Mapping crop types in Levubu area of Limpopo using Landsat 8 and Sentinel-2 sensing data

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Declaration – Plagiarism

I, Thivhafuni Portia Tshigoli (Student number: 1822218), hereby declare that the research report titled “Mapping crop types in Levubu area of Limpopo using different remote sensing data” is my own work. This report is being submitted for the Degree of Master of Science in Geographic Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. This serve to confirm that the work in this report has not been submitted before for any degree or examination at any other University. All the sources quoted in this research have been re-written and acknowledged in the reference list.

24 September 2020

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Abstract

Of late food security has become one of the serious global challenges; hence crop production and monitoring plays a crucial role. One of the solutions to food security challenges is through developing proper management systems of agricultural resources. Remote sensing offers unique opportunities for frequent monitoring and management of crop types. This is done through mapping the distribution of crops which provides farmers, policy makers, decision makers and researchers an opportunity to develop better strategies for crop management and production. The study used Landsat 8 OLI and Sentinel-2 MSI, which were acquired for a single date, in mapping the spatial distribution of different crop types in Levubu area in the Limpopo province, South Africa. Two main objectives were followed in this study: firstly, to assess the potential of Landsat 8 and Sentinel-2 data in understanding the distribution pattern of crop, secondly, to determine the potential of the random forest algorithm in classifying different crops using different remote sensing datasets. Eight classes (Avocado, Banana, Built up, Macadamia nut, Maize, Mango, Vegetation and Water body) were classified in this study using random forest (RF) machine learning classifier. Other classes such as Built up, Vegetation and Water body were classified to assess the ability of RF to distinguish between crop classes and non-crop classes. The results show overall accuracies of 77.08% and 87.04 % with kappa coefficients of 70.72% and 83.56% for Landsat 8 and Sentinel-2 using RF, respectively. The study found that the overall accuracy, user's and producer's accuracy results of Sentinel-2 MSI were better than Landsat 8 OLI. Therefore, Sentinel-2 MSI is suitable for more accuracy and increased details in mapping crops in Levubu area.

Dedication

I am dedicating this research to my family, Petrus Tshigoli, Joyce Tshigoli, Vhonani tshigoli, Pertunia Tshigoli, Fhatuwani Tshigoli, Mboneni Victor Tshigoli, and Selina Muofhe. Thank you for your love, support, encouragement and believing in me. You all are the best and I could not have made it without you. God bless.

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List of Abbreviations

Dark Object Subtraction method = DOS

Environment for Visualizing Images = ENVI

European Space Agency = ESA

Feature Band Set = FBS

Gaofen satellite no. 1 = GF-1

Global Positioning System = GPS

Gross Domestic Product = GDP

Land Cover Land Uses = LULC

Land Use Land Cover Classes

Moderate Resolution Imaging Spectroradiometer = MODIS

Multilayer perceptron = MLP

Multispectral Imager =MSI

Near-infrared = NIR

National Aeronautics and Space Administration = NASA

Normalized Difference Vegetation Index = NDVI

Object-Oriented Classification = OOC

Operational Land Imager = OLI

Out-of-bag = OOB

Random Forest = RF

Satellite Pour l'Observation de la Terre = SPOT

Short Wave Infrared = SWIR

Spectral Angle Mapper = SAM

Support Vector Machine = SVM

Pushbroom hyperspectral imager = PHI

Thermal Infrared Sensor = TIRS

United States = US

United States Geological Survey = USGS

Visible and Near-Infrared = VNIR

CHAPTER ONE

INTRODUCTION

1.1 General Introduction

Across the globe, crop production is the main source of food, supporting human livelihood and contributing to economic growth (Massey *et al*., 2017). In addition, there is more dependency of mankind to agricultural resources (Nema *et al*., 2018). However, agricultural resources are facing serious challenges, as a result of rapid population growth, climatic changes and competition for space. For example, the United Nation (UN) projected a population growth of 9 billion by 2050 (UN, 2014), this means that the world will experience a population growth of approximately 83 million people every year (Orynbaikyzy *et al*., 2019), feeding such a huge population will be a serious challenge (Nema *et al*., 2018). This emphasizes the need for crop production monitoring at regional, national and global levels for sustainable food security.

Crop mapping plays a critical role in developing strategies for food security concerns, such as adapting to climate change impacts and suitability assessment (Massey *et al*., 2017). This information can guide the government and agricultural producers in understanding the production condition and techniques of agriculture at a regional level. This facilitates agricultural planning, such as adjustments in planting patterns and proper land utilization (Massey *et al*., 2017). Mapping crops also assist in maintaining crop health to ensure better production or to boost productivity. Qiao *et al*., (2018) observed that climatic factors and type of farming method affect the production of crop. In this regard, crop mapping will assist in the monitoring of crop water requirements for sustainable use of water resources, especially in the light of climate change impacts, as well as in improving farming methods (Fazel *et al*., 2016 & Ouzemou *et al*., 2018).

Traditionally, crop mapping was achieved using ground-based conventional approaches. Census, land surveys and communication from farmers are some of the conventional methods used to identify crops for crop type mapping (Ouzemou *et al*., 2018). Although these methods are known to be accurate, they are very expensive, time consuming, require intensive labour and are prone to several errors (Massey *et al*., 2017). In addition, ground-based approaches lack the spatial representation of crops and are limited to small geographical coverage. These cause challenges in regular crop mapping over time (Zhong, 2012).

Unlike the traditional methods, mapping of crops using remote sensing provide vital information about the crop's spatial distribution (Nema *et al.,* 2018). Crop spatial distribution and their environmental characteristics can also be obtained using remote sensing data with high resolution (spatial, spectral, temporal and radiometric) covering a large area (Qiao *et al*., 2018). For example, remote sensing sensors such as Landsat, Satellite Pour l'Observation de la Terre (SPOT), EROS, GeoEye, and WorldView satellites are suitable for crop mapping and in properly differentiating crop types (Forkuor *et al.,* 2014). The Sentinel-2 satellites images are equipped with Multispectral Imager (MSI) and their characteristic of high revisiting frequency (temporal resolution-5 days) and high spatial resolution (10 m to 60 m) serve as an advantage of mapping cropland with improved accuracy and efficient monitoring of agriculture. Remote sensing data can also be used to detect growth, health and yield of crops as a result of temporal variability of sensors which offers data for continuous seasonal or annual monitoring over time (Nema *et al*., 2018). In this case, remote sensing can be used in observing the impacts of climate change on crop production (Qiao *et al*., 2018).

1.2 Problem statement

Agriculture is one of the major sectors of the economy in South Africa. In the Limpopo Province, it is accounted for 2.2% of the provincial Gross Domestic Product (GDP) in 2016 and 10% of employment in 2016 (LPT, 2019). Crop production provides employment for the locals and it is among the major farming sectors which have been growing fast in Limpopo province (Wisborg *et al*., 2013). It is a major source of income, providing food for the population and ensuring food security (Oni, 2012). Levubu crops contribute to the economic growth of South Africa through food processing of fruits, vegetables and macadamia nuts (Oni, 2012).

In the Limpopo province, 37.7% of the land is suitable for arable farming based on the characteristics of soils and the type of climate (Oni, 2012). The farming systems in Levubu consists of small scale and commercial farming (Oni, 2012). In commercial farming, farmers utilize tractors as a source of man power for on-farm tillage and transport work whereas in small scale farming tractors, oxen, donkeys, mules and hand labour are used for transport and in tillage (Oni, 2012). Information on crop type distribution is vital for agricultural management and food security in Levubu area. Some studies observed that climatic factors, such as the temperature of the region influence the distribution, growth, production and development of crops (fruit tree) (Qiao *et al*., 2018).

Mostly, farmers in commercial farming apply inorganic fertilizers for better production of crops, whereas subsistence farming applies organic manure in the form of kraal manure because of a lack of capital (Tshikhudo, 2005). To achieve better crop farming production, there must be a strong relationship between the farm size, cropping system, type of fertilizer applied, number of farm workers and yield (Tshikhudo, 2005). Crop mapping provides information that is clear, easy to understand and essential for future planning, decision making and policy making (Massey *et al*., 2017). For example, Massey *et al*. (2017) indicated that accurate, long term and comprehensive information of crop types and their spatial distribution assist for better production and water usage estimate towards food security. Crop mapping in Levubu area is significant in developing strategies used to address the problem of food security. Enhancement of crop production contributes towards achieving sustainable development goal of global food security and improved nutrition (Griffiths *et al*., 2019). This is because food security is a serious concern in most countries including Southern Africa (Nhamo *et al*., 2019). Also, South Africa is considered as one of the driest countries in the world and experiencing a serious challenge of water scarcity (Nhamo *et al*., 2019), as a result new crop management strategies need to be developed and implemented.

Using satellite images and ground surveys enable one to retrieve information on spatial coverage and spectral responses of cropland for sustainable management of agricultural resources (Fazel *et al*., 2016). The recent availability of optical and radar time series images, such as the Sentinel series offer opportunities to map crops with high spatial and temporal resolutions. Sentinel-2 sensors can collect dense time series and allow for a revisit time of 5 days (Demarez *et al*., 2019). It has an improved temporal frequency of cloud free data acquisition which is advantageous for monitoring crop growth (Immitzer *et al*., 2016). Studies have been done mapping crops using different remote sensing data with low spatial resolution such as MODIS and traditional algorithms such as maximum likelihood and decision tree (Massey *et al*., 2017; Song *et al*., 2017; Nema *et al*., 2018 & Ouzemou *et al*., 2018). Mapping crops using low spatial resolution satellites produce results with a high mixture of crop classes (Song *et al*., 2017). Classification of crops using traditional classifier is challenging as it requires more ground truth data which is costly and time-consuming to the researcher (Zhong, 2012). However, this study explored the use of new sensors (i.e. Landsat 8 and Sentinel-2) with advanced spatial, temporal, spectral, and radiometric resolution to improve crop production monitoring. The study further assesses the potential of advanced classification such as random forest (RF) which has been developed to improve the classification accuracy using remote sensing data (Breiman, 2001). Furthermore, no studies have been done mapping crops using remote sensing data in Levubu area. Remote sensing data differs in spectral resolution and the number of bands which result in different levels of accuracies. The use of Landsat 8 and Sentinel-2 open data sources remote sensing data were compared in terms of their level of accuracy in mapping crops in Levubu area.

1.3 Aim and objectives

1.3.1 Aim

The aim of this study was to map crop types in the Levubu area of the Limpopo Province, South Africa, using Landsat 8 and Sentinel-2 data.

1.3.2 Objectives

a. Determine and characterize the spatial distribution of crops in Levubu area

b. Assess the potential of Landsat 8 and Sentinel-2 in understanding the distribution pattern of different crop types

c. Determine the potential of the RF algorithm in classifying different crop types using different remote sensing datasets

1.4 Thesis structure

This thesis report has been organised into six chapters which are as follows:

- Chapter one: Provides the Introduction, which covers the background of the research, motivation for the study, defines the research problem statement, and further provides research aim and objectives.
- Chapter two, Review of the literature related to the research project, from the use of traditional methods to remote sensing methods and the classification algorithms available in mapping crops.
- Chapter three, Methodology, provides a brief description of the study area, datasets and the software used and the methods that were followed throughout the research to achieve the research objectives.
- Chapter four, Results, presentation of the results of each method used in the study.

- Chapter five, Discussion, discussion of the results that were obtained from determining and characterizing the spatial distribution of crops, evaluating the potential of Sentinel-2 and Landsat 8 and the potential of using the RF classifier.
- Chapter six, provides a conclusion of the main findings of the study, limitation and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 The relevance of crop mapping

Crop distribution is a major factor affecting crop production (Qiao *et al*., 2018). Understanding the distribution pattern of different types of crops provide guidance to develop better policies in food security and agriculture worldwide, such as adjusting cultivations system to improve crop production (Massey *et al*., 2017). For example, a study done by Song *et al*. (2017) in China observed an increase in the production of Maize and Rice and a decrease in wheat, as a result of changes in crop distribution. Qiao *et al*. (2018) also found that yield response of different crops to climate change vary with their spatial distribution. For example, some crops respond positively and some negatively to climate change depending on their climatic requirements (Qiao *et al*., 2018). Consequently, crop mapping enables assessing the response of various crops to environmental changes as well as for suitability assessment purposes.

2.2 Approaches for monitoring the spatial distribution of crops

2.2.1 Ground data approach

Ground data methods which are mostly used in collecting field data include census, land survey and communication from farmers (Ouzemou *et al*., 2018). Ground data is very important, especially when doing accurate classification (Massey *et al*., 2017). It provides the actual measurement from the field and it is used for accuracy assessment of remotely sensed derived results. The disadvantages of ground data collection are that it is expensive in terms of time and cost which is a serious challenge for researchers (Massey *et al*., 2017). For example, Bouwmeester *et al*. (2016) used convenience sampling method in conducting a survey to map crop diseases in East African highlands. Farmers were interviewed to estimate yield loss as a result of bacterial wilt in banana farms. Results showed that a disease map was produced using this method. Although in some areas the study observed the spread of disease over the farm and severe impacts, there was a lack of data in the district where farmers could not be interviewed and predictions were not made (Bouwmeester *et al*., 2016). This method is very challenging, especially when collecting data that cover larger areas and in inaccessible areas.

2.2.2 Remote sensing approach

Remote sensing can be used to solve some of the challenges of conventional methods such as census and surveying in crop type mapping as it is efficient, faster and synoptic methods (Ouzemou *et al*., 2018). For example, Landsat 8 OLI and TIRS sensors have a revisit time of 16 days covering a large area (swath width) which makes it suitable for crop mapping. Sentinel-2 sensors consist of 10-20 m spatial resolution with a 5-day revisit time. The temporal resolution of these sensor plays an important role in monitoring crop condition (Ouzemou *et al*., 2018). Remote sensing covers a large area providing an opportunity for monitoring crop and the changes in agricultural production, providing up-to-date information with different temporal and spatial resolutions (Nema *et al*., 2018). Remote sensing data in crop mapping is cost-effective; for example, Landsat 8 and Sentinel-2 data are freely available, offering opportunity for monitoring of crop types.

2.2.2.1 Crop mapping using multispectral remote sensing

Multispectral remote sensing satellites images such as Landsat, Sentinel and SPOT are used for mapping crops in extensive agricultural systems at global and regional scales because of their high resolution. (Ouzemou *et al*., 2018). Furthermore, mapping of crops with these sensor images allow for monitoring of crop health and crop growth's, contributing to crop yield predictions and adaptation of crops to climatic change (Ouzemou *et al*., 2018). For example, Landsat with its temporal resolution of 16 days allows for monitoring changes of crops that have occurred over a certain period of time. The range of spatial resolution of satellite images used for identification of crops are from low to high and decision to choose which spatial resolution to use depend on typical field size of crop mapping (Song *et al*., 2017). Landsat images for example, cover a large area at high resolution (temporal and spatial). However, mapping crops using Landsat images in a highly heterogeneous agricultural landscape can be problematic, leading to results with mixed pixels, merging of agricultural field borders and low accuracy (Immitzer *et al*., 2016 & Ouzemou *et al*., 2018).

Multispectral remote sensing such as SPOT has high resolution and has been used in crop mapping. For example, SPOT 5 image was used in evaluating the performance of RF and maximum likelihood classification in classifying different agricultural crops in a study done in Karacabey Plain by Ok *et al*. (2012). The study used pixel based and parcel based with maximum likelihood and RF to classify the image. The study observed that SPOT was able to distinguish some crops; however, some crop classes produced lower producer and user's accuracy. Furthermore, some crop classes could not be distinguished well and were confused with others. For higher accuracy results, the study recommended the use of parcel based with RF classifier.

In China, a new high-resolution multispectral sensor, Gaofen satellite no. 1 was launched, which was designed to cover large areas and for monitoring purposes (Song *et al*., 2017). The satellite acquires multispectral imagery in a spectrum ranging from 450 to 890 nm, at 16 m spatial resolution every 4 days, which improves crop mapping. The use of this multi-seasonal satellite was explored by Song *et al*. (2017) in mapping regional cropping patterns. Their findings show that the sensor was able to efficiently and accurately map regional crops with an overall accuracy of over 80%. Given the unique spectral characteristics of the sensor imagery, better results were yielded with the use of textual features. The study also observed that the use of the multi-temporal GF-1 data further increased the accuracy to 93.08%, which is far better than when a single data set was used. However, spectral mixture was observed in the study as a result of limited spectral resolution (four bands in the Blue, Green, Red and Near-infrared), making it difficult to identify all crops.

Some studies have observed that using single date imagery in mapping crops produce reliable results. For example, Saini & Ghosh (2018) explored the use of Sentinel-2 single date imagery in mapping crops in Roorkee of India using RF and SVM classifier. It was observed that the 4 bands used (NIR, Red, Green and Blue bands) produced better results when using RF than SVM. It was further observed that the overall accuracy in RF was 2.37% higher than SVM. The study concluded that the use of Sentinel-2 single date imagery has great potential in terms of mapping crops.

Multispectral and multi-temporal remote sensing images are also used to map crops at different farming systems including irrigated crops for water use quantification and accounting (Demarez *et al*., 2019). These images are used to map crop types at various seasons and in diverse cropping systems (Demarez *et al*., 2019). For example, Demarez *et al*. (2019) used Landsat 8 and Sentinel-1 Time series in mapping in-season irrigated crops in southwest France. The study used Radar images from the C-SAR instrument of Sentinel-1A satellite (Interferometric Wide Swath mode) with a revisit time of 12 days and 10 m spatial resolution along a 250 km swath. The results revealed that the combined use of Sentinel-1 and Landsat 8 data improves the accuracy of the classifications when compared to those performed with optical or radar images alone.

Vegetation indices have been used successfully and produce better results in mapping crops in heterogeneous agricultural areas. For example, Ouzemou *et al*. (2018) mapped crop types from pansharpened using Normalized difference vegetation index (NDVI) of Landsat 8 data for the period of 10 agricultural seasons. The study was carried out as a case study on highly fragmented and intensive agricultural system of Tadla Irrigated Perimeter in central Morocco. Ouzemou *et al*. (2018) study used Landsat 8 (OLI) images with spatial resolution of 15m (panchromatic band) to 30m (multispectral bands) and radiometric resolution of 16 bits. These sensors are said to be reliable and good in terms of mapping crops. The findings revealed that the overall accuracy achieved by classification algorithms method used (Spectral Angle Mapper, Support Vector Machine (SVM) and RF) was between 57% and 89%. The study also found that the use of time-series pan-sharpened OLI NDVI data enhanced the overall accuracy together with the use of machine learning classifier. RF and Landsat 8 data showed the ability to map crops in central Morocco especially because the area is characterised by very fragmented and heterogeneous agricultural landscape. Nomura & Mitchard, (2018) study also evaluated the performance of Sentinel-2 texture indices in mapping small plantations in a complex forest landscapes. The study observed that Sentinel-2 was able to differentiate crops even though they visually appeared to be similar to each other. Sentinel-2 was able to achieve high accuracy than the other classification methods used, however more accuracy was achieved (greater than 90%) with the use of texture indices. The study further observed that misclassification occurred with young plantations as they were confused with other classes. The Author recommended that older tree plantation be used for better results and to avoid confusion of land use and land cover classes (LULCC).

The use of multi-source (datasets from different sensors) and multi-temporal data (dataset acquired in different time frame) also plays an important role in improving the overall accuracy of classification results of multispectral remote sensing data. For example, Sun *et al*. (2019) tested the accuracy of using multi-source and multi-temporal remote sensing data in mapping crop type in subtropical agricultural region in China. Firstly, the study tested the use of single remote sensing data to classify crops and found that Sentinel-2 outperformed the other sensors by producing an overall accuracy of 91% and Kappa coefficient of 0.89. However, the overall accuracy increased to 93% with kappa coefficient of 0.91 when the three dataset (Sentinel-1, Sentinel-2 and Landsat 8) were combined. The study also noted that RF classifier showed best performance than the other advanced machine learning algorithms used (SVM and Artificial Neural Network) by identifying crops well in classification process.

Some studies have also observed that the use of Red edge bands plays an important role in improving the overall classification performance and accuracy. For example, Forkuor *et al*. (2018) tested the performance and contribution of Sentinel-2 Red edge bands in land-use and land-cover mapping in Burkina Faso. The performance of the bands was tested using RF, SVM and stochastic gradient boosting machine learning algorithms. The results showed that classification using all the Sentinel-2 bands and the ones common to Landsat 8 produced overall accuracy, which was 5% better than Landsat 8 results. However, when the Sentinel-2 image was classified using only the Red edge bands, the overall classification improved by 4%. These results were better than the ones achieved when the other Sentinel-2 bands and Landsat 8 bands were used.

2.2.2.2 Crop mapping using hyperspectral remote sensing

Hyperspectral imagery offers better opportunity as compared to multispectral imagery, and this is because they consist of more contiguous spectral bands that have narrow bandwidths (Zhang *et al.*, 2016). Apart from their characteristics of providing more accurate physical parameter inversion, hyperspectral datasets are known for having another distinct spectral characteristic in crop monitoring studies. They can recognise the feature well and identify and distinguish different crops (Adam *et al*., 2010 & Thenkabail *et al*., 2013). These characteristics make them suitable for classifying crops which also plays an important role in planning and management of precision agriculture (Thenkabail *et al*., 2013).

Different studies have therefore used these datasets for more accurate crop mapping. For example, Zhang *et al*. (2016) used hyperspectral images in classifying crops based on the feature band set construction and object-oriented approach in a study done in Japan. The authors developed their classification algorithm method (Object-Oriented Classification: OOC) which involve construction and optimization of the vegetation feature band set (FBS). The proposed classification method was validated by two airborne hyperspectral images, the Pushbroom hyperspectral imager (PHI) acquired in an agricultural area of Japan and an airborne hyperspectral image acquired by PHI in rice breeding area. The overall accuracy achieved in distinguishing different crop classes was 97.84% and a kappa coefficient of 0.96 for the first image, which was acquired in the rice breeding agricultural area. The second image produced an overall accuracy of 98.65% and a kappa coefficient of 0.98. Zhang *et al*. (2016) study found that the new proposed algorithm performed better, overcoming the known hyperspectral classification limitation by reducing the salt-and-pepper noise, retained the patch information effectively and enhancing the separability of crop classes. However, the shortcomings of the OOC method in hyperspectral classification were that classification was controlled by the quality of the segmentation. As a result, repeated trials will need to be done to find the most suitable segmentation level.

The advantages of hyperspectral images in identifying different crops make them suitable for crop mapping in a complex landscape. This is because of their finer resolution, which can detect smaller objects. Boitt *et al*. (2014) used the AISA Eagle Visible and Near-Infrared (VNIR) hyperspectral remote sensing data in identifying crops in a cultivated agricultural landscape in Taita hills, Kenya. The imagery was acquired with a spectral resolution of 9 nm and spatial resolutions of 0.6 m. A physically-based spectral classification (Spectral Angle Mapper (SAM)) algorithm was used for classification of these images. The study achieved an overall accuracy of 77% and a kappa coefficient value of 0.67. The study finding shows that hyperspectral data was able to discriminate various crops in a cultivated landscape using AISA Eagle VNIR data and the SAM algorithm. Although hyperspectral images produce better results than multispectral images in crop mapping, they are complex and very costly (Teke *et al*., 2013), also classification of hyperspectral images is very challenging (Dhumal *et al*., 2013).

2.3 Available classification algorithms for crop mapping

Crop maps are traditionally retrieved by classifying an image or a series of images using the classifier concepts and algorithms that are available (Nema *et al*., 2018). There are different algorithms developed that can be used for classification of remote sensing images. These algorithms are generally identified as supervised classification algorithms (e.g. Maximum Likelihood Classifier, Decision Tree, Minimum Distance-to-Means, K-Nearest Neighbors and machine learning Classifier), and unsupervised classification algorithms (e.g. k-means and the Iterative Self-Organizing Data Analysis).

Maximum likelihood classifier, a supervised classification is widely used for classification and traditionally to test the ability of other existing algorithms, such as curve-fitting, decision tree, and object based classification (Zhong, 2012). This method requires sufficient ground truth data for training to achieve high accuracy (Zhong, 2012). It assumes that probabilities are equal for all classes and that the input bands have a normal distribution (Nema *et al*., 2018). Maximum likelihood classifier was used by Nema *et al*. (2018) in classifying different crops such as Wheat, Gram, Sugarcane and other crops using Landsat 8 image in Hoshangbad district of Madhya Pradesh, India. The classification results showed that Wheat crop occupied majority of the area (84.90%), Gram crop occupied a small portion of the area (10.23%) and other crops in the area occupied only a minimum area. Although some misclassification of crops was observed in the study, maximum likelihood classification achieved an overall classification accuracy of 89.80% showing that the training areas were classified well and that there was a good agreement between the training sites. However, Zhong (2012) reported that the maximum likelihood classifier requires a large set of ground truth data which is costly and time consuming to collect.

Some studies have observed that traditional pixel based classification improves the overall accuracy in parcel based approaches. For example, Kussul *et al*., 2016 compared parcel based and pixel-based classification approach in classifying crops using Landsat 8 and Sentinel-1A data in Ukraine. The finding of the study shows that the overall classification accuracy results were increased from 85% by 4% yielding the best results for the pixel based approach when using parcel boundaries.

Generalized classifiers are used in crop mapping to overcome the limitation and challenges of a traditional classifier. These algorithm builds a classifier model using training data which can be used for a location and different time period without having to add another set of training data (Phalke & Özdoğan, 2018). Massey *et al*. (2017) developed the two novel and automated decision tree classification approach, the generalized classification approach and the year-specific approach in mapping crop types across the conterminous United States (U.S.). Overall, results indicated high classification accuracies between 70% and 80%. Year-specific approach accuracies were slightly better than generalized approach with no statistically significant difference between the two approaches (Massey *et al*., 2017). However, the study reported classification errors and large similarities between different crop types in the NDVI time-series as a result of the low spatial resolution of the sensor (Massey *et al*., 2017).

RF is widely used successfully in crop mapping (Reynolds *et al*., 2016) as it performs better than many tree-based algorithms (Ok *et al*., 2012). RF has been found to have a number of advantages, including the ability to produce results with higher accuracy (Song *et al*., 2017), ability to classify unbalanced dataset (Gao *et al*., 2019), ability to handle large dataset (Reynolds *et al*., 2016), insensitive to noise (Ok *et al*., 2012) and cost effectiveness (Reynolds *et al*., 2016). Past studies indicated that RF classifier performs better than the other classifiers such as maximum likelihood (Ok *et al*., 2012) and SVM (Adam *et al*., 2014 & Saini & Ghosh, 2018), in classifying different crops. Reynolds *et al*. (2016) also used the supervised RF machine learning algorithm for classification of Landsat 8 images to assess the conservation status of critical Cerrado habitats in MatoGrosso do Sul, Brazil. The algorithm was used because it produces accurate results than other traditional classifiers (Reynolds *et al*., 2016) such as maximum likelihood. The overall mapping accuracy achieved by RF was high with 88% and Kappa Coefficient of 0.67% (Reynolds *et al*., 2016).

Deep learning is a powerful technique which has emerged recently in classifying remote sensing images. It is a subset of machine learning algorithms and it has been developed to solve the shortcoming of traditional artificial intelligence (Guo *et al*., 2016). Kussul *et al*. (2017) explored the use of deep learning algorithms using remote sensing data in classifying the land cover and crop types in Ukraine. The study used a multilayer perceptron (MLP) and RF algorithms comparing them with convolutional NNs (deep learning algorithm). It was observed that convolutional NNs produced better results than the other algorithms with the overall accuracy of 94.6%. Deep learning algorithm was used because of its advantage of producing better results, discriminating crop types, solving issues that arise in image processing, computer vision, signal processing, and natural language processing. However, the shortcoming of deep learning observed by the authors were that the final classification map was smoothed and misclassification occurred in some small objects.

The review above shows that remote sensing methods provide better results than traditional methods. This is because remote sensing is fast, time efficient and produces accurate results. This makes remote sensing data ideal for crop monitoring and crop mapping in different seasons and in a complex landscape. It has been shown that remote sensing classification algorithms such as supervised classification achieve better results when combined with ground data. In remote sensing, selection of appropriate resolution is very important. The decision to select spatial resolution depends on the application type as well as the amount of details that are required from such dataset. For example, forest analysis requires less details compared to urban analysis research. Mapping and monitoring crops using remote sensing is very important as it informs further research and can be used for decision making and future planning.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study area description

3.1.1 Study area location description

The research is based on the agricultural sites situated at Levubu area under Vhembe district municipality, Limpopo Province South Africa (Figure 1). Vhembe district is one of the five districts in Limpopo province. The name Levubu is derived from the name of the river dominant in the area called Luvuvhu (Nefale, 2000). Its geographical coordinates are Latitude: -23°20'0"S; Longitude: 30°20'0"E and Latitude: -22°50'0"S; Longitude: 30°0'0"E with the elevation of 755 m above sea level. Levubu is commonly known as a white farming area with locals calling it ‘Mavhuruni’ (Nefale, 2000). This is because most farms are owned by white people who are Afrikaans speaking (Nefale, 2000). The study area covers an area of 0.41km^2 with a population of 207 (504.42 per km^2) and households of 97 (236.37 km^2) (Census, 2011). Levubu is characterized by subtropical temperatures with relatively high humidity. According to Stats SA (2011) its winters last from June to August and it is characterized by mild afternoon with cool evenings. Summer is warm and often humid temperatures and the afternoons occasionally have thunderstorm (Stats SA, 2011). Levubu’s annual rainfall is approximately 500 mm per annum (Thulamela municipality, 2016). The pattern of rainfall is mainly influenced by Orographic rain effect from the Drakensberg Mountains joining the Soutpansberg Mountains perpendicularly (Thulamela municipality, 2016). Rainfall pattern ranges from November to March (Stats SA, 2011). The Levubu area has two major rivers, the Luvuvhu (Main River) and Lotonyanda River (Nefale, 2000).

3.1.2 Crop types in Levubu

Majority of the crops that are found in Levubu area are subtropical crops and only a few citrus crops such Orange is found. The area is dominated by tree crops and small varieties of cultivated crops are found depending on the season of the year. Levubu crops are rain-fed and also irrigated using different irrigation systems. Majority of the tree crops bear fruit seasonally and the harvesting time differs with each crop type. Major crops found in Levubu area are Macadamia nut, Avocadoes (hass, fuerte and pinkerton), Banana, Mango, Litchi, Sweet potato, Guava, Maize, Butternut, Baby marrow, Gem squash, Cabbage, Chillies, Grain and Sorghum. Some of these crops (such as Macadamia nut, Banana, Mango and Avocado) are exported to international markets (DAFF, 2012). For example, in South Africa three provinces (Limpopo (Tzaneen and Levubu), Mpumalanga (Barberton, Nelspruit and Hazyview), and Kwazulu Natal) are said to be producing the best Macadamia nuts, which are exported to international markets (such as the United States of America, Europe and Asia) (DAFF, 2012). These countries are considered the biggest Macadamia export markets (DAFF, 2012).

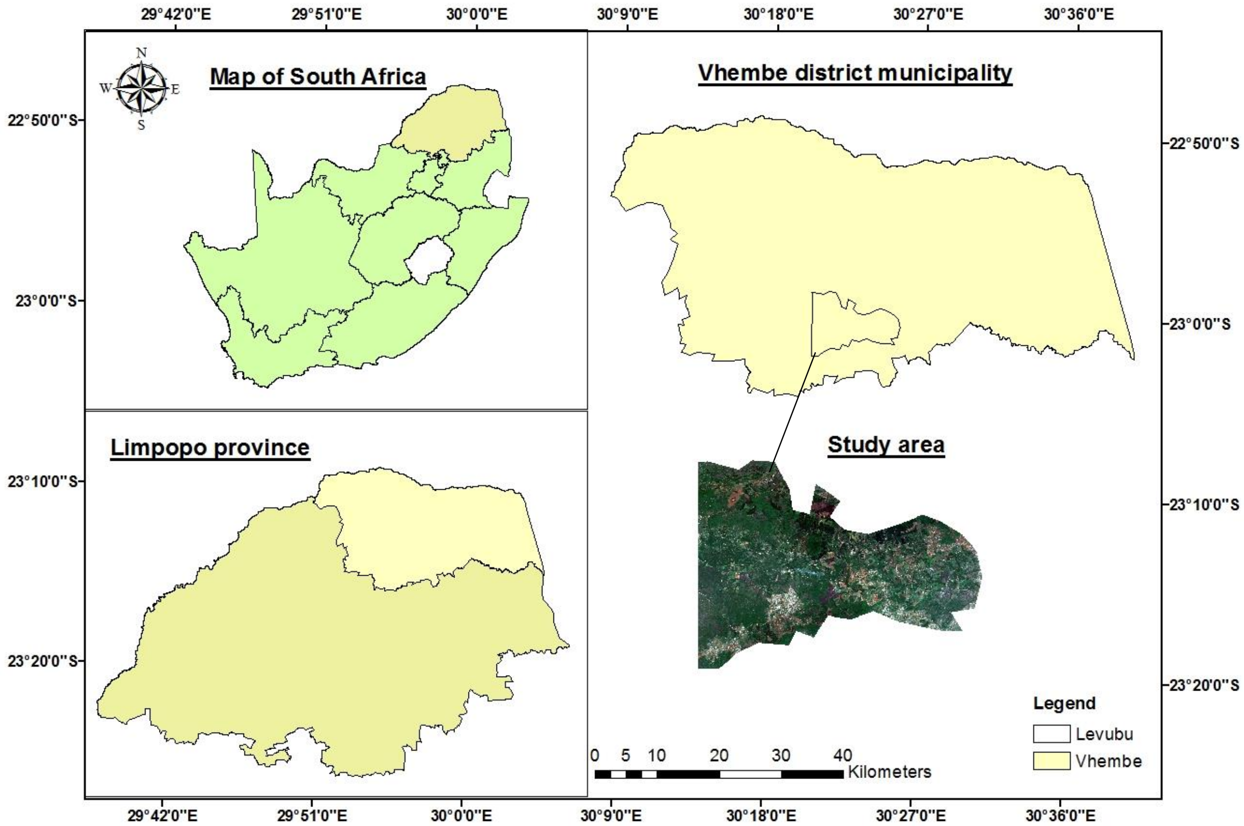

Figure 1: Location of the study area

3.1 Remote Sensing data acquisition

Landsat 8 OLI and Sentinel-2 MSI satellite images were both captured under cloud-free conditions. The two cloud free images which cover the study area were downloaded for the month of December, 29. The image acquisition dates from both sensors were selected according to the availability of cloud free images for the period that corresponds with ground data collection. Both images, Landsat 8 OLI and Sentinel-2 MSI are multispectral imagery which are freely available.

3.2.1 Landsat 8 OLI image

Landsat 8 OLI imagery was obtained from the United States Geological Survey (USGS) archive. These images are freely available at the Earth Explorer platform (https://earthexplorer.usgs.gov). Landsat 8 OLI was launched by NASA on February 11th, 2013 and it is formally known as the Landsat Data Continuity Mission. Landsat 8 OLI spatial resolution ranges from 15 m for the panchromatic band and 30 m for multispectral bands with a radiometric resolution of 16 bits in OLI images (Ouzemou *et al*., 2018). Landsat 8 OLI has a revisit time of 16 days at an altitude of 705 km (Ouzemou *et al*., 2018). This study used a Landsat 8 OLI/TIRS C1 Level-1 multispectral image at 30 m spatial resolution with 9 bands. Landsat 8 has 9 spectral bands in OLI from shorter wavelengths of visible to Short Wave Infrared (SWIR) and Thermal Infrared Sensor (TIRS) data (Table 1) (Ouzemou *et al*., 2018). The two imaging instruments collect multispectral digital images coincidentally in the reflective as well as thermal atmospheric windows (Pahlevan & Schott, 2013).

3.2.2 Sentinel-2 MSI image

Sentinel-2 MSI image was downloaded from the European Space Agency (ESA) Copernicus Open Access Hub website. These images are freely available on https://scihub.copernicus.eu/dhus/#/home. Sentinel-2 is a newly powerful source of radar and optical data with high spatial resolution which is used for agro-environmental monitoring (Kanjir *et al*., 2018). Sentinel-2 MSI has two identical satellites (Sentinel-2A and Sentinel-2B) which both operate in the sun-synchronous orbit (Djamai & Fernandes, 2018). Sentinel-2A was launched first on 23rd of June 2015 and later on, Sentinel-2B was launched on 7 March 2017 by the ESA (Djamai & Fernandes, 2018). Sentinel-2 MSI has 13 bands from Visible and Near-Infrared (VNIR) to the SWIR region (Table 1). The Red edge bands in the spectrum part are said to be very important and useful for crop monitoring. It has spatial resolutions of 10 m, 20 m and 60 m (Table 1). Sentinel-2 MSI data has the ability to monitor the entire crop or pasture lifecycles and land change (Kanjir *et al*., 2018). Features are captured at high temporal resolution of 5 days by enabling the continuous monitoring over space and time or throughout the growing season (Kanjir *et al*., 2018). All these characteristics makes it adequate for mapping crop types in Levubu area by discriminating all crop types and their spatial distribution pattern.

3.3 Image pre-processing

Atmospheric correction of satellite imagery was conducted on both Sentinel-2 MSI and Landsat 8 OLI images. This process involves the processing of the digital image to significantly decrease the overall influence of errors and inconsistencies observed in the data, due to the atmospheric interference (scattering and absorption effects) (Demarez *et al*., 2019). Landsat 8 OLI image was radiometrically calibrated and atmospherically corrected using Environment for Visualizing Images (ENVI 5.4) 2017 software package. FLAASH algorithm was used for atmospheric correction of the image in the ENVI software. FLAASH is a module used for atmospheric correction and atmospheric disturbances correction in the ENVI software package. This makes it possible to carry out corrections of significant geometric distortions that are occurring as a result of the number of faults, such as altitude, as well as attitude and velocity of the sensor platform (Demarez *et al*., 2019). The spectral reflectance values that correspond with the GPS points collected from the study area were extracted by overlaying ground points on the image. For further analysis, the points were then exported to csv file format using ArcGIS software package to be able to use them in R programming language software package.

Sentinel-2 image was corrected using ESA SNAP software, this was done utilising the Sen2Cor plugin in SNAP software. The Sen2Cor is a plugin in Snap software package which was developed by ESA for processing and atmospheric correction of all the Sentinel-2 products. The bands with 20 m spatial resolution (5, 6, 7, 8A, 11 and 12) were resampled to 10 m resolution; this was done to capture the smallest details of the crop distribution in the study area. Resampling of the Sentinel-2 image bands resulted in the image having 10 bands (2, 3, 4, 5, 6, 7, 8, 8A, 11 and 12) out of the original 13 bands (Table 1). The corrected Sentinel-2 image with 10 spectral bands were combined from the single band raster to multi-band RGB composites using the composite bands tool in ArcGIS 10.5 software package. The spectral reflectance values were extracted that corresponds with the GPS points collected from the study area by overlaying ground points on the image. For further analysis, the points were then exported to csv file format to be able to use them in R programming language.

Table 1: Resolutions of Sentinel-2 MSI and Landsat 8 OLI

Sentinel-2 (MSI)			**Landsat 8 OLI**		
Sensor Band	Resolution (m)	Bandwidth (nm)	**Sensor Band**	Resolution (m)	Bandwidth(nm)
B1 (Coastal/Aerosol)	60	443	**B1(Coastal/Aerosol)**	30	0.43 - 0.45
B2 (Blue)	10	490	**B2 (Blue)**	30	0.45 - 0.51
B3 (Green)	10	560	**B3 (Green)**	30	0.53 - 0.59
B4 (Red)	10	665	**B4 (Red)**	30	0.63 - 0.67
B5 (Red Edge)	20	705	**B5 (NIV)**	30	0.85 - 0.88
B6 (Red Edge)	20	740	**B6 (SWIR-1)**	30	1.57 - 1.65
B7 (Red Edge)	20	783	**B7 (SWIR-2)**	30	2.11 - 2.29
B8 (NIR)	10	842	**B8 (Pan)**	15	0.50 - 0.68
B8a (Red Edge)	20	865	**B9 (Cirrus)**	30	1.36 - 1.38
B9 (Water vapour)	60	940			
B10 (SWIR - Cirrus)	60	1375			
B11 (SWIR)	20	1610			
B12 (SWIR)	20	2190			
Orbit altitude	**786 km**			**705 km**	
Swath width	**290 km**			**185 km**	

3.5 Field data collection

The first important step in supervised classification is to select samples or training fields. The training data set were retrieved by collecting ground truth information in the form of ground control points using the global positioning system (GPS) device. Ground reference data were collected from Levubu commercial farming areas using field survey tools for summer season crops during December of 2019. The GPS equipment was used to collect field data on each point of different crops in the Levubu area. 1425 points of 8 different LULCC were randomly collected using GPS and the details of the points collected per each class are presented in Table 2. The GPS points were taken in Levubu area at the end or driveways of different crop fields. Reference data were split into training and testing subset where 70% of the data was taken for training and 30% for testing (Table 2). This exercise was done using the R programming language in the R statistic interface. Training data was used in classifying Sentinel-2 MSI and Landsat 8 OLI images. The test data was then used in validating the accuracy results of the classification of both the images.

Table 2: Training and test reference data

LULCC	Code	Attribute	Total	Training	Test data	Total points
Avocado	Avo	Avocado	68	48	20	
Banana	Ban	Banana	118	83	35	
Built up	Bui	Residential and commercial structures	486	341	145	
Macadamia	Mac	Macadamia nut	296	208	88	
Maize	Mai	Maize	58	41	17	
Mango	Man	Mango tree	45	32	13	
Vegetation	Veg	Woody vegetation & grasses	286	201	85	
Water body	Wat	Dam, river, wetlands & borehole	97	68	29	
						1425

3.6 Image classification

RF, which is a supervised machine learning classifier, was used in classifying the Landsat 8 OLI and Sentinel-2 MSI images. RF make use of bagging or bootstrap aggregating in classification process, this is done to form an ensemble of classification and regression tree (CART)-like classifiers (Gislason *et al*., 2006). RF uses tree-type classifiers that are created by the samples of training data. Since RF is a non-parametric method, it does not rely on data distribution assumption in order to classify an image (Ok *et al*., 2012 & Reynolds *et al*., 2016). It can classify discrete or continuous data and it can handle unbalanced data sets (Adam *et al*., 2014 & Gao *et al*., 2019). RF algorithm was used to identify the features that were relatively useful in conducting crop classification and to evaluate feature importance (Song *et al*., 2017). The algorithm was implemented and trained using R programming language software.

RF classifier was chosen because of its accuracy in mapping crops compared to other classifier methods (Reynolds *et al*., 2016 & Song *et al*., 2017). Most studies which have been done assessing the accuracy of RF have found that it produces results with a high level of accuracy (Ok *et al*., 2012; Reynolds *et al*., 2016 & Song *et al*., 2017). The algorithm is not sensitive to noise and it is not subject to overfitting, which makes it superior to many of the tree-based algorithms (Ok *et al*., 2012). RF techniques can handle a large number of training samples and to measure each of the input variables into importance levels (Reynolds *et al*., 2016). Reynolds *et al*. (2016) indicated that RF has low cost requiring only fewer user defined parameters and it is easier to operate. Because of its level of accuracy, it has gained popularity in remote sensing applications, such as image classification (Reynolds *et al*., 2016).

RF requires that the user define the number of trees to grow and the variables which will be used in splitting each node, these are the N and M parameters (Ok *et al*., 2012). It also involves the combination of multiple decision trees with each tree contributing a single vote. RF randomly selects drawing samples through generation of multiple decision trees, this is done with replacement from the training data. Each decision tree node where there is the best split of training data is determined, making consideration of the maximum number of features that were randomly selected (Griffiths *et al*., 2019). The default number of tree grown (ntree) in RF is 500 and the default mtry value, which is the number of variables is derived by the square root of the total number of the spectral bands that were used. The mtry grid value ranged from 1 to 7 for Landsat 8 image and 1 to 10 for Sentinel-2 image and the ntree grid value parameters ranged from 500 to 10000 for both sensors. The accuracy of RF classification depends on the ntree and mtry user defined parameters. The ntree and mtry are the two tuning parameters which are used in RF, the ntree represent the number of trees forming ensemble and used in the dataset and mtry indicates the total number of the variable that were used in splitting the nodes in the dataset (Saini & Ghosh, 2018).

3.7 Accuracy assessment

Accuracy assessment of the derived thematic maps was evaluated by the test sample using confusion matrix and kappa coefficient. This was done to assess the ability of Landsat 8 and Sentinel-2 to discriminate the different types of crops in Levubu area. The kappa coefficient, the overall accuracy, producer and user's accuracy were computed using equation 1, 2, 3 and 4 adopted from Foody *et al*. (2002). Kappa coefficient (Equation 4) measures the difference that exists between the reference data and the classifier algorithm used when classifying the image with the actual agreement (Adam *et al*., 2014). Confusion matrix is commonly used in crop mapping to measure the level of errors that occurred in classifying an image (Nema *et al*., 2018). The confusion matrix measures the accuracy in terms of misclassification that occurred, this is done by comparing a sample of the test pixels on the classified image with the reference data (ground data) (Nema *et al*., 2018). The number of accuracy measures can be determined from the overall accuracy, which includes the user and producer's accuracy (Nema *et al*., 2018). The overall accuracy (Equation 1), producer's accuracy (Equation 2) and user's accuracy (Equation 3) were computed by generating confusion matrices from the R programming language. The producer's accuracy represents the test data samples that were accurately classified in each LULCC and the User's accuracy represent the possibility of the test samples belonging to another LULCC in the field (Adam *et al*., 2017). The Overall accuracy is indicated in percentage and it represents the probability of the point in the classified image being classified correctly on the map (Adam *et al*., 2014).

Overall accuracy, Equation (1) (Foody *et al*., 2002) is calculated by dividing the total number of pixels that were classified correctly with those in the test dataset. Where q represents the number of classes, $\mathrm{n_{ii}}$ represents the diagonal elements of the confusion matrix and n indicates the total number of pixels that were considered.

$$\text{Overall accuracy} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{q}} \mathrm{n_{ii}}}{\mathrm{n}} * 100 \qquad (1)$$

Equation (2) (Foody *et al*., 2002) calculates the producer's accuracy where $\mathrm{n_{+i}}$ is the marginal sum of the column in the confusion matrix.

$$\text{Producer's accuracy} = \frac{\mathrm{n_{ii}}}{\mathrm{n_{+i}}} * 100 \qquad (2)$$

User's accuracy is calculated using equation (3) (Foody *et al*., 2002) where $\mathrm{n_{i_+}}$ is the marginal sum of all the rows in confusion matrix

$$\text{User's accuracy} = \frac{n_{ii}}{\mathrm{n_{i_+}}} * 100 \qquad (3)$$

Kappa coefficient is calculated using equation (4) (Foody *et al*., 2002)

$$\text{Kappa} = \frac{n\sum_{i=1}^{q} n_{ii} - \sum_{i=1}^{a} ni + n_{+i}}{n^2 - \sum_{i=1}^{q} n_i + n_{+i}} * 100 \qquad (4)$$

CHAPTER FOUR

RESULTS

4.1 Determining the spatial distribution of crops in Levubu area using Sentinel-2 and Landsat 8 data

The results show the maps of the spatial distribution of different crops in Levubu area using two satellite images, Sentinel-2 and Landsat 8. The overall performance of both sensors were fairly well with the overall accuracy of more than 70% obtained. Although both sensors were able to classify all the crops well, some differences between Landsat 8 and Sentinel-2 classification map results were observed (Figure 2 and 3). The results show that Sentinel-2 MSI classification results were better than classification results produced by Landsat 8 OLI. The differences of classification results between Sentinel-2 and Landsat 8 was 10% in terms of the overall accuracy. These difference resulted because of the finer resolution of Sentinel-2, which allows for smaller object to be detected than the Landsat 8 resolution. Landsat 8 image showed a few misclassifications in some crop classes but better results were obtained in crops classes such as Macadamia nut (Figure 2). Sentinel-2 produced better results and only a few misclassifications were observed in Avocado, Maize and Mango crops (Figure 3).

Landsat 8 and Sentinel-2 classification results both show better distribution of crops in Levubu area. Both images show better results in Avocado, Banana, Macadamia nut, and Waterbody. From the results of both sensors the distribution pattern of the crops can be detected. The results show that the most dominant crop which covers a larger area in Levubu is Macadamia nut followed by Banana, Avocado and Mango. The other crops such as Maize only covers a small portion in the area. Although both sensors show that Macadamia nut is dominant in Levubu area, Sentinel-2 map shows more parts that are covered by Macadamia nut which are not indicated by the Landsat 8 map. Another difference that can be seen is maize, Landsat image show differences in terms of the area covered by Maize compared to Sentinel-2 results. Landsat image shows more coverage by Maize, this is because the overall accuracy of Maize in Landsat 8 was lower compared to Sentinel-2 image. All the other crop's spatial distribution pattern in both maps (Figure 2 and 3) shows only a slight difference in the area coverages in Levubu area. The overall classification results demonstrate the potential of both sensors (Landsat 8 OLI and Sentinel-2 MSI) in mapping the spatial distribution pattern of crop types in Levubu area.

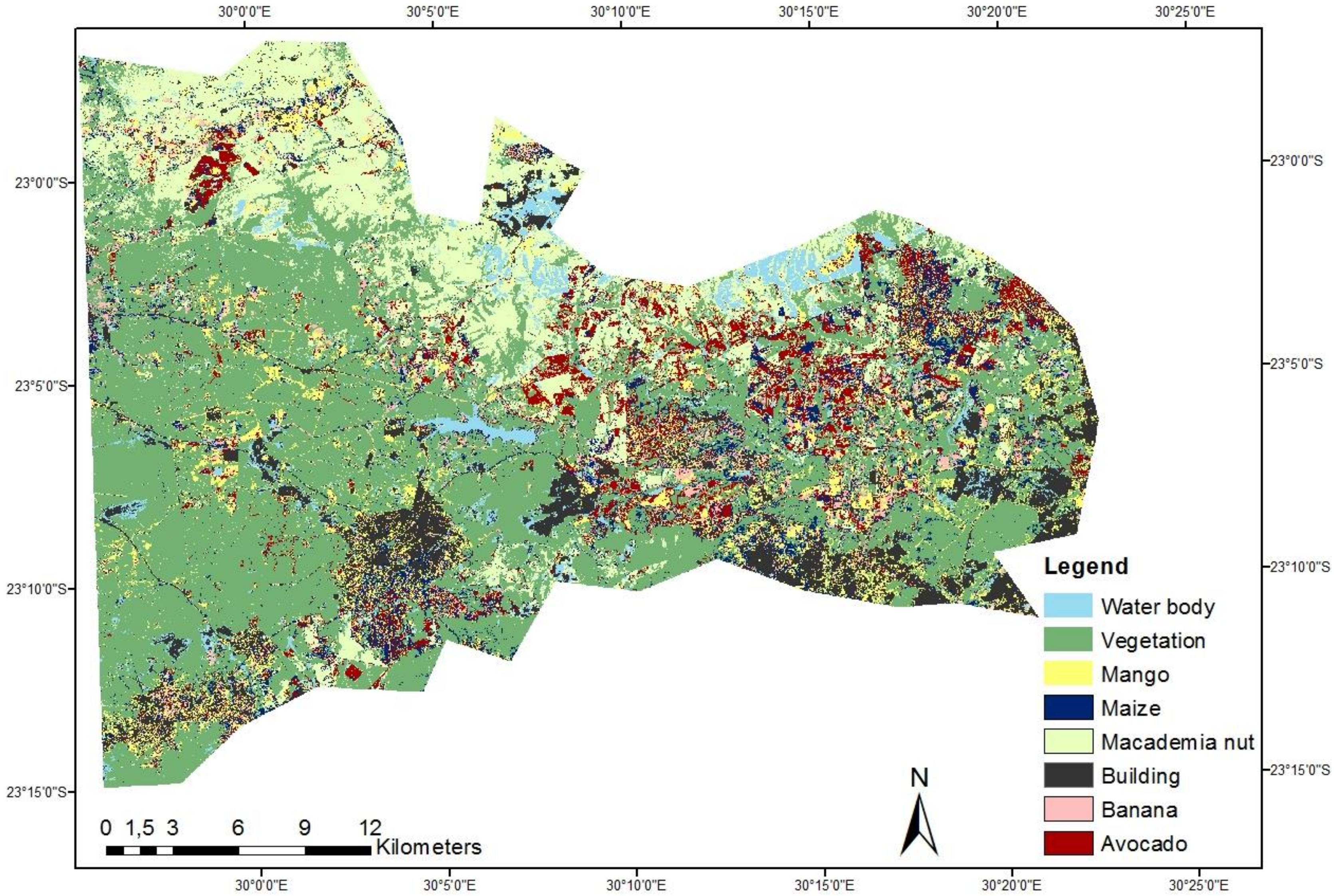

Figure 2: Landsat 8 derived crop mapping results for Levubu

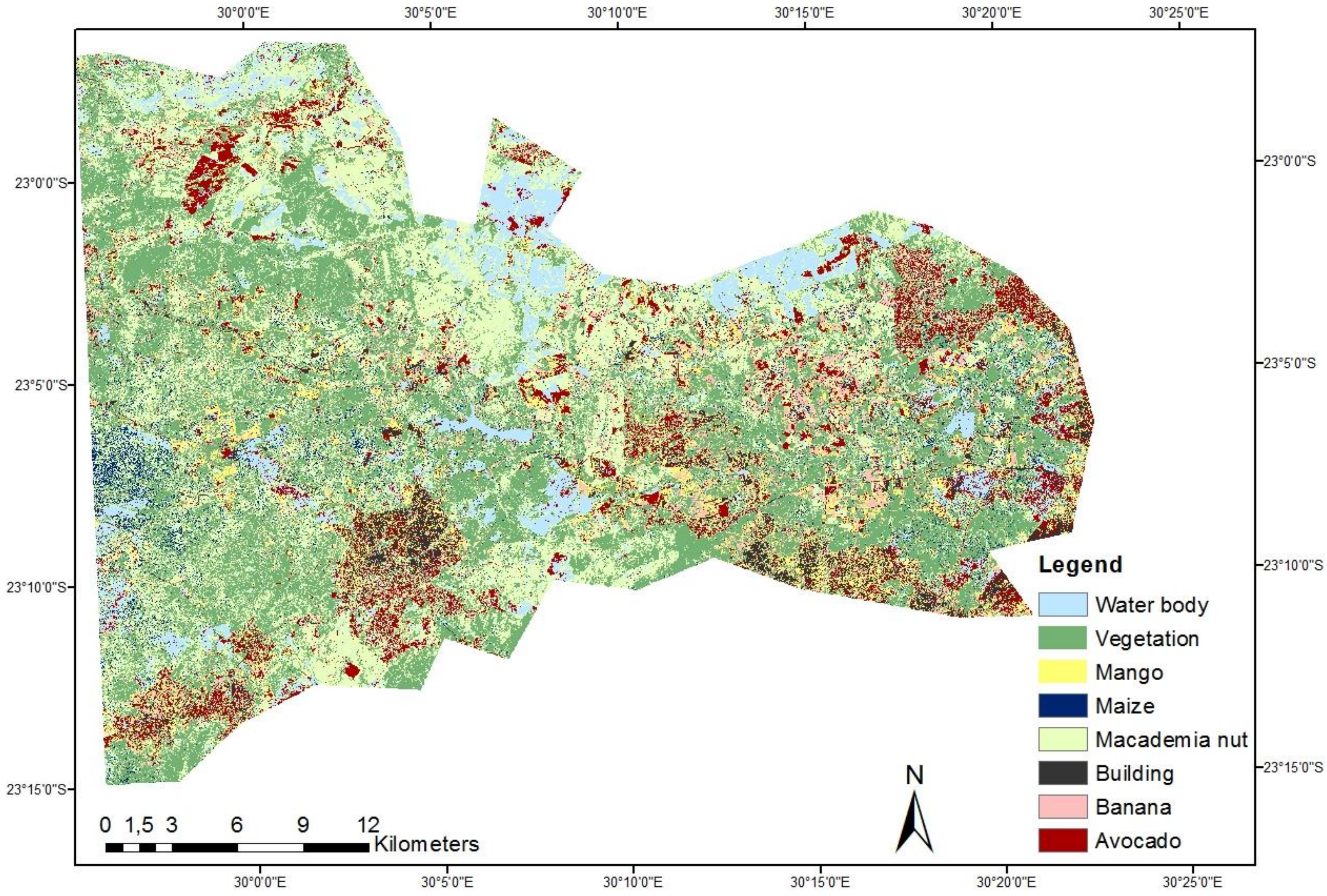

Figure 3: Sentinel-2 derived crop mapping results for Levubu

4.2 The potential of Landsat 8 and Sentinel-2 in mapping the distribution pattern of crop

4.2.1 Bands importance of Landsat 8 OLI and Sentinel-2 MSI in mapping the distribution pattern of crop

Variable importance measurement indicates the contribution of all the bands, this includes bands that contributed more and the ones that have the least contribution in the classification process. The level of importance of these bands is indicated by the mean decrease in accuracy, i.e. the higher the mean decrease in accuracy the more the bands contribution and the lower the mean decrease in accuracy the lower the bands contribution (Figure 4). The measure of variable importance was computed by RF classifier during the process of classifying both Landsat 8 OLI and Sentinel-2 MSI images. This process helped in identifying the bands that played an important role in the classification of Sentinel-2 and Landsat 8 images.

For the Landsat 8 OLI image, the bands that had the most contribution in classifying crop types in Levubu area were Coastal, Red, and Green (Figure 4). On the other hand, bands that showed the least contribution were SWIR-1, SWIR-2, Blue, and NIR (Figure 4). The most significant bands had the contribution of more than 40 and the bands that had the least significant contributed less than 40 (Figure 4).

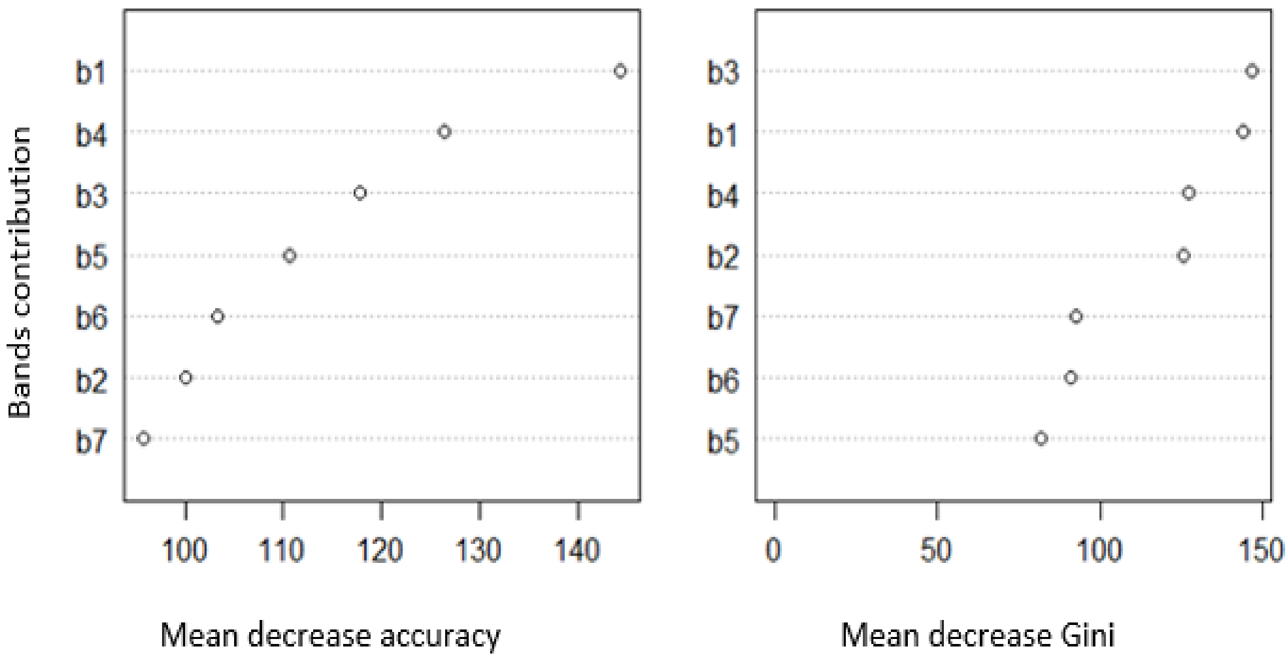

Figure 4: Landsat 8 band important for crop mapping

Figure 5 also shows the most important bands for the Sentinel-2 MSI in classifying. The bands that played the most important role in classifying different crops were Blue, Red, Green and NIR (Figure 5). The bands that had the least contribution were the four Red edge bands and the two SWIR band. The bands that contributed most had a contribution of more than 40 and the bands that had the least contribution contributed less than 30 (Figure 5). This means that the bands with the least contribution did not play any significant role in the model and even if they were to be removed will not affect the classification accuracy, but if one was to remove the bands that has the most contribution, this will affect the classification accuracy results.

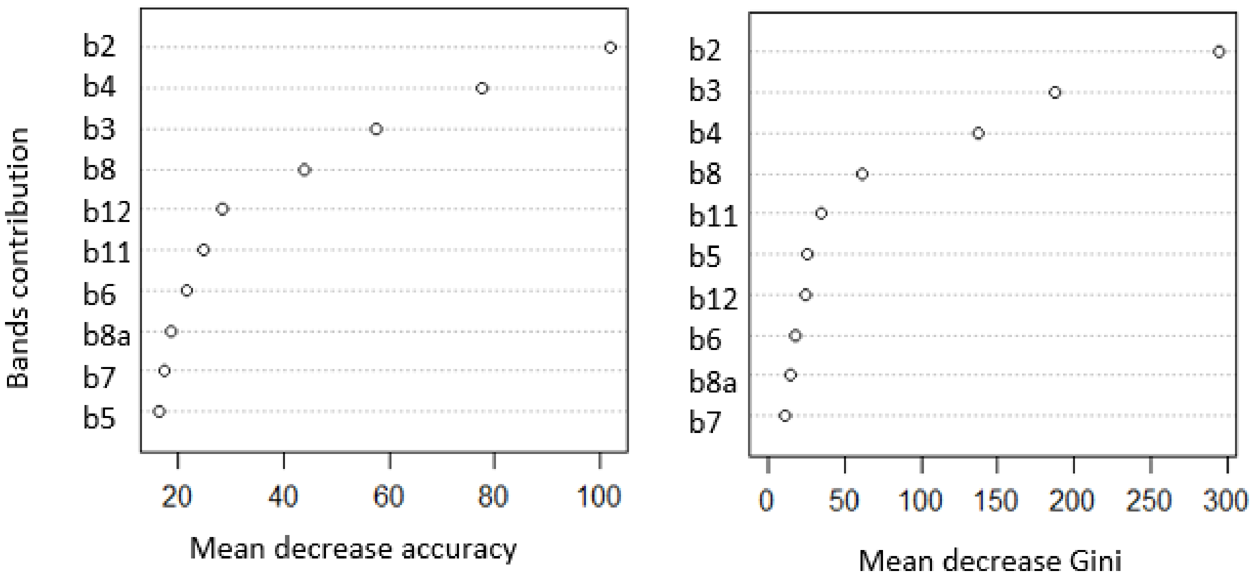

Figure 5: Sentinel band important for crop mapping

4.3 Performance of RF (in Landsat 8 and Sentinel-2 images) in classification of crops

The mtry and ntree parameters were optimised in order for the best parameters to be determined in training the RF. This was done during classification of all the crops used in Levubu area for both sensors image. The two parameter, (mtry and ntree) affect how RF classifier performs significantly. The N bootstrap samples in both images were drawn from the training data set of 2/3 and the other 1/3 out-of-bag (OOB) was used for training data in testing the error made by the model in making predictions. The performance of the classification method is mostly affected by the process which is used in selecting parameters. Figures 6 and 7 show the results obtained from the training set OOB error for Landsat 8 OLI and Sentinel-2 MSI.

The ntree values of 500 to 10000 and the mtry values of 1 to 7 were used for Landsat 8. The OOB error rate produced by Landsat 8 ranged from 22.0 to 23.75. The lowest OOB error rate produced by Landsat 8 OLI was 22.0 from the combination of mtry value of 3 and ntree of 1000 and the highest OOB error produced by Landsat 8 OLI was 23.75 produced from the mtry and ntree combination of 7 and 8000 (Figure 6).

For Sentinel-2, the ntree values used were 500 to 10000 and the mtry values of 1 to 10. The OOB error rate produced by Sentinel-2 ranged from 10.5 to 13.0. Sentinel-2 produced the highest OOB error of 13.0 from the mtry value of 2 and ntree value of 9000. It produced the lowest OOB error rate of 10.5 from the combination of mtry value of 10 and the ntree value of 10000 (Figure 7).

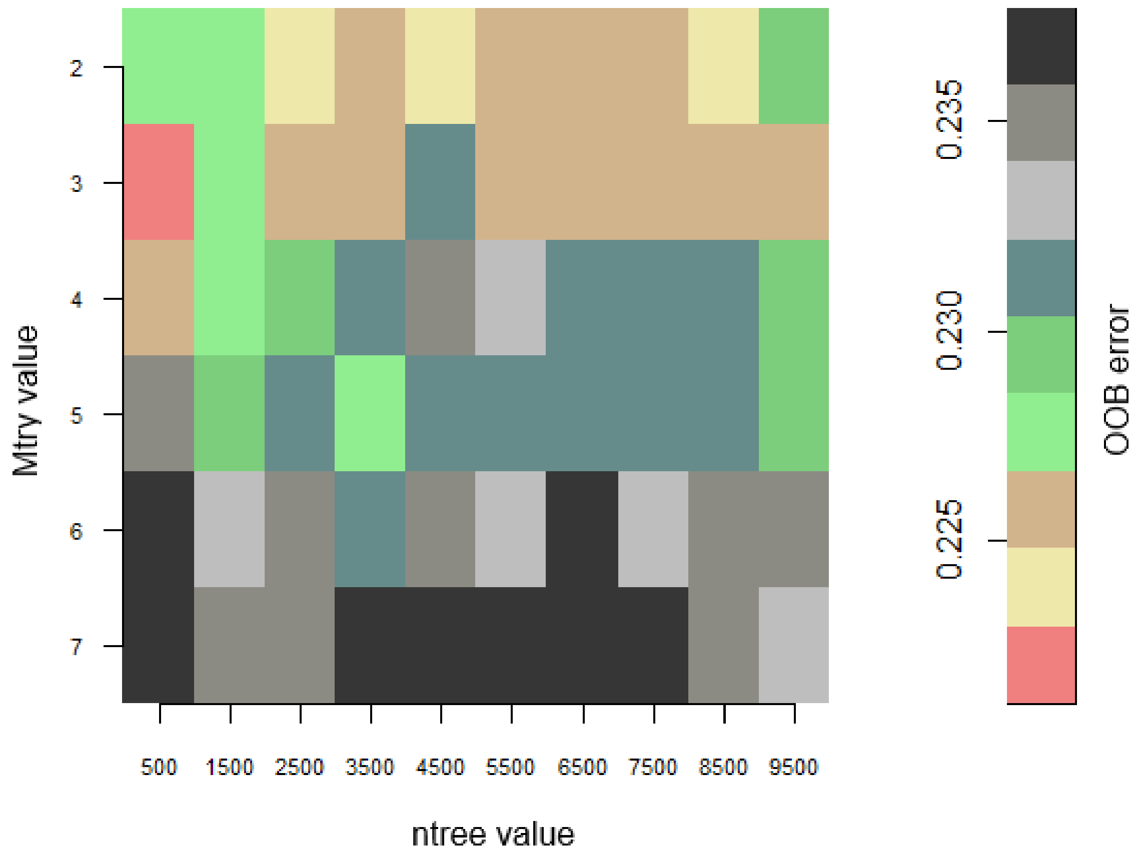

Figure 6: Random Forest optimisation of parameters (mtry and ntree) of Landsat 8 OLI

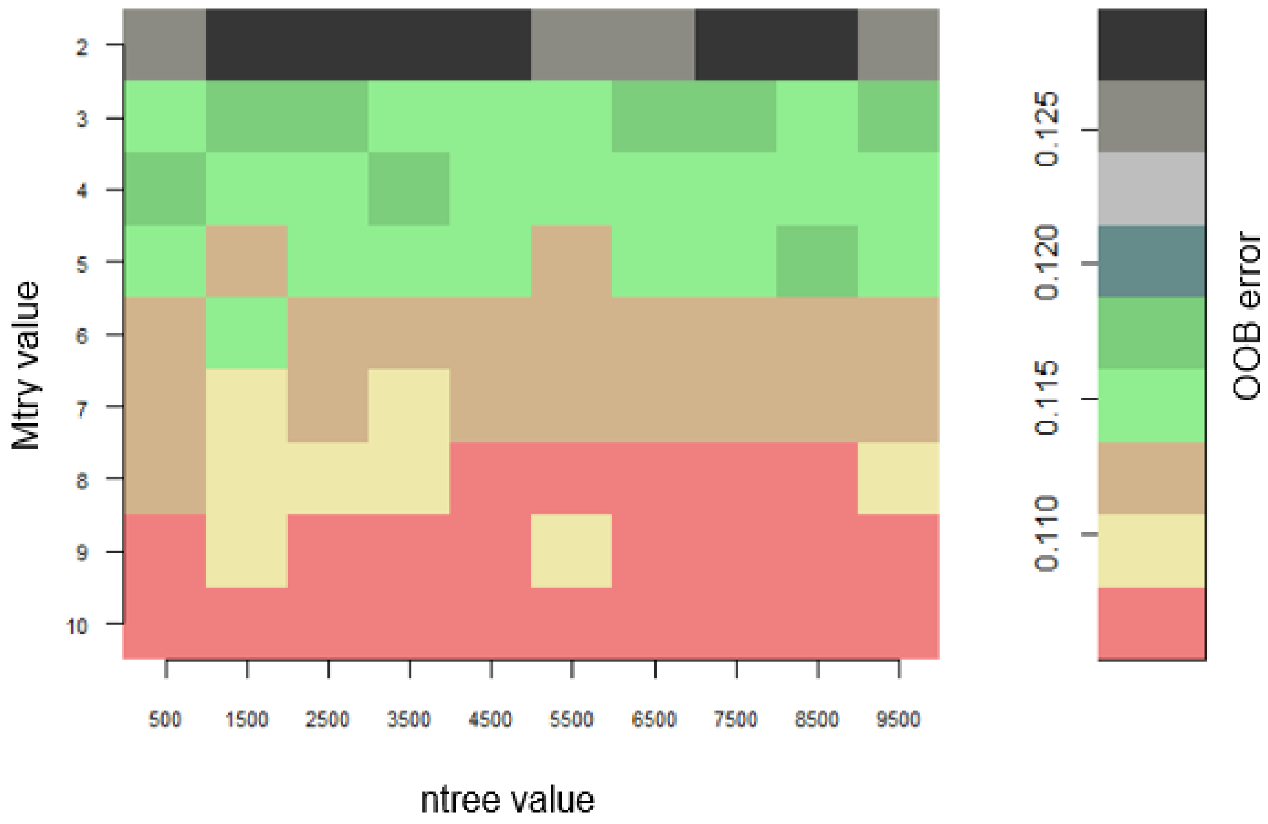

Figure 7: Random Forest optimisation of parameters (mtry and ntree) of Sentinel 2 MSI

4.4 Accuracy assessment

4.4.1 Accuracy assessment of Landsat 8 OLI in classifying different crops

The results show that Landsat 8 produced the overall accuracy of 77.08% and kappa coefficient of 70.72%. Over 70% of producer's accuracy was achieved by Macadamia nut and the other classes achieved average accuracy (50% to 60%) in Landsat 8 image (Table 3). It further achieved over 80% of the user's accuracy in Macadamia nut (Table 3). Amongst all the other crop classes, Macadamia nut produced the highest user and producer's accuracy of 81.2% and 78.4% respectively. Mango produced the lowest user's accuracy of 50.0% and the lowest producer's accuracy was produced by Maize (52.9%) in all the crop classes in Landsat 8 (Table 3).

4.4.2 Accuracy assessment of Sentinel-2 MSI

Results show that Sentinel-2 MSI produced higher accuracy compared to the Landsat 8 OLI. The overall accuracy produced by the Sentinel-2 image was 87.04% with a kappa coefficient of 83.56%. Majority of the crops (Avocado, Banana and Macadamia nut) achieved over 70% of the user's accuracy (Table 4). Over 70% of the producer's accuracy was achieved by majority of crop classes (Banana and Macadamia nut) (Table 4). Macadamia nut achieved the highest user's and producer's accuracy (80.9% and 86.4%) as compared to the other crop types classes. The lowest user's and producer's accuracy were produced by Maize (60.0% and 52.9%) in the Sentinel-2 image.

The overall classification results show that user's accuracy and producer's accuracy of Sentinel-2 MSI crop mapping results were better than that of Landsat 8 OLI. In general, Sentinel-2 performed better in all crop classes than Landsat 8. Both sensors performed well and achieved high accuracy in classifying Macadamia nut. However, differences were observed in terms of the crop mapping that had the lowest user and producer's accuracy in both sensors. This was caused by some crop pixel that were incorrectly classified as other crop classes. Table 3 and 4 shows the confusion matrix with further details of the accuracy assessment of both Sentinel-2 MSI and Landsat 8 OLI for all the 8 classes.

Table 3: Landsat 8 OLI confusion matrix

Classes	Avo	Ban	Bui	Mac	Mai	Man	Veg	Wat	Sum	Producer accuracy (%)
Avo	**9**	4	2	1	1	1	1	0	19	**55.0**
Ban	4	**19**	4	3	0	2	2	0	34	**57.1**
Bui	4	6	**136**	2	2	1	0	2	153	**93.8**
Mac	0	3	0	**69**	1	0	6	6	85	**78.4**
Mai	0	0	2	2	**8**	1	2	0	15	**52.9**
Man	3	2	0	1	0	**5**	0	0	11	**54.6**
Veg	0	1	0	6	5	1	**74**	0	87	**87.1**
Wat	0	0	1	4	0	0	0	**21**	26	**72.4**
Sum	20	35	145	88	17	11	85	29	**430**	
User accuracy	**52.4**	**60.6**	**90.1**	**81.2**	**56.3**	**50.0**	**86.0**	**80.8**		

Overall accuracy (%): 77.08
Kappa: 0.71

Table 4: Sentinel-2 MSI confusion matrix

Classes	Avo	Ban	Bui	Mac	Mai	Man	Veg	Wat	Sum	Producer accuracy (%)
Avo	**12**	2	0	0	0	0	0	0	14	**60.0**
Ban	2	**25**	2	0	0	4	0	0	33	**71.4**
Bui	1	2	**142**	0	0	0	0	0	145	**97.9**
Mac	3	4	0	**76**	7	0	3	1	94	**86.4**
Mai	0	0	0	3	**9**	0	0	3	15	**52.9**
Man	2	2	1	0	1	**9**	0	0	15	**69.2**
Veg	0	0	0	6	0	0	**82**	0	88	**96.5**
Wat	0	0	0	3	0	0	0	**25**	28	**86.2**
Sum	20	35	145	88	17	13	85	29	**432**	
User Accuracy	**85.7**	**75.8**	**97.9**	**80.9**	**60.0**	**60.0**	**93.2**	**89.3**		
Overall accuracy:	**87.04**									
Kappa:	**0.84**									

CHAPTER FIVE

DISCUSSION

5.1 Discussion

The importance of crop production monitoring cannot be overemphasized and this is because crop production plays an important role in the food production which caters for food security and the economic growth of the country (Massey *et al*., 2017). Traditional methods were mostly used for crop monitoring and mapping in the past. Today, the focus has shifted to a more advanced method such as remote sensing in crop mapping. Remote sensing is mostly preferred because of the advantages it offers in monitoring crop production. Remote sensing data has been used successfully in crop mapping, for example, most studies have used multispectral remote sensing data in mapping crops and achieved better results (Ouzemou *et al*., 2018; Demarez *et al*., 2019 & Sun *et al*., 2019). This has made multispectral remote sensing data to receive more attention in crop mapping (Immitzer *et al*., 2016 & Orynbaikyzy *et al*., 2019) than the finer spatial resolution remote sensing data (e.g. hyperspectral remote sensing) because of their availability, cost effectiveness and users knowledge and experience (Li *et al*., 2014). This study has assessed the potential of both Landsat 8 OLI and Sentinel-2 MSI in mapping crop types. The study also aimed at examining the distribution pattern of crops in Levubu area of the Limpopo Province, South Africa, using remote sensing.

5.1.1 Potential of Sentinel 2 and Landsat 8 in determining the spatial distribution of different crops in Levubu

The findings of this study show that both sensors were able to produce an accurate result in mapping crop types in the Levubu area. However, Sentinel-2 MSI classification results were better compared to Landsat 8 OLI classification results as indicated in Table 3 and 4. Similar results were also obtained by the study conducted by Forkuor *et al*. (2018). Forkuor *et al*. (2018) study also found that Sentinel-2 MSI performed and produced better results than Landsat 8 OLI. The results demonstrate the potential of Sentinel-2 in distinguishing different crops and other classes in the classification process (Nomura & Mitchard, 2018 & Sun *et al*., 2019). Although the overall user and producer’s accuracy of both sensors were slightly different, they were relatively high, indicating the capability of remote sensing sensors in mapping crop types in the Levubu farming area. RF classifier was also able to map and distinguish all the crop classes and the other LULCC in Sentinel-2 MSI and Landsat 8 OLI images. This shows that RF has the ability to produce accurate results in mapping crop types in different landscapes as also observed by Nomura & Mitchard (2018) and Saini & Ghosh (2018).

The overall accuracy result of Sentinel-2 MSI and Landsat 8 OLI were satisfying, however some studies have found that the overall accuracy results can be improved by using vegetation texture and indices. For example, (Nomura & Mitchard, 2018 & Ouzemou *et al*., 2018) used NDVI in mapping heterogeneous agricultural landscape. The authors observed that Landsat 8 and Sentinel-2 achieved an overall accuracy of over 80% and 95% respectively using vegetation indices. Their results are better as compared to the overall accuracy achieved in this study. Furthermore, the finding shows that using vegetation indices can improve the overall classification accuracy results of both sensors.

In this study Sentinel-2 bands such as Red, Blue and Green performed better than the other bands such as all the vegetation Red edge bands, SWIR and NIR. The performance of bands in Sentinel-2 could have been caused by the differences in spatial resolution of the Blue, Red, Green and NIR bands, which is 10 m as compared to the other bands that performed poorly. This results differ from the findings in other studies, for example, Forkuor *et al*. (2018) found that Sentinel-2 MSI Red edge bands played an important role in classification of different crop’s land-use and land-cover mapping. The Red edge bands in Forkuor *et al*. (2018) study improved classification results. Forkuor *et al*. (2018) further observed that the use of Sentinel-2 Red edge bands improved classification results than other Sentinel-2 bands and Landsat 8 bands. The poor performance of Red edge bands in this study suggest that there could be factors leading to this results. Some of the factors could be the season or time at which the images were acquired corresponding to ground data acquisition. Images for this study were acquired during the rainy period were all the vegetation and crops were green meaning that spectral reflectance of different crops are likely to be related.

5.1.2 Determine the potential of the RF algorithm in classifying different crops using different remote sensing datasets

This study has demonstrated the effectiveness of RF in classifying different crops in Levubu area. The findings of this study also indicated that Sentinel-2 and Landsat 8 images were successfully classified with accurate results obtained using RF. Several literatures reviewed in this study indicated that RF achieved better results in classifying crops using remote sensing data (Reynolds *et al*., 2016; Ouzemou *et al*., 2018 & Saini & Ghosh 2018). These studies found that RF was able to discriminate different crops, the same results were also found in this study in both Landsat 8 and Sentinel-2 images. The study observed that different crops are distributed differently in Levubu area. For example, Macadamia nut are distributed in large part of Levubu area followed by Banana, Avocado, Mango and Maize respectively. Both images show that plantation crops (Macadamia, Banana, Avocado, and Mango) occupy a larger area in average than the other crop such as Maize. This shows that tree plantation crops cover a larger area than the other crops in Levubu.

CHAPTER SIX

CONCLUSION

6.1 Conclusion

Remote sensing has been observed to be a reliable method in mapping crop types for a farming area with heterogeneous crop farming like the Levubu farming area. It has been proven that it is reliable, covers larger areas and can access inaccessible areas. This study and some others have successfully mapped crops, in general, using Sentinel-2 and Landsat 8 sensors. The two sensors are mostly preferred because of their high resolution, availability and ability to map and distinguish different crop classes. The objectives of this study were achieved by determining the spatial distribution of crop types using the RF classifier. Also, Sentinel-2 MSI has been proved to perform better than Landsat 8 OLI in this study as part of the objectives. It has demonstrated the potential to map the spatial distribution pattern of crops in Levubu area as a result of its fine resolution of 10 m, which enabled for the detection of smaller objects. These characteristics make Sentinel-2 MSI suitable to map and detect the distribution pattern of crop types in Levubu area.

Landsat 8 OLI imagery also demonstrated its potential of determining the spatial distribution of crop types in Levubu area despite its spatial resolution of 30 m which is lower than that of Sentinel-2. The shortcoming of Landsat 8 was that it could not detect other crops classes well (i.e. Mango) even with its advantage of increased radiometric resolution and other spectral characteristics. The performance of both sensors user and producer’s accuracy achieved in this study were over 50%. Furthermore, Sentinel-2 MSI overall accuracy, user’s and Producer’s accuracy results were also better than Landsat 8 OLI. The use of Sentinel-2 is therefore recommended for more accuracy and increased details in mapping crops in Levubu area.

The most important bands that were demonstrated by RF in mapping crops in Levubu area were different in Sentinel-2 as compared to the performance of Red edge bands in other studies. Red edge bands have been proved to play a very important role in mapping crops. However, the findings of this study indicate that the red edge bands performed poorly in the classification process of Sentinel-2. This is found to be more interesting as they differ with the findings of other studies in mapping crop. Therefore, more studies need to be done to test the performance of Red edge bands in mapping crop types using Sentinel-2 MSI in Levubu area. The results of this study indicated that the time at which the image was acquired played an important role in the overall accuracy. This shows that the quality of the image used in the study is very important as opposed to the quantity. In this study, ground data was collected during summer season on 29 December and the satellite images were acquired during the time that corresponds with the ground data collection. Image acquisition dates could be one of the factors that lead to misclassification in some crop classes (i.e. Mango). The results of this study has demonstrated the usefulness and applicability of remote sensing sensors such as Sentinel-2 and Landsat 8 in crop mapping.

6.2 Limitations

Most of the images that correspond with the acquisition date of the ground data had cloud, this caused limitation in acquiring cloud free imagery data that covers the study area properly. Accessibility in collecting ground data in some parts of Levubu area was a challenge in that the routes were poor and some were gated. As a result, the researcher collected data only in accessible areas. The study was also limited in terms of literature reviews. There were only few literatures that used Sentinel-2 & Landsat 8 images in mapping crops in subtropical areas. As a result, there were not enough articles to compare the results of this study.

6.3 Recommendations

The study recommends that several factors be considered when mapping crop types in Levubu area to improve the overall performance of Landsat 8 and Sentinel-2, firstly if crop mapping is to be done during December period, the use of multiple dataset and multi-date dataset should be considered, Secondly, fusion of images with different resolution and using vegetation indices should also be considered in Levubu area as it has been proved to increase the overall accuracy of classification results, Lastly more studies should be done in mapping crop type in different seasons and months in Levubu area to test if time factor plays a role in the performance of RF in Sentinel-2 and Landsat 8 datasets.

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