimately an aggregated decision tree define the final classification. An Out-of-Bag (OOB) sample was utilized to measure the accuracy that produces the results. Key parameters (i.e. *ntree* & *mtry*) dictates the success of the RF algorithm. Since it is quick to run and requires less parameters, this algorithm is gaining an audience from the remote sensing community (Rodriguez-Galiano *et al.* 2012). As with SVM, the grid search method using 10-fold cross validation was used for RF. After running the RF model in EnMap-Box software, the optimal model yielded an OOB accuracy of 75%, generated by *ntree* value of 100 and *mtry* of 2. As with SVM, RF was also executed at pixel-based image analysis platform PBIA.

3.2.3.2. *Accuracy assessment & map comparison*

To determine the accuracy of the thematic maps derived from classifying Landsat 8 OLI image using SVM and RF at PBIA, a confusion matrix was generated using the 30% independent validation data (n = 118) in EnMap-box software (Adelabu *et al.* 2013). For each classifier, overall (OA), user accuracies (UA) and producer accuracies (PA) were computed and reported for each class (Congalton and Green 1999, Petropoulos *et al.* 2012). For comparison purposes, error matrices for each thematic map were computed using the same set of the validation samples (n=118). The McNemar's test was utilised to assess whether the accuracies obtained for SVM and RF were significantly different. More details on the McNemar's test are furnished in (Dingle Robertson and King 2011, Whiteside *et al.* 2011). Given two algorithms, SVM and RF have a similar deviation rate, McNemar's test compares the quantity of instances incorrectly allocated A_{SVM}, but correctly allocated by A_{RF} (f_{12}), with the number of instances incorrectly allocated using A_{RF}, but not using A_{SVM} (f_{21}) (Bostanci and Bostanci 2013). The test utilizes a *z*-score (Equation 1) to evaluate the dissimilarities between the two classifications methods.

$$z = \frac{(f_{12} - f_{21} - 1)}{\sqrt{(f_{12} + f_{21})}} \qquad (1)$$

A confidence interval of 95% was used to report the accuracies obtained by SVM and RF. Two classification accuracies can be considered significantly different if $\boldsymbol{z}$ is above 1.96 at 5% significant level. Furthermore, f_{11} and f_{22} were incorporated for instances that were wrongly grouped at both platforms and the number of instances that were correctly grouped at both SVM and RF correspondingly.

3.3. RESULTS

3.3.1. *Accuracy and statistical assessment*

A summary of confusion matrices derived from SVM and RF based on the Landsat 8 OLI image are presented in Table 3.2 and 3.3 respectively. SVM yielded an overall accuracy of 77.97% and a kappa coefficient of 0.74 while RF yielded 71.2% and 0.68 in overall accuracy and kappa respectively. However, when compared to RF, SVM yielded 7 % improvement in overall accuracy. Individually, SVM yielded 6% improvement in producer's and user's accuracies for sugarcane compared to RF (83.33 & 93.75%). Generally, SVM had three classes with user's accuracies above 90% while RF had one classes. From a producer's perspective, SVM had four classes with producer accuracies above 80% while RF had two. Per Individual class, fallow (F) scored the lowest producers and user's accuracies for both algorithms.

Table 3.2 Summary of accuracy assessment results derived from SVM & RF classification including OA, PA, UA (%) and Overall Kappa.

	SVM		RF	
CLASS	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**
S	83.33	93.75	77.78	87.50
DV	78.71	70.5	64.29	64.29
SV	77.78	93.33	77.78	77.78
F	44.44	66.67	44.44	61.54
BA	91.67	73.33	83.33	66.67
BS	77.78	70	66.67	60
WB	90	100	80	100
CR	84	66.67	78	62.50
OA	**77.97**		**72.1**	
Kappa	**0.74**		**0.68**	

Meanwhile, a confusion matrix was utilized to compare the accuracies of SVM and RF at PBIA investigated in this study using the McNemar's test. Results indicated that there was no statistical significant difference ($p \geq 0.05$) in the observed classification accuracies of SVM and RF.

Table 3.3. Comparison of PBIA SVM and PBIA RF using McNemar test.

		PBIA SVM		
		Correctly classified	Misclassified	Total
PBIA RF	Correctly classified	102	2	104
	Misclassified	0	14	14
	Total	102	16	118

NB: McNemars *z* score = 0.500

3.3.2. *Areal extent delineation & visual comparison*

Figure 3.2 summarizes areas (hectares) derived from the thematic maps obtained from SVM and RF classifications. Results indicated that SVM assigned 3155.01 ha (i.e. 3.4% cover of the study area) while RF assigned 6613.38 ha (4.8% cover) to sugarcane, an approximate 3458.37 ha difference. Moreover, Figure 3.2 shows that RF allocated 3458.37 more hectares to sugarcane compared to SVM. Generally, areas of other classes in the study site also attests the relative competence of both algorithms (Figure 3.2). Sparse vegetation is the dominant class while water-bodies is the least dominant in the study area. Nevertheless, both algorithms allocated almost equivalent areas of classes in the study area. Farm records on sugarcane area for the August month were not available for comparison with those obtained in the study.

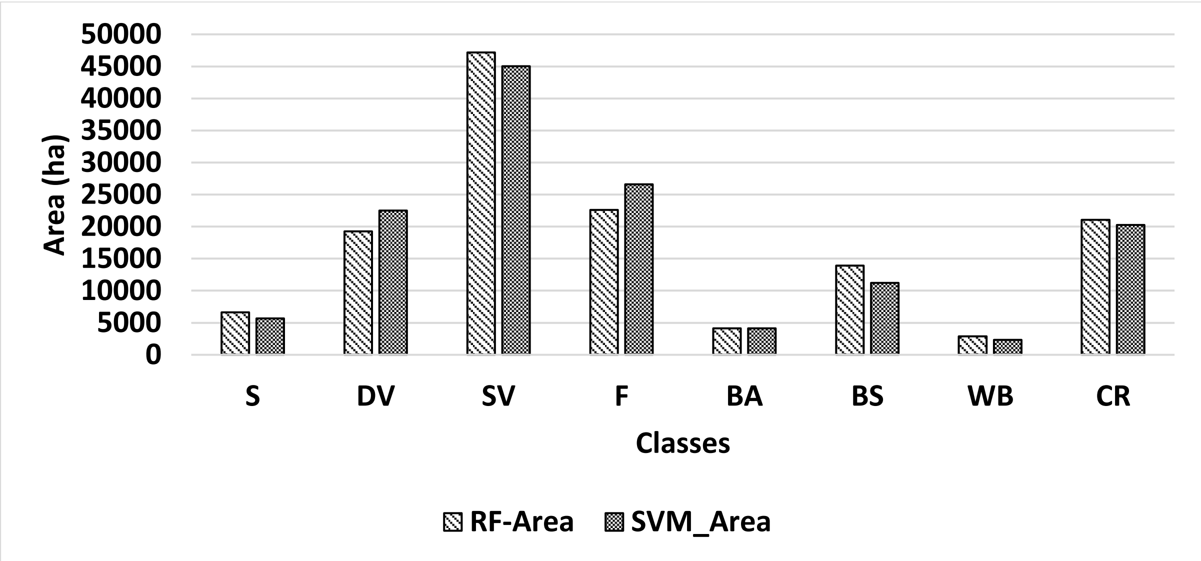

Figure 3.2. Smallholder sugarcane areas derived from RF and SVM algorithms

Figure 3.3. Shows sugarcane distribution maps derived from RF and SVM classifications using Landsat 8 OLI imagery. Results show that both SVM and RF were able to identify sugarcane well as portrayed on the Landsat 8 OLI image of the study area (Figure 3.4B & C). A confusion was observed between sugarcane and vegetation classes in listed in Table 3.1. However, traces of sugarcane spatial disagreement are slightly high in RF classification than SVM (Figure 3.3A, B & C). The spatial disagreement in the distribution of sugarcane was observed more on the northwestern, south and eastern portion of the study area. Moreover, traces of the salt and pepper are present in both SVM and RF classification.

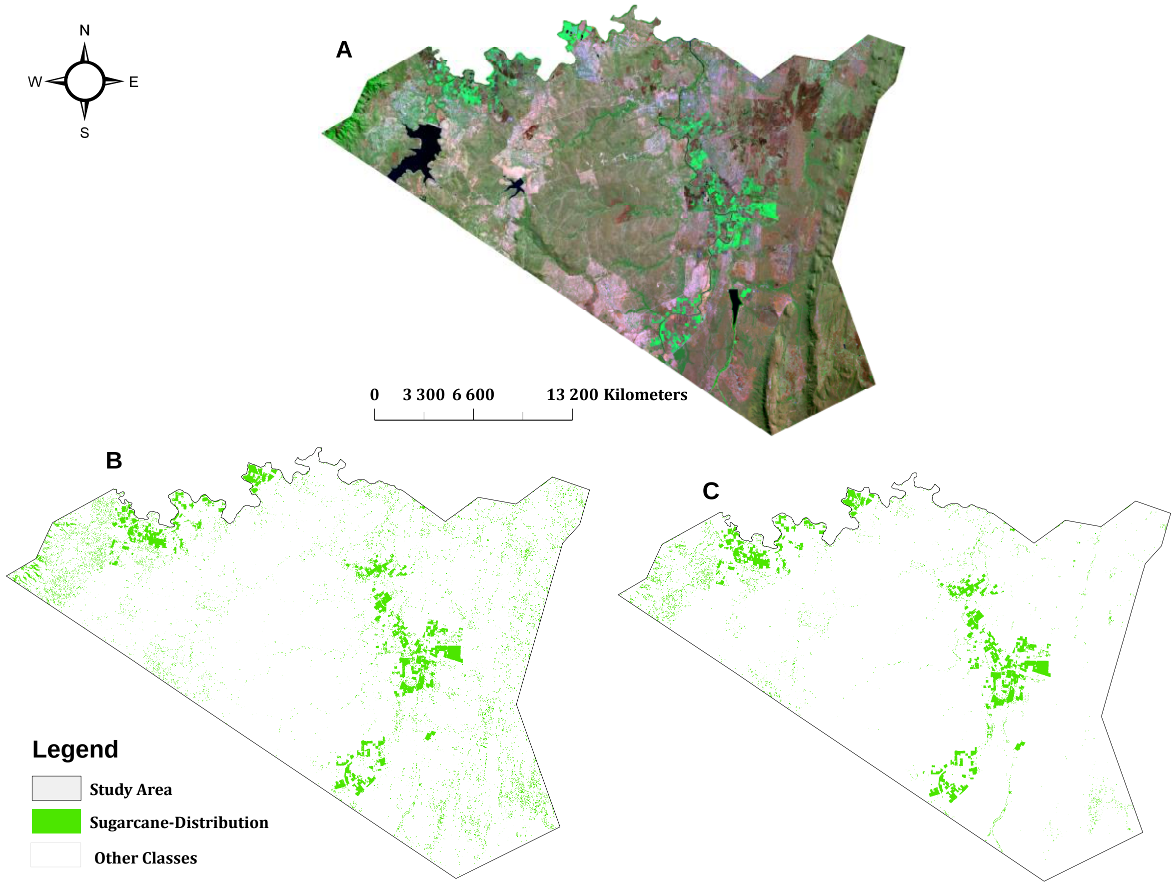

Figure 3.3. Sugarcane distribution maps derived from PBIA SVM and PBIA RF classifications: A) Landsat 8 OLI false color composite, B) PBIA RF classification C) PBIA SVM classification.

3.4. DISCUSSION

This study explored the competence of SVM and RF in delineating the areal extent of the smallholder sugarcane fields based on Landsat 8 OLI satellite data. Specifically, this study sought to determine which classifier is optimal for classifying smallholder sugarcane areas in the context of southern African landscapes.

3.4.1. *Accuracy and statistical assessment*

Findings of this study showed that SVM performed better than RF in classifying smallholder sugarcane areas by a magnitude of 7%. However, The McNemar's test results indicated that this 7% magnitude of difference between SVM and RF was not significantly different, statistically. Nonetheless, the somewhat better performance by SVM could be explained by the RBF kernel used for this classifier. The RBF kernel used in this study was reported to significantly enhance classification accuracy due to its ability to overcome the inseparability challenges among classes (Nitze *et al.* 2012, Adam *et al.* 2014).

Meanwhile, the almost classification similarities could largely be explained by the fact that SVM and RF are both robust algorithms (non-parametric) which do not consider distribution assumptions on the input data (Mather & Foody, 2008). In addition, both SVM and RF are insensitive to small training datasets, this distinct them as optimal classifiers when compared to the customary algorithms such as Maximum likelihood (Grinand *et al.* 2013). Nevertheless, comparisons of users and producers accuracies per class indicate that SVM yielded higher producer (83.33) and user accuracy (93.75%) for sugarcane than other vegetation classes compared to RF (77.78 & 87.50 %), a 6% accuracy difference. These results suggest that SVM classifier is ideal for mapping smallholder sugarcane in fragmented landscapes based on the Landsat 8 OLI satellite image, relative to RF. The high discrimination level of sugarcane compared to other spectrally similar classes observed in this study can be attributed to the crop's vigour due to the abundance of moisture through irrigation practices. Considering the fact that the image used in this study was obtained during the dry period (June-August), the spectral reflectance of natural vegetation is lower than that of the irrigated facilitating its discrimination from sugarcane.

Challenges were encountered when attempting to directly contrast findings of this study with previous studies due to different environmental setting and data used. However, the outcomes of this study are closely related to those of (Everingham *et al.* 2007, Nitze *et al.* 2012, Sonobe *et al.* 2014) who found SVM marginally outperforming RF with accuracies ranging between 3 and 12%. For instance, Nitze *et al.* (2012) evaluated the utility of SVM and RF for crop type mapping using multi-seasonal Rapid-Eye Imagery. They reported a 12% difference in accuracy between SVM (68.6%) and RF (55.8%). Everingahm et al. (2007) compared RF and SVM for mapping sugarcane varieties using Hyperion data and found a 3% difference between SVM (90%) and RF (87%). Meanwhile, other studies showed that SVM and RF performed equally in overall accuracy (Pal and Mather 2005, Sesnie *et al.* 2010, Adam *et al.* 2014, He *et al.* 2015) with a marginal difference of 1%. However, the accuracy difference (1% or less) obtained for SVM against RF was lower than the one found in our study (7%), which was insufficient for deriving conclusions on which classifier was superior to the other. For example, Pal (2005) assessed the accuracy of SVM and RF in classifying crop types using Landsat Thematic Mapper ™. Their results indicated that SVM (96.67%) and RF (96.3%) performed equally. Adam et al (2014) evaluated the performance of SVM and RF for mapping Land Use/Cover (LUC) in heterogeneous landscape. They found no statistical significant difference between RF and SVM.

3.4.2. *Areal extent delineation and map comparisons*

Generally, both SVM and RF showed similar patterns in sugarcane distribution and other classes (Table 3.1). However, a confusion was observed between sugarcane and the dense vegetation, mostly appearing on the north-western portion within the study boundary (Figure 3.4A & B) Nevertheless, the spatial disagreement of the two maps was found to be insignificant. Generally, discriminating between classes with similar spectral signatures is challenging (Xavier *et al.* 2006), especially when classifying at pixel level. The results obtained generally demonstrate that the selection of a certain classifier affects the overall accuracy of delineating fragmented smallholder fields using Landsat 8 OLI image. Official records on sugarcane areas for the August month were not available for comparison with estimated areas in this study. Moreover, in South Africa, no comparative analysis attempt between SVM and RF has been made in delineating areas of smallholder sugarcane fields using Landsat 8 OLI image. As such, the findings could not be directly contrasted to the finding of others. However, Chemura and Mutanga (2016) tested Landsat 8 OLI and Landsat Enhanced Thematic Mapper (ETM+) for developing age specific coffee maps in large scale farms using RF. Their results indicated that Landsat 8 OLI estimated areas were closely consistent to farms records. Their findings demonstrate that the combined use of advanced classifiers and medium resolution imagery yields higher accuracies, which could not be previously obtained using customary classifiers for mapping heterogeneous landscapes.

Overall, this study contributes towards the usefulness of advanced machine leaning algorithms in mapping smallholder farming systems, especially in fragmented landscapes. The improved accuracies obtained by both algorithms suggest that they offer an alternative and cost-effective method to customary classifiers; especially in developing regions with lack of advanced algorithms due to limited resources. However, this study focused on irrigated smallholder farming areas, as such, these methods need to be tested in other farming conditions (e.g. Rain-fed) in order to broaden the use of these techniques

3.5. CONCLUSIONS

From the outcomes of this study. It was concluded that:

1. SVM outperformed RF, by a margin of 7% accuracy, despite the fact that the differences observed between the two algorithms were not statistically significant.

2. SVM and RF have great potential in delineating smallholder sugarcane areas, especially in fragmented landscapes.
3. This approach has potential to be extended to mapping smallholder maize fields where techniques for estimating yields and areas under maize are desperately required by policy makers in South Africa.

Altogether, this study contributes towards the utility of advanced classification algorithms in delineating the fragmented smallholder farming systems. The sugarcane area distribution thematic map can be used for farm level management while national department can benefit from employing the advanced classifiers for developing reliable agricultural land-use/cover maps.

CHAPTER 4

Synthesis

4.1. Review of objectives and conclusion

Mapping the distribution and areal extent of smallholder farming is hampered by their spatial configuration which is characterized by small plots of irregular sizes (Debats *et al.* 2016). Such landscape settings, therefore require specialized techniques which are currently partially established. Object-based image analysis (OBIA) platform was designed to surpass such challenges by integrating spatial, spectral and textural variations during the classification process (Blaschke 2010). However, OBIA is associated with high costs in acquiring the appropriate software which hampers its operational use in developing countries, such as South Africa with limited resources. In that regard, pixel-based image analysis (PBIA) has remained the core platform for image analysis in such areas because its operations are associated with limited costs. Nevertheless, literature reported a marginal difference in terms of accuracy between OBIA and PBIA (Castillejo-González *et al.* 2009, Myint *et al.* 2011). This magnitudinal difference could have been due to the classifiers employed during the comparison other than the features, i.e. spectral, information integrated into classification. For instance, Myint et al., (2011) compared the performance of PBIA and OBIA using Maximum likelihood (MLC) and Nearest Neighbor (NN) for land-cover classification. They obtained an accuracy difference of 22.8% between the two platforms. Meanwhile, He et al., (2015) noted that classifiers have different classification properties, which results in different accuracy outputs of the same ground cover. The innovation of advanced machine-learning algorithms, such as but not limited to SVM and RF, led to improved and reliable classifications (Duro *et al.* 2012). This is because advanced classifiers can manage huge amounts of information in heterogeneous settings (Mountrakis *et al.* 2011). In that regard, this study demonstrated that exploring advanced machine-learning algorithms improves our ability to delineate areas of smallholder sugarcane fields in fragmented landscapes. For this study, chapter 2 tested whether SVM can be able to reduce the accuracy difference between OBIA and PBIA while improving the classification accuracy when delineating the areal extent of smallholder sugarcane fields. Upon establishing the potential of SVM, it was then of interest to compare the performance of this classifier with its competitive classifiers, i.e. RF in this case in chapter 3. The two overall aims were established through the questions which were (i) can SVM reduce the accuracy difference between PBIA and OBIA platforms in delineating smallholder sugarcane fields? (ii) what is the performance of SVM compared to its competitively advanced machine-learning algorithms in estimating the areal extent of smallholder sugarcane fields using Landsat 8 OLI imagery?. Based on the findings derived when answering these two research questions, the following conclusions were drawn.

4.2. To evaluate the performance of SVM in delineating fragmented smallholder sugarcane fields at object-based and pixel-based image analysis platforms using Landsat 8 OLI imagery

OBIA incorporates attributes that can surpass challenges faced when delineating smallholder farming systems characterised by fragmented plot sizes and irregular sewing calendars. Although OBIA provides improved accuracies when delineating fragmented landscapes, developing countries such as South Africa with limited financial resources to acquire expensive software necessary to operate such techniques remain reliant on the cheap and readily available PBIA techniques. Moreover, comparative studies obtained high accuracy difference between PBIA and OBIA. Meanwhile, He et al (2015) noted that classification algorithms portray different properties which ultimately produce different accuracy outputs, which could have been the case for the previous comparative studies. This accuracy difference necessitated the need to find optimal yet cheap classifiers that could bridge the gap between the two classification platforms while surpassing the challenges encountered when delineating fragmented smallholder fields, especially in resource scarce regions such as South Africa. Findings in this chapter indicated that, when using SVM the differences in accuracies between PBIA and OBIA were statistically insignificant. These results are in agreement with our hypothesis that advanced classifiers such as SVM could reduce the marginal differences between the accuracy of PBIA and OBIA. The findings in this chapter underscore SVM as one of the advanced classifiers that can be utilised in estimating areas of smallholder sugarcane fields using Landsat 8 OLI, especially in fragmented landscapes.

4.3. To compare the performance of SVM against its competitive advanced classifiers in delineating areas of smallholder sugarcane fields using Landsat 8 OLI

From an earth observation’s viewpoint, the key factor limiting the frequent delineation of smallholder farming systems in most developing countries such as South Africa is the extreme prices associated with the data and software. The lack of accurate classification techniques in such regions is also a contributing factor to the problems faced when mapping smallholder fields. The availability of datasets such as Landsat 8 OLI at limited cost coupled with advanced classification algorithms have been demonstrated to offer prospects in agricultural landscape mapping (Chemura & Mutanga 2016). After discovering in chapter 2 that SVM as one of the advanced classifiers has the potential to delineate fragmented smallholder sugarcane farming systems, a question as to how this algorithm would perform compared to other competitive classifiers was triggered. As such, this chapter compared SVM and RF based on the Landsat 8 OLI image in delineating the areal extent of smallholder sugarcane farming systems. Based on the findings, SVM outperformed RF by a marginal 7% in overall accuracy. Furthermore, the McNemar's test indicated no statistical significant difference between accuracies obtained using SVM and RF. Collectively, the improved classification accuracies obtained using advanced machine-learning classifiers expose the simplicity at which areas of smallholder sugarcane fields can be delineated using such advanced algorithms. Delineating the location and spatial extent of smallholder fields is of paramount for informing decision on import and export decisions as well as decisions on irrigation arrangements, planting and harvest plans (Schmidt *et al.* 2004). The outcomes in this section provides an understanding into the use of advanced machine-learning algorithms in delineating smallholder sugarcane fields.

4.4. Recommendations

- Since smallholder farmers practice crop rotation and often neglect their plots, further research should consider the use of modern space instruments such as Sentinel-2 multispectral imager, which are freely available at high spatial and temporal resolution suitable for covering different phenological stages of sugarcane.
- The present study established that both SVM and RF can delineate irrigated smallholder sugarcane farming systems. It will therefore be insightful to investigate the performance of such algorithms in discriminating other agricultural crops that are irrigated and rain-fed in smallholder farm settings. Moreover, further studies should incorporate other features such as spatial and texture for delineating such landscape crops in smallholder farm settings since this study only used spectral information to allow a fair comparison between OBIA and PBIA. Literature shows that the utility of spectral information only has several drawbacks such as confusion amongst classes with similar spectral signatures.
- From an operational perspective, research institutions such as the agricultural research council as well as government institutions would benefit if they can utilize advanced

machine-learning classifiers (i.e. SVM & RF) for generating maps with improved accuracy.

- Validate the methods with smallholder maize and canola producers where the approach could unlock a huge potential in accurately quantifying the contribution of small scale farms to the total national agricultural output.

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