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Estimating maize grain yield from crop growth stages using remote sensing and GIS in the Free State Province, South Africa

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Clearance by Supervisor

I certify that the content of this dissertation was done by the undersigned student and has not been previously submitted to any other university for an award of a qualification either in part or in its entirety.

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Abstract

Early yield prediction of a maize crop is important for planning and policy decisions. Many countries, including South Africa use the conventional techniques of data collection for maize crop monitoring and yield estimation which are based on ground-based visits and reports. These methods are subjective, very costly and time consuming. Empirical models have been developed using weather data. These are also associated with a number of problems due to the limited spatial distribution of weather stations. Efforts are being made to improve the accuracy and timeliness of yield prediction methods. With the launching of satellites, satellite data are being used for maize crop monitoring and yield prediction. Many studies have revealed that there is a correlation between remotely sensed data (vegetation indices) and crop yields. The satellite based approaches are less expensive, save time, data acquisition covers large areas and can be used to estimate maize grain yields before harvest. This study applied Landsat 8 satellite based vegetation indices, Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Moisture Stress Index (MSI) to predict maize crop yield. These vegetation indices were derived at different growth stages. The investigation was carried out in the Kopanong Local Municipality of the Free State Province, South Africa. Ground-based data (actual harvested maize yields) was collected from Department of Agriculture, Forestry and Fisheries (DAFF). Satellite images were acquired from Geoterra Image (Pty) Ltd and weather data was from the South African Weather Service (SAWS). Multilinear regression approaches were used to relate yields to the remotely sensed indices and meteorological data was used during the development of yield estimation models. The results showed that there are significant correlations between remotely sensed vegetation indices and maize grain yield; up to 63% maize yield was predicted from vegetation indices. The study also revealed that NDVI and SAVI are better yield predictors at reproductive growth stages of maize and MSI is a better index to estimate maize yield at both vegetative and reproductive growth stages. The results obtained in this study indicated that maize grain yields can be estimated using satellite indices at different maize growth stages.

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Dedication by candidate

This dissertation is dedicated to my late father, my mother and siblings.

Acronyms

NGO:	Non-Governmental Organization
NDVI :	Normalized Difference Vegetative Index
SAVI :	Soil Adjusted Vegetative Index.
MSI :	Moisture Stress Index.
RMSE:	Root Mean Square Error
DAFF :	Department of Agriculture, Forestry and Fisheries
GIS :	Geographic Information Systems.
USGS:	United States Geological Survey.
NIR :	Near Infrared.

CHAPTER 1: INTRODUCTION

1.1 Background

Monitoring crop condition and crop yield forecasting are important for agriculture and economic departments at state, national and even international levels (XIJIE, 2013). Maize is an economically important crop; it serves as valuable human food in many regions of the world. In developing countries, like South Africa, maize is consumed directly and serves as staple diet for over 200 million people (DAFF, 2003). Yield potential of maize is essentially dependent on environmental conditions under which it is planted (i.e. the amount of intercepted radiation, water and nitrogen supply) (Robertson et al*.,* 2000). Planting time of maize is known to influence yield through the effect of environmental conditions on canopy production function and maize development processes (Birch et al., 2000). Maize yield potential varies according to location, due to different growth conditions (Birch et al*.,* 2000). Identification and evaluation of the environmental factors contributing to year-to-year fluctuation in maize yields can provide a basis for the assessment of production risk (i.e. getting low yield than the potential yield) and for adjustment in management practices to reduce this risk (Raymond, 2007). Weather, particularly rainfall and temperature during the growing season, are the major determinants of maize yield. Management activities can be planned to maximize yields provided environmental conditions of a particular area are known (Raymond, 2007). Understanding environmental conditions of an area can help in planning the planting dates of maize as mentioned that maize production depends on weather conditions.

Optical remote sensing techniques, in particular, are well suited for agricultural applications (precision agriculture), because the techniques are able to provide information on the actual status of maize crop at different growth stages via their spectral signatures (Ruiz et al., 2004). Yield forecasting around the world is done with crop simulation models, remote sensing, statistical techniques, scouting reports, and combinations of these methods (Guindin-Garcia, 2010). Scouting reports or sampling agricultural field is a reliable way to estimate yield, however; this method is time-consuming, costly and does not allow yield estimates before harvest. In contrast, data obtained from remote sensing and simulation models allow government agencies, private industry, and researchers to estimate yield before harvest (Guindin-Garcia, 2010).

Previous studies focused their analysis on two major techniques. The first technique relates vegetation indices (VIs) with a final yield at a specific growth stage (e.g. vegetative or reproductive) during the growing season (Shanahan et al., 2001; Lobell et al., 2002; Martin et al., 2007). This technique helps in identifying the best stage to estimate maize yields, thus, giving food markets enough time on price planning. The second technique relates to the final yield with cumulative values of Vegetation Index (e.g. Normalized Difference Vegetation Index) obtained during the entire growing season (Labus et al., 2002; Mkhabela et al., 2005; Wall et al., 2008). This technique leads in estimating maize gain yields after harvest, which is time-consuming to policy and decision makers. Therefore, this technique is not relevant as it is similar to ground-based techniques. Monteith (1972), introduced one form of agro-meteorological yield model that defines the relationship between light use efficiency (LUE) and biomass production. This approach makes use of observations of the fraction of absorbed Photosynthetically Active Radiation (fPAR) at different crop stages; it converts the amount of usable energy intercepted by the vegetation canopy to crop-specific biomass production (Alganci et al., 2013). This technique also lends itself well to satellite-based estimates of crop because light absorption by plants is the key driver of crop growth during the growing season and can be directly measured over large areas using remote sensing (Field et al., 1995).

Regional maize growth estimates based on field reports are often expensive, prone to errors, and cannot provide real-time, spatially explicit, estimates or forecasting of maize condition (Bing-fang et al., 2007). Acquiring the maize growing condition information at early stages of maize growth is even more important than acquiring the exact production after harvest. This gives decision-makers and policy planners enough time to plan for maize import in case of shortage and export in case of surplus. Estimating maize yield before harvest also helps food market in planning of maize price. Remote sensing and Geographic Information Systems (GIS) techniques in particular are well suited for agricultural applications, because the techniques are able to provide information on the actual status of crops at different growth stages via their spectral signatures (Ruiz et al*.,* 2004).

On the other hand, remote sensing may provide temporal information on crop growing conditions that could be related to final yield without the use of crop simulation models (Guindin-Garcia, 2010). Although satellite remote sensing has the advantage of providing spatial data over large areas, work to date using these images with spatial resolution sufficient for parcel-based analyses have been fraught with temporal resolution constraints, since daily to weekly observations are required to capture rapid changes in crop development (Alganci et al., 2013). There is also a limitation which needs to be considered when using information retrieved using remote sensing i.e. the lack of understanding of agricultural crop dynamics e.g. a better understanding of how maize yield is formed and which crop growth stage(s) is involved in determining yield, improving the accuracy of agricultural crop monitoring and enhancing final yield estimates (Doraiswamy et al., 2005).

The spectral reflectance of plants has a high correlation with the vegetation status of various crops. Research has revealed significant relationships between spectral vegetation indices and crop yields (Groten, 1993; Wiegand et al., 1991). Researchers also documented that vegetation indices are sensitive to vegetation changes in terms of physiological development and thus, they can be used as indicators of crop health, which will determine the potential yield of crops (Asrar et al., 1984; Liu et al., 2012; Myneni et al., 1995; Wang et al., 2001).

Maize is one of the most important grains in Africa and is produced throughout the continent. Maize is widely used as food in the African countries where it is grown (Obilana et al., 1980). The fresh grains are eaten roasted or boiled on the cob. The grains can be dried and cooked in combination with edible leguminous crops like cowpeas or beans. The grains can also be milled and boiled as porridge with or without fermentation. It can be baked into a form of bread. Generally, the bulk of the concentrates fed to farm animals consists of grains, and maize is the most important one in the tropics (Saunders, 1930). Maize supplies carbohydrates mainly for the release of energy for the various essential activities of farm animals.

Maize is a key crop, contributing to food security in Southern Africa, but accurate estimates of maize yield prior to harvesting season is limited An ability to predict maize yield before harvesting helps in ensuring regional food security (Kuri et al., 2014). In Southern Africa, maize yield estimates are traditionally obtained after ground surveys are done by field staff who use eyeballing and pace along the edges of the sample maize field to estimate the area under maize and expected yield (Masocha et al., 2014). South Africa also uses traditional ground-based surveys in predicting maize yields and this method cannot cover large areas. This study aims at estimating maize yield before harvest using remote sensing techniques, i.e. relating remotely sensed vegetation indices with a final yield at a specific growth stage.

1.2 The need for crop yield estimation before harvest

The main purpose of crop yield and production forecast activities is the reduction of risks (shortage and surplus) associated with local or national food systems. Accurate estimates of crop yield and prediction on regional and national scales are becoming increasingly important in developing countries and have sustained importance in developed countries (Guindin-Garcia, 2010). Yield estimation is an important issue in agro-economic planning because it optimizes price setting and storage policy on different governmental levels (Bach, 1998). Since crop yield influences prices and subsidization, it is also important at the farming level to reliably estimate its expected value as early as possible during the growing season (Bach, 1998). Realistic and timely estimates of crop yield expectations form the basis for monetary decisions in fields such as credit business and the stock exchange. The production of crops and prediction of crop yield have direct impact on year-to-year national and international economies and play an important role in the food management and food security (Prasad et al., 2005). Remotely sensed crop yield estimates greatly benefit farmers as well as researchers and policymakers concerned with food production (Sawasawa, 2003).

The agronomic variables (maturity, population density, vigour, disease, and weed infestation) can be used as yield indicators upon which crop models are based (Clevers et al., 1994). Estimating crop yield well before harvest is crucial, especially in regions characterized by climatic uncertainties (Sawasawa, 2003). This enables planners and decision makers to predict how much to import in case of shortfall or optionally, to export in case of surplus. It also enables governments to put in place strategic plans in redistribution of food during times of famine (Sawasawa, 2013). Therefore, monitoring of maize crop development, growth, and early yield prediction are generally important. With the development of satellites, remote sensing images provide access to spatial information at the field level of features and phenomena on earth on an almost real-time basis (Reynolds et al. 2000). Remote sensing technology can be used to identify and provide information on spatial variability and permit more efficiency in the field scouting (Schuler, 2002). Remote sensing could, therefore, be used for crop growth monitoring and yield estimation before harvest.

1.3 Problem statement

Crop yield estimation in many countries is based on conventional techniques of data collection, crop and yield estimation based on ground-based field surveys. Such reports are often subjective, costly, time consuming and are prone to large errors due to incomplete ground observations, leading to poor crop yield assessment and crop area estimations (Reynolds et al., 2000). In most countries the data becomes available too late for appropriate actions to be taken to avert food shortage. Objective, standardized and possibly cheaper/faster methods that can be used for crop growth monitoring and early crop yield estimation are imperative. There are difficulties in comparing statistics and validating information collected by various ground-based techniques because they use different methodologies for monitoring and measuring production. When using these traditional techniques, the availability of production estimates is only close to harvest time. These cannot cover large areas also, therefore, there is a need to use remote sensing applications to estimate maize yield from crop growth stages. There are few studies on estimating maize yield based on growth stages using remote sensing in South Africa and this study will use this technique to cover this gap. Combination of vegetation indices and meteorological data have not been used in estimating maize grain yields based on crop growth stages. Policy and decision makers cannot plan for future pricing, or plan how much maize needs to be imported or exported if they do not know the yields prior to harvest time. This study attempts to use remote sensing and GIS techniques to eliminate time taken to predict maize grain yields.

1.4 Research Aim and Objectives

1.4.1 Research Aim

The primary aim of this study is to predict maize yield before harvest based on crop growth stages using remotely sensed vegetation indices (NDVI, SAVI and MSI).

1.4.2 Specific objectives

- To characterise maize crop growth stages (vegetative and reproductive stages) based on Vegetation Indices;
- To apply regression models at different growth stages to predict maize yield; and
- To validate yield predicted from remote sensing with ground-based techniques.

1.5 Research questions

- To what extent can Vegetation Indices derived from maize during different growth stages be used to estimate the final maize yields in a growing season?
- To what extent can regression models that integrate vegetation indices and climate variables suitable to predict maize yield based on growth stages?

1.6 Hypothesis

The spectral reflectance is a manifestation of all important factors affecting the agricultural crop and cumulative environmental impacts on crop growth (Liu & Kogan, 2012; Singh et al., 2002), therefore remotely sensed data can be used to monitor maize crop conditions through vegetation indices (e.g. Normalized Difference Vegetation Index-NDVI, Soil Adjusted Vegetation Index-SAVI, or Moisture Stress Index-MSI).

1.7 Assumption

The spectral reflectance of crops is strongly related to crop growing conditions, which can be related to the final crop yield. The growing conditions are influenced by factors such as soil characteristics, cultural practices, socioeconomic factors and other biotic factors. Spectral data are an integration of all the factors affecting crop growth.

1.8 Research outline

Chapter 1 introduces the research problem, the aim and the objectives. It introduces the importance and relevance of maize yield estimation before harvest time. It discusses challenges faced by the traditional approaches to yield estimation such as field surveys, which remote sensing can overcome.

Chapter 2 provides a comprehensive review of literature with emphasis on: application of remote sensing approaches to maize yield estimation globally, the need to apply remote sensing data to predict maize grain final yield, the capability of remote sensing on maize crop monitoring and yield estimation and the applicability of different vegetation indices to predict maize yield on different growth stages.

Chapter 3 provides a detailed description of the study area and an overview of the materials and methods that were used in this study. The statistical approaches used to achieve the results obtained were discussed in this chapter.

Chapter 4 presents the results of the study. The outcomes of the research are presented in the form of tables with brief statements attached to each table.

Chapter 5 offers discussion of the results of the research. Remote sensing techniques advantages and shortfalls are discussed in this chapter. The procedures used to test the statistical significance of the results are explained with emphasis on NDVI, SAVI and MSI. The conclusion of the study is revealed based upon the analysed results.

Chapter 6 highlights the suggested suitable recommendations and policies that can be implemented to improve the yield estimation methods.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of literature with emphasis on: application of remote sensing approaches to maize yield estimation globally, the need to apply remote sensing data to predict maize grain yield, the capability of remote sensing on maize crop monitoring and yield estimation and the applicability of different vegetation indices to predict maize yield on different growth stages.

2.2 Remote sensing

Remote sensing is the acquisition of information about an object or phenomenon without being physically in contact with the object and thus, in contrast on site observation (Aggarwal, 2000**).** Remote sensors collect data by detecting energy that is reflected from an object on the Earth's surface. These sensors can be on a satellite or mounted on an aircraft. Some sensors are handheld, e.g. GreenSeeker handheld crop sensor, which is an affordable, easy-to-use measurement device that can be used to assess the health or vigour of a crop (Del Corso et al., 2010). The usual problem about handheld sensors is that they focus on one crop growth factor, e.g. GreenSeeker focuses on the application of fertilizer only (Del Corso et al., 2010). Therefore, these kinds of sensors are not useful for maize crop yield estimation because the maize yield is determined by many factors that include temperature and rainfall.

Satellite technology provides valuable information over large areas and possess temporal data collection capabilities, has been widely used in crop yields assessments in a variety of environments (Alganci et al., 2014). Remote sensing offers great potential for monitoring regional maize production (Lobell et al., 2003). Regional estimates of maize yield are desirable for managing large agricultural lands and determining food pricing and trading policies (Asner et al., 2003). The use of remote sensing has proved to be very important in monitoring the growth of agricultural crops (Prasad et al., 2006). The production of maize and prediction of maize crop yields has a direct impact on year-to-year national and international economies and play an important role in the food management and food security (Presad et al., 2006). Using remotely sensed vegetation cover as crop predictor has an advantage in a way that it also captures the effect of soil type, relief, climate, vegetation type and other socio-economic factors that influence crop performance such as management practices adopted by farmers (Kuri et al., 2014).

Remote sensing offers great potential for monitoring regional production, yet the uncertainties associated with large-scale yield are rarely addressed (Asner et al., 2003). Alganci et al., (2014) used satellite images combined with meteorological data and digital photographs to estimate maize and cotton yields. They found that the relative errors of yield estimates were under 5% in test parcels and less than 10% on a regional basis, therefore, the technique can be used to estimate maize yield. Lobell et al., (2003) used remote sensing in regional crop production in Mexico to estimate and predict uncertainties in crops, they discovered that accurate yield predictions can be achieved using only one image, provided that the image is acquired at the peak of development for most crops. Peak development stage of maize is a stage when the crop is starting to fill grains (mature stage). Lobell et al., (2003) also discovered that applications of remote sensing in different regions may need to consider additional sources of uncertainty, for example water stress, temperature variability and crop management. Various techniques based on remotely sensed data (crop models, empirical models) have been employed for assessment of crop yield (Sakamoto et al., 2013).

2.3 The spectral response of maize crops

The spectral response of the crop represents the integrated effect of all cultural, soil, and meteorological factors affecting crop growth and development (Bauer et al., 1980). When energy strikes on a surface material, it is either absorbed or reflected back through the electromagnetic spectrum. The intensity of crop reflectance is commonly greater than from most inorganic materials (Ruiz et al., 2009). Consequently, crops appear bright in the Near-Infrared (NIR) wavelengths due mostly to the sensitivity of these wavelengths to internal plant pigmentation (Soria-Ruiz et al., 2009). The visible (400-700 nm wavelengths) and NIR (700-2500 nm) region of the electromagnetic spectrum is the region at which most agriculture studies carry out measurements. This is because the spectral region includes wavelengths, which are sensitive to physiological and biological functions of crops (Lillesand, et al., 2008).

Generally, healthy vegetation will absorb most of the visible light that falls on it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum (Holme et al 1987). The spectral characteristics of healthy crops are distinctive with low reflection in blue, high in green, very low in red and very high in the NIR (Ren et al., 2010; Genc et al., 2013). In the visible part of the spectrum plants absorb light in the blue (450 nm) and red (600 nm) regions and reflect relatively more on the green portion due to the presence of chlorophyll, which is the main factor, which determines whether a plant is healthy or not (Sawasawa, 2003). In general, healthy crops are associated with high potential yield therefore, if the crop highly reflects at NIR it can be estimated that the crop will have a high potential yield. In cases where crops are subjected to the moisture stress or other conditions that make it difficult for crop growth, the chlorophyll production will decrease; this leads to less absorption in the blue and red bands, this also helps in understanding whether the crop is healthy or not (Dadhwall and Ray, 2000; de Wit and Boogard, 2001; Jansen and Huurneman, 2001; Woldu, 1997).

The canopy greenness of crops increases, either due to increasing crop density or chlorophyll content, therefore, canopy greenness is related to the percentage of red reflectance absorbed and the percentage of NIR reflected (Lillesand et al., 2008). This implies that, the reflectance spectral techniques are very suitable for providing relevant information on both crop foliar and canopy. This information could be related to nutrient status, and stress factors on the crops, which can be used to estimate the yields. These factors are some of the factors which determine potential yield of crops.

As the leaves dry out or as the crop senesce, there is a reduction in chlorophyll pigment, this results in the general increase in reflectance in the visible spectrum and a reduction in reflectance in the NIR portion of the spectrum due to cell deterioration (Sawasawa, 2013). Thus, the spectral response of a crop canopy is influenced by the plant health, percentage of ground cover, growth stage, differences in cultural practices, stress condition and the canopy architecture (Verma et al., 1998). The deferential reflection of green plants in the visible and infrared parts of the spectrum makes it possible for the detection of healthy plants from satellite data because other features on Earth's surface do not have such unique step-like characteristics in the 650-750 nm spectral range (Sawasawa, 2013). This signature is unique to green plants only thus this principle is used in vegetation indices.

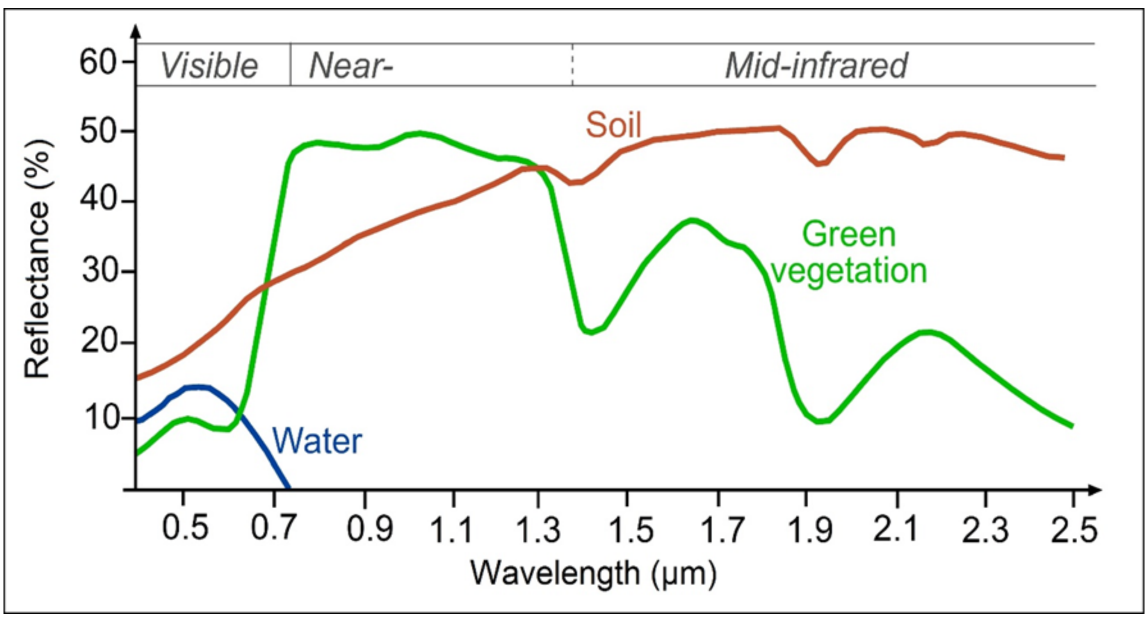

Figure 2.1: Spectral reflectance curves for soil and crop (green vegetation) according to Scotford and Miller, 2005

2.4 Vegetation Indices (VIs)

A vegetation index is an indicator that describes the greenness, the relative density and health of vegetation for each picture element, or pixel, in a satellite image. The main purpose of spectral vegetation indices is to enhance the information contained in spectral reflectance data, by extracting the variability due to vegetation characteristics and to minimize soil, atmospheric, and sun-target-sensor geometry effects (Moulin and Guerif, 1999). More specifically, VIs have been considered as measures of vegetation density or cover, photosynthetically active biomass, leaf area index, green leaf density, photosynthesis rate, amount of photosynthetically active tissue and photosynthetic size of canopies (Wiegand, 1991). The vegetation indices provide information on the state of vegetation on the land surface (Dadhwall and Ray, 2000; de Wit; Gielen and de Wit, 2001). Vegetation indices can be more useful in yield estimation because the health of crops and their densities are associated with the potential yield of crops.

Biophysical features of plants can be characterized spectrally by vegetation indices defined as radiometric measures. They are calculated as ratios or differences of two or more bands in the VIS, NIR and SWIR wavelengths. The usefulness of a vegetation index is determined by its high correlation with biophysical parameters of plants and low sensitivity to factors hampering remote sensing data interpretation, e.g. soil background, relief, nonphotosynthesizing elements of plants, atmosphere, viewing and illumination geometry (Huete and Justice, 1999). The most commonly used index is the Normalized Difference Vegetation Index (NDVI), proposed by Rouse et al. (1974) and calculated as a quotient of the difference and sum of the reflectance in NIR and red regions. Green parts of plants reflect intensively in the NIR region due to scattering in the leaf mesophyll and strongly absorb red and blue light via chlorophyll (Ayala-Silva and Beyl, 2005).

The NDVI index is used most frequently to determine the condition, developmental stages and biomass of cultivated plants and to forecasts their yields. The NDVI has become the most commonly used vegetation index and many efforts have been made aiming to develop further indices that can reduce the impact of the soil background and atmosphere on the results of spectral measurements. An example of a vegetation index limiting the influence of soil on remotely sensed vegetation data is SAVI (Soil Adjusted Vegetation Index) proposed by Huete (1988). Another, the VARI index (Visible Atmospheric Resistant Index) (Gitelson et al., 2002), strongly reduces the influence of the atmosphere. Still more have been developed to consider differences in reflectance in the NIR and SWIR ranges indicating the occurrence of lack of water for plants: MSI (Moisture Stress Index) (Reiser et al., 1986). Hamar et al., (1996) established a linear regression model to estimate corn and wheat yield at a regional level based on vegetation indices computed with Landsat MSS data. The results showed that vegetation indices are highly correlated with the crops yields.

2.4.1 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyse remote sensing measurements and assess whether the target being observed contains presence or absence of live green vegetation (Holme et al., 1987). The NDVI is closely correlated with green biomass and leaf area, and is one of the most widely used indices for agricultural monitoring (Rouse et al., 1973). This VI can be derived from various satellite data and well-understood vegetation index (de Wit and Boogard 2001). It has been found to correlate better with yields than other vegetation indices and thus, continues to be used as a vegetation indicator using remotely sensed data (Andrew et al., 2000; Mohd et al., 1994)

Studies have noted that plant development, stress, and yield potentials are expressed in the spectral reflectance from crop canopies and that crops’ growing conditions can be quantified using NDVI (Tucker, 1979; Jackson et al., 1986; Weigand and Richardson, 1990). A study by Benedetti and Rossini (1993) was the first to apply NDVI derived from remotely sensed images to grain yield assessment and forecasting. The study was based in Emilia Romagna, Italy, with simple linear regression model from 1986 to 1989. The predicted wheat yields had greater than 10% but less than 19% difference from the actual wheat yield. Labus et al., (2002) examined NDVI during wheat's growing season and estimated wheat yield at regional and farm scales in Montana from 1989 to 1997. The study found a strong relationship between actual wheat and estimated wheat yield from NDVI both throughout the whole growing season and at the grain-filling stage.

In recent years, Jianqiang et al., (2007) used NDVI from MODIS to estimate the winter wheat yield in one of the main winter-wheat-growing regions in Shandong province, China. The results showed that the relative errors of the predicted yield using MODIS-NDVI are between -4.62% and 5.40% and that whole Root Mean Square Error (RMSE) was 214.16 kg per hectare lower than RMSE (233.35 kg per hectare) of agro-climate models in the region. These results depicted that the method was good for predicting the regional winter wheat yield (Jianqiang et al., 2007).

Mkhabela et al., (2005) conducted a study to evaluate the capability of the NDVI in forecasting the maize yield and to identify the best time for making a reliable forecast in Swaziland using four agro-ecological regions. The results showed that the NDVI can be used effectively to forecast maize. The best time for making an accurate forecast was found to be from third week of January to the third week of March (grain-filling stage) depending on agro-ecological region environmental effects; therefore, yield estimation can be made 2-3 months' prior harvest. Few studies to date have examined NDVI variables with surface temperature, precipitation, and soil moisture in estimating crop yields (Prasad et al., 2006; Balaghi et al., 2008). Prasad et al. (2006) examined corn and soybean yields for the state of Iowa from 1982-2001. An average of NDVI throughout the growing season was used as the input to the model to estimate crop yields. However, these results should be treated with caution because the signs of rainfall coefficients were negative for both corn and soybean, meaning more rainfall would reduce crop yields.
Other vegetation indices have been developed to take into account the soil effect on vegetation reflectance, especially at low vegetation levels (Sawasawa, 2013). These indices provide better results than NDVI at low vegetation level because they eliminate the soil background effect, that include Perpendicular Vegetation Index (PVI), Weighted Difference Vegetation Index (WDIV), Soil Adjusted Vegetation Index, and Transformed

Soil Adjusted Vegetation Index (de Wit and Boogard 2001; Huete, 1999; Qi et al., 1994; Rondeaux et al., 1996).

Although NDVI models established by several researchers have become widely used in the application of vegetation monitoring and yield assessment, it has to be emphasized that all models have limitations. Firstly, the NDVI is less sensitive to the crop at low level, i.e. when soil surface is still exposed (Sawasawa, 2013). This means NDVI has less or no capability to eliminate soil background reflectance; therefore, it cannot be used to accurately estimate or monitor crop at a very low crop cover. NDVI results generalize the health of vegetation, i.e. doesn't count for specific causes of plants health e.g. crop moisture stress or drought (Gu et al., 2007).

2.4.2 Soil Adjusted Vegetation Index (SAVI)

The spectral reflectance of a plant (maize) canopy is a combination of the reflectance spectra of plant and soil components, governed by the optical properties of these elements and photon exchanges within the canopy (Rondeaux et al., 1995). The effect of soil brightness exerts considerable influence on the computation of vegetation indices. The reflectance of the soil background and the environment varies spatially in relation to soil structure, texture, colour, the materials, as well as soil moisture (Colwell, 1974; Rao et al., 1979; Kollenkark et al., 1982; Huete et al., 1984; Major et al., 1990). As the vegetation grows, the soil contribution progressively decreases but may remain significant, depending on plant density, row effects, canopy geometry and wind effects.

Soil background is one source of variations that has received much attention in recent years, and Soil Adjusted Vegetation Index (SAVI) has been introduced to address this issue (Gilabert et al., 2002). The soil-adjusted vegetation index was developed as a modification of the NDVI to correct for the influence of soil brightness when vegetative cover is low. SAVI minimizes the influence of soil background from sparse to dense vegetation conditions (Bausch, 1993). This is done by considering first-order soil vegetation interaction by means of a soil-adjusted parameter (L), which usually depends on the vegetation amount and has to be empirically determined, although it can also be measured or modelled. In particular, for the case of low vegetation canopy level, L = 1, at intermediate vegetation canopy level, L = 0.5 and high vegetation canopy level, L = 0 (Melia et al., 2002). SAVI is used at early stages of crops, where the soil surface is still exposed.

The main function of SAVI is to compensate for the effects of disturbing factors on the relationships between vegetation spectral reflectance as measured by crop characteristics (Panda et al., 2010). This index assumes linear relationship between near infrared and the visible reflectance from bare soil (Sawasawa, 2003). SAVI is anticipated to provide better results than NDVI at low vegetation cover because it eliminates the soil background. Although this index appears to be more reliable and less noisy than the NDVI, it is not widely used except in theoretical studies. The reason for this may be either the index's more complex formulation or the fact that it has not been convincingly demonstrated to improve on the NDVI in the assessment of vegetation parameters. For these reasons, this study focuses on testing the applicability of different vegetation indices, including SAVI in estimating maize grain yields at different growth stages (from low vegetation to high vegetation levels).

2.4.3 Moisture Stress Index (MSI)

Moisture Stress Index (MSI) is a reflectance measurement that is sensitive to increasing and decreasing of leaf water content. MSI for maize plant is a measure of the effects of drought and catastrophic wetness on crop (Champagne, 2001). This index is applied on canopy stress analysis, productivity prediction and modelling. Moisture stress, either lack or an abundance of soil moisture during critical growth stages of the crop, affects average crop yields (Champagne, 2001).

Moisture stress occurring at various vegetative and reproductive stages of growth and development of a maize crop may reduce final grain yields. The extent of grain yield reduction depends not only on the severity of the stress but also on the stage of crop development when the stress occurs (Classen and Shaw, 1971). No studies in South Africa that combine different indices including those that count for crop moisture stress or drought e.g. MSI to estimate maize grain final yields.

Lastly, previous studies either used summed NDVI values or the average across the growing season as the input for their regression models. None has examined the relationship between the change of NDVI from early season to the end of grain-filling stage and crop yield. Motivated by the above mentioned gaps from literature, this thesis attempts to use NDVI in combination with SAVI and MSI to estimate maize yield at specific growth stages in South Africa at a provincial level.

2.5 Forecasting of yield using remote sensing

Remote sensing has been used to forecast crop yields based primarily upon statistical–empirical relationships between yield and vegetation indices (Casa and Jones 2005). Information on expected yield is very important for government agencies, commodity traders and producers in planning harvest, storage, transportation and marketing activities. The sooner this information is available, the lower the economic risk, translating into greater efficiency and increased return on investments.

Walsh et al., (2012), conducted research on winter wheat, using ground-based spectra to forecast yield at the beginning of shooting stage. Many authors draw attention to the development phase of plants, as a critical component of yield forecasting (Wójtowicz et al., 2005 and Piekarczyk, 2011). For instance, the most accurate yield forecasts of winter oilseed rape were achieved when the spectral measurements were performed in the phase of full budding of the crop (Wójtowicz et al., 2005). However, Piekarczyk et al., (2011) showed that the strongest relationship between the spectral data and the winter rape yield was obtained at the beginning of the flowering stage, while wheat yields were most accurately predicted when the plants were in the shooting phase. Many studies have shown the usefulness of the NDVI index for yields forecasting (Piekarczyk et al., 2004, Wójtowicz et al., 2005, Walsh et al., 2012), but good correlations with predicted yield were also obtained for RVI (Ratio Vegetation Index) and ELAI (Estimated Leaf Area Index) indices (Wójtowicz et al., 2005). According to Piekarczyk et al., (2011), before oilseed rape flowering, the strongest correlation with yield was best when indices were calculated on the basis of reflectance in green and NIR wavelengths (550 and 775 nm, respectively). For yield forecasting, at the time of rape flowering, indices calculated on the basis of reflectance in NIR wavelengths and their logarithmic transformation were better than non-transformed spectral data (Piekarczyk, 2011).

The usefulness of aerial photographs for forecasting maize yield, using portions of the VIS and NIR ranges several times during the growing season, has been extensively studied (Chang et al., 2003). Airborne remote sensing data can substantially improve crop yield forecasting models. Launay and Guerif (2005) developed such a model that assimilates information obtained from images taken throughout the growing season. Yield estimates were improved decreasing the root mean square error (RMSE) from 20% to about 10%. The robustness of the model depended on the number and timing of images which defines the number and the type of plant biophysical parameters that can be assessed. When yield estimations were compiled for areas for which the soil was poorly characterized the forecasts generated by the model were improved (the RMSE decreased from 21% to 15%) if late in the season remote sensing data were assimilated. The study also found that the crop model was considerably less reliable in severe drought conditions. Yield predictions can be also derived based on data recorded from an UAV platform. An unmanned helicopter was used by Swain and Zaman (2013) to obtain multispectral images to estimate rice yield. With the use of a linear Wójtowicz et al., application of remote sensing methods in agriculture, regression model the study proved a high relationship between spectral data and rice yield (R^2=0.76) existed.

On a regional scale, crop yield estimation was carried out based on vegetation indices derived from AVHRR/NOAA satellite image data (Prasad et al., 2006). The model developed by the study, describing relationships between satellite spectral data and crop yield in Iowa gave high R^2 values for corn (0.78) and soybean (0.86). Dąbrowska-Zielińska et al. (2008) used the method to monitor the growth and yield of cereals on the basis of AVHRR/NOAA images in Polish conditions. The authors developed a model which estimated wheat yield (with an error RMSE=13%) on the basis of LAI and evapotranspiration indices calculated from AVHRR images. Galvão et al. (2009) studied the possibility of using satellite Hyperion hyperspectral images to estimate the yield of soybean obtaining a high correlation (r = 0.74) between vegetation indices and weight of harvested seed. The model developed by Li et al., (2008) used an artificial neural network structure and enabled the prediction of yields of maize and soybean using MODIS sensor at a regional scale. Model results produced an accuracy of 85%. Doraiswamy et al., (2004) also studied the possibility of using MODIS satellite data for forecasting yields using a calibrated form of the model developed by Li et al. (2008). Model calibration was accomplished using ground reflectance measurements. Simulated yield results were in good agreement with yields reported by USDA–National Agricultural Statistics Service (NASS) for corn and soybean with -3.12 and 6.62 percent difference, respectively. Based on the gaps discovered above, this study will use different vegetation indices in combination with meteorological data to estimate maize grain yield before harvest.

CHAPTER 3: MATERIALS AND METHODS

3.1 Introduction

The study was conducted in the Kopanong Local Municipality in Free State province of South Africa. The Kopanong Local Municipality area is situated in the southern Free State. It has the largest surface area of the three local municipalities in the Xhariep district, covering 15 190 square kilometres (44,5%). The nine towns situated in Kopanong are Trompsburg (municipal head office), Gariep Dam, Springfontein, Bethulie, Philippolis, Jagersfontein, Fauresmith, Edenburg, and Reddersburg.

During 2000/2001, according to the Low Drop Out (LDO) documents, the Kopanong population was estimated to be 53 947, with an average of 3,55 people per square kilometre. This is about 41,9% of the total Xhariep population. Of these 76,3% live in urban areas, whereas 23,7% live in rural areas. According to the latest figures received from the nine towns in Kopanong it seems as though the population density could presently be more than the figure given above. It will be updated as soon as the latest data from STATS SA becomes available.

Trompsburg, serves as the regional administrative seat within Kopanong and is situated approximately 108 km South of Bloemfontein. Access to the town is via the N1 between Bloemfontein and Colesberg. The main social & economic functions of the town include: (a) main local municipal administrative centre, (b) regional agricultural services centre, (c) regional social centre for health services, (d) social functions such as residence, education & social development services, and (e) transport support services on major routes.

The town Gariep Dam, (the youngest town in South Africa) situated alongside the N1, and is perhaps better known to most for the manmade Gariep Dam (which is the largest dam in South Africa with a radius of 360 square kilometres) which forms part of the Orange River Development Scheme. The sheer magnificence of this more than 100km long and 24km wide dam, is indeed sufficient to testify to the exceptional engineering and success of Africa's largest water supply scheme.

The Free State province lies between latitudes 26.6^0 South and 30.7^0 South and between longitudes 24.3^0 East and 29.8^0 East (Moeletsi et al., 2012). The province was selected because it is one of the main maize producing regions in the country. The province lies on a succession of flat grassy plains covered with pastureland. It reclines on a general elevation of 1158.24 metres above sea level, only broken by the occasional hills. The rich soil and pleasant climate (temperature and rainfall) allow for a thriving agricultural industry. With more than 30 000 farms, which produce more than 70% of the country's grains, it is known locally as South Africa's breadbasket (statistics South Africa, 2013). The Free State province contributes to the agricultural economy of the country with an average of 3 million tons of maize per year, which is over 30% of the national maize production (De Jagger et al., 1998; Department of Agriculture Forestry and Fisheries (DAFF), 2000). Agriculture in the province is mostly rain-fed with less than 10% of arable land under irrigation (Moeletsi et al., 2012). Geographically, Kopanong is located in the southern Free State province has the largest surface area of the three local municipalities in the Xhariep District, covering 15190 square kilometres.

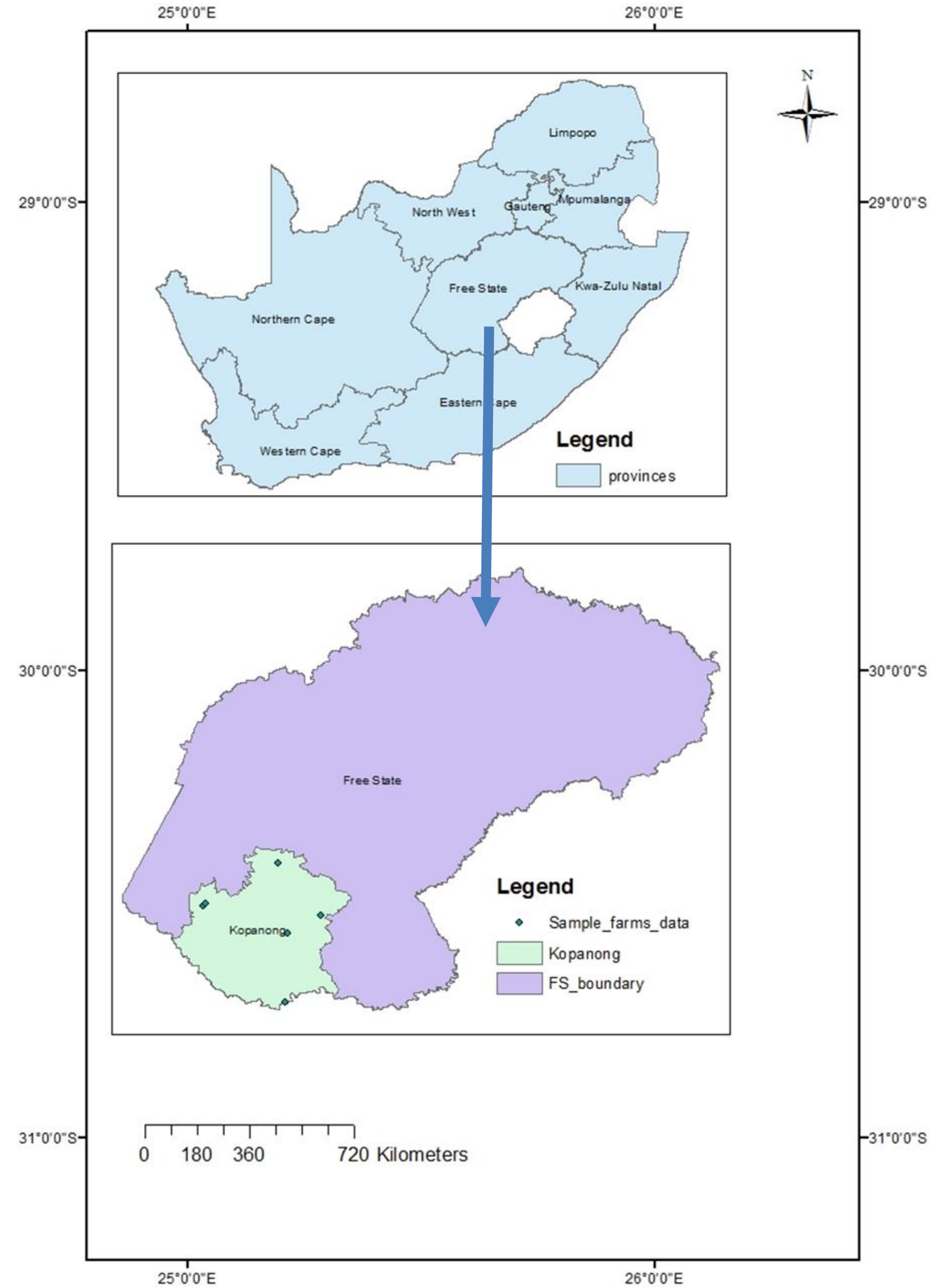

Figure 3.1: Location of the Study Area

Another reason for choosing the area is because of the temporal resolution of Landsat imagery, i.e. 16 days, the whole of Free State province could not be used for this study because Landsat imagery cannot cover the whole province within one month. Maize calendar was also used to confirm the growing period in the province and the months were covered in the available imagery. Kopanong Local Municipality had six planted farms in 2013/2014 growing season. This season was chosen based on availability of data. This information is confirmed from yield data collected from DAFF (Figure 3.1). The farm locations in the area were verified using Google Earth.

3.2 Climate

Free State province experiences a continental climate (Continental climates are climates with significant annual variation in temperature), characterized by warm to hot summers and cool to cold winters (Moeletsi et al., 2012). Areas in the East experience frequent snowfall, especially on the Drakensburg range, whilst the West can be extremely hot in summer (up to 33^0C during the day). Almost all rainfall falls in summer with brief afternoon thunderstorms, with aridity increasing towards the West (Moeletsi et al., 2012). Areas in the eastern part of the province are well watered. The average annual rainfall of the province is between 559 and 680 millimetres. The average temperatures in the province is between 31^0 C summer and 17^0 C winter (Moeletsi et al., 2012). Maize yield is affected by extreme weather conditions. Too high or too low temperatures will decrease yields and drought or floods will also decrease maize yields.

3.3 Data acquisition

Four data different sets are going to be discussed below They are:

- Remote Sensing Data;
- Maize Data;
- mage pre-processing;

3.3.1 Remote sensing data

Landsat 8 images for November – December 2013 and January – April 2014 growing seasons were collected from Geo-Terra Image. GEOTERRAIMAGE is a privately owned company, which has been providing geographical information, services and products to a wide range of public and commercial sectors, e.g. agriculture, in support of business intelligence and planning decisions since 1999. The choice of the 2013 / 2014 growing season was considered based on the availability of data. Specific months, i.e. November – April (growing season) were selected based on the maize calendar of the Free State province. These data sets were selected on the basis of cost, availability, spectral and spatial resolution of the sensor. Landsat imagery has proved to be very effective in vegetation monitoring (University of Michigan, 1979), and there is substantial reason to believe that Vegetation Indices derived from Landsat can be used in the crop yield estimation. Vegetation Indices (VIs) have been considered to be a useful way of crop yield assessment models using various approaches from simple integration to more complicated transformation (Prasad et al., 2006). Spatial resolution of Landsat TM (Thematic mapper) is 30 metres. Landsat imagery is often used for explaining plant and soil variability in agriculture because of the ability to use several spectral bands (Kumhalova et al., 2014).

The Landsat 8 imagery has four useful bands in vegetation monitoring, these are Band 2 (blue), Band 3 (green), Band 4 (red) and Band 5 (NIR). Visible light (Band 2, Band 3 and Band 4) part of the spectrum can be used to distinguish soil from vegetation. This can be done by observing the absorption of light by chlorophyll in plants and reflectance of light by soil. Band 5 (NIR), this is especially important for crops because healthy crops reflect NIR, water in the leaves scatters the wavelengths back into the sky (Curran, 1989). The optical properties in the near infrared spectral domain are explained by leaf structure. The spongy mesophyll cells located in the interior or back of the leaves reflects NIR light, many of which emerges as strong reflection rays. The intensity of NIR reflectance is commonly greater than most inorganic materials, so vegetation appears green in NIR wavelengths.

Table 3.1: Landsat 8 useful bands properties for vegetation monitoring

Band	Wavelength	Useful for mapping
Band 2 – blue	0.45 - 0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 – green	0.53 - 0.59	Emphasizes peak vegetation, which is useful for assessing plant vigour
Band 4 – red	0.64 - 0.67	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.85-0.88	Emphasizes biomass content and shorelines

Source:**http://landsat.usgs.gov/best_spectral_bands_to_use.php**.

3.3.2 Maize data

The study used actual maize yield statistics from DAFF for the growing season of 2013 / 2014. Experienced agricultural technical and extension officers through sample-based field surveys collected data on each farm within the Free State province. The data were in the form of Microsoft Excel spreadsheet in point format with coordinates, and then converted to a Shape file using Arc Map. From converted farms points ArcGIS was used to extract the six farms of the Kopanong Local Municipality.

3.3.3 Weather data

The maximum (max) and minimum (min) daily temperature data for the concerned period, i.e. 2013 / 2014 growing season were collected from the South African Weather Service (SAWS). SAWS records daily air temperatures and rainfall. This data was from the weather stations surrounding the study area. The data were necessary because the maize yield is affected by growing conditions such as temperatures and rainfall. Maize yield is very sensitive to temperatures, e.g. at very high extreme temperatures and low average rainfall we expect low yield.

3.3.4 Image pre-processing data

Image pre-processing is the process in which the correction of distorted or degraded data is performed, create a more meaningful representation of the original scene (Lillesand et al., 1999). This process consists of processes aimed at improving the ability to interpret qualitative and quantitative image components. The main purpose of image pre-processing is to eliminate data registration errors. Pre-processing of images has been performed before the actual processing of images. Image pre-processing involved geometric correction, radiometric correction and noise removal (Thillou et al., 2004). Image restoration process is highly dependent upon the characteristics of the sensor. The images from Geo-Terra Images were already georeferenced with South African projection UTM WGS84. Therefore, there was no further image pre-processing required.

3.4 Vegetation indices

Of all six farms that were in the Kopanong Local Municipality during the growing season 2013 / 2014, vegetation indices were calculated on Landsat 8 images. NDVI (appendix 1, 4, 7, and 10), SAVI (appendix 2, 5, 8, and 11) and MSI (appendix 3, 6, 9, and 12) were calculated from 04/11/2013 (appendix 13), 06/12/2013 (appendix 14), 23/01/2014 (appendix 15) and 28/03/2014 (appendix 16) Landsat 8 images. NDVI was calculated to understand the state of vegetation on leaf surface, i.e. greenness and the health of the maize crop throughout the growing season (Holme et al., 1987). SAVI was calculated to take into account the soil effect on maize crop reflectance, especially at low vegetation level (Sawasawa, 2013). MSI was used to estimate the leaf water content at canopy level, this index is useful in monitoring drought and early warning of water stress (Gao et al., 2007). The above-mentioned indices were calculated as follows:

$$\text{NDVI} = \frac{NIR-Red}{NIR+Red} \quad (1)$$

$$\text{SAVI} = \frac{NIR-Red(1+L)}{NIR+Red} \quad (2)$$

$$\text{MSI} = \frac{MidIR}{NIR} \quad (3)$$

Where NIR is a Near Infrared band, Red is red band and MidIR is a Mid-Infrared band of the electromagnetic spectrum.

These indices were calculated using ERDAS IMAGINE software. They were automatically calculated in an automated index calculator. The results for index were extracted using ArcGIS software commands and put into spreadsheet to generate regression model. The main purpose of calculating these results was to; 1) understand the growing conditions of maize crop throughout the growing season and, 2) to identify the index which best correlate with grain yield throughout the growing season. Thus, the above-mentioned two facts were trying to answer the first and second question, i.e. can vegetation indices obtained from maize during different growth stages be used to accurately estimate the final maize yields in a growing season? And, which vegetation index correlates well with grain yield throughout the season?

Due to the unavailability of Landsat 8 images of February and April that covered Kopanong Local Municipality during growing season 2013/2014, February and April were not used in the study.

3.5 Statistical data analysis

Actual maize grain yields were regressed on vegetation indices (NDVI, MSI and SAVI), rainfall and temperatures (as predictors). The regression analysis was repeated at different maize growth (vegetative and reproductive) stages. The main purpose of regression model was to; 1) check whether the vegetation indices obtained from maize during different growth stages are suitable to accurately estimate the final maize yields in the growing season, 2), to identify the vegetation index that best correlate with the maize grain yield throughout the growing season, and 3) to identify the stage in which maize grain yield can be accurately estimated. The multi - regression model was used to answer the above-mentioned questions. The coefficient of determination (R^2) was used to check the goodness of fit of the model. The values of R^2 range from zero to one, with zero indicating that the proposed model does not improve prediction and one indicating perfect prediction (Prasad et al., 2006). Improvement in the regression model results in proportional increases in R^2. Random resampling was performed to increase the sample size from 6 points to 90 points. This was done to meet multilinear regression requirements i.e. to perform regression analysis 30 and above sample size are required to get meaningful results.

Table 3.2: Shows multilinear regression models performed on statistical analysis

Dependent variable	Independent variable (s)
Yield	NDVI * Maximum temperature (Max temp)
Yield	SAVI * Max temp
Yield	MSI * Max temp
Yield	NDVI
Yield	Max temp * average rainfall (Avg rain)
Yield	Avg rain
Yield	MSI
Yield	Avg rain * minimum temperature
Yield	Average temperature * NDVI

3.6 Predictive performance validation methods of the models

Model validation is one of the most important works in scientific research. The common method to validate models is to plot the measured/observed values against the predicted values and the correlation coefficient is used to validate the results (Jianqiang et al., 2008). The study used the coefficient of determination (R^2) together with root Mean Square Error (RMSE) to assess the predictive accuracy of the model. RMSE indicates the absolute fit of the model to the data, i.e. how close the observed data points are to the model's predicted values. R^2 is a relative measure of fit whereas RMSE is an absolute measure of fit. RMSE has the useful property of being in the same units as the predicted variables. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response/dependent variable, and is the most important criterion for fit if the main purpose of the model is predicting. The main purpose of this study was prediction therefore, it was ideal to choose RMSE to validate the model. The combination of different variables was used in the regression model to see if they could improve the fit of the model.

Chapter four presents results of this research exercise and presents them aided by graphs and tables as visual aids and regression and vegetation indices and meteorological data.

CHAPTER 4: RESULTS

Yield estimations of maize grain were determined for six selected farms by performing regression analysis on meteorological (temperature and rainfall) data, satellite indices and actual harvested maize yields.

4.1 Application of satellite vegetation indices derived at various maize growth stages to estimate maize yields

Throughout the growing season, the maize crop undergoes a series of different developmental stages from a seed at planting to a tall plant at harvest. These developmental growth stages are divided into vegetative and reproductive growth stages. A fundamental understanding of the growth and development processes of the maize crop is critical in order to estimate what to expect at harvest time. These developmental and growth stages are important because researchers may use them in understanding how the maize plants respond to weather conditions throughout the growing season.

In this study, different vegetative indices obtained at different growth stages together with temperatures and rainfall were major factors in models estimating maize grain yields. Different vegetation indices were derived separately for four months (November 2013, December 2013, January 2014 and March 2014) of the 2013/2014 growing season on the six farms. Regression models were applied separately with observed maize yield, three different vegetation indices (Normalized Difference Vegetation Index, Soil Adjusted Vegetation Index, and Moisture Stress Index), temperatures and Average rainfall (Avg rainfall) for each month as the main variables. The values of the different vegetation indices during the four months of 2013/2014 growing season on the six farms are shown in Table becomes 4.1

Table 4.1: Depicts the values of different vegetation indices (Normalized Difference Vegetative Index, Soil Adjusted Vegetative Index and Moisture Stress Index) in four months during 2013/2014 growing season for the six farms. 1-6 presents farm 1 - farm 6

Date	Index	1	2	3	4	5	6
Nov-13 (Vegetative stage)	NDVI	0.19	0.18	0.17	0.15	0.19	0.19
	SAVI	0.30	0.30	0.25	0.23	0.29	0.22
	MSI	1.38	1.44	1.48	1.34	1.41	1.42
Dec-13 (Vegetative stage)	NDVI	0.13	0.22	0.12	0.13	0.12	0.16
	SAVI	0.28	0.28	0.27	0.23	0.30	0.24
	MSI	1.42	1.45	1.53	1.44	1.44	1.42
Jan-14 (Reproductive stage)	NDVI	0.20	0.18	0.22	0.24	0.27	0.17
	SAVI	0.31	0.27	0.33	0.35	0.40	0.26
	MSI	1.36	1.42	1.41	1.21	1.26	1.36
Mar-14 (Reproductive stage)	NDVI	0.32	0.46	0.49	0.28	0.55	0.30
	SAVI	0.49	0.69	0.73	0.43	0.83	0.45
	MSI	1.17	1.87	1.84	1.09	1.78	1.10

The NDVI values varied from 0.15 to 0.19 (Table 4.1) in November 2013. This means that the maize crop in the region was at a yearly growth stage (Vegetative growth stage) because NDVI values increase with the increase in crop canopy. Multi linear regression analysis results between maize yields, cumulative NDVI and maximum (Max) temperature showed poor correlation in November with a coefficient of determination value of R^2 =0. 13 and p = 0.003 (Table 4.2).

Table 4.2, presents regression model results between observed maize yields, remotely sensed data (NDVI) and maximum temperature during four months of 2013/2014 growing season.

Table 4.2: Multi linear regression results between maize yields and cumulative Normalized Difference Vegetative Index (NDVI), Maximum temperature for four months on 2013/2014

Month	R	R^2	p-value
November (vegetative stage)	0.35	0.13	0,003
December (vegetative stage)	0.31	0.09	0,012
January (reproductive stage)	0.73	0.54	0,000
March (reproductive)	0.72	0.40	0,000

The Soil Adjusted Vegetation Index (SAVI) values in November were higher than that of NDVI, ranged from 0.23 to 0.30 (Table 4.1).

The regression model results between actual maize grain yields, SAVI and maximum temperature were similar to NDVI results. There was better relationship between SAVI, maximum temperature and maize grain yields in January with $R^2 = 0.52$ (Table 4.3). In all four months, regression results showed high significances judging from small p values.

Table 4.3: Multi linear regression results between maize yields, cumulative Soil Adjusted Vegetative Index, and Maximum temperature in four months of 2013/2014 growing season

Month	R	R^2	p-value
November (vegetative stage)	0.35	0.13	0.003
December (vegetative stage)	0.26	0.07	0,04
January (reproductive stage)	0.73	0.52	0,001
March (reproductive stage)	0.72	0,53	0,000

Values of Moisture Stress Index (MSI) ranged from 1.30 to 1.50 (Table 4.1).

NDVI and SAVI yielded similar results when regressed with meteorological (temperature) data in all four months (November 2014, December 2014, January 2014 and March 2014). Therefore, these vegetative indices can be used interchangeably to estimate maize grain yields in these four months.

The regression model results between actual maize grain yields, MSI and maximum temperature during four months of 2013/2014 growing season are shown in Table 4.4. In November there was better correlations between MSI, maximum temperature ($R^2 = 0.55$). However, the results were not significant ($p>0.05$). All other three months, there were poor correlations with significant results.

Table 4.4: Multi linear regression results between maize yields and cumulative Moisture Stress Index (MSI), maximum temperature in four months of 2013/2014 growing season

Month	R	R^2	p-value
November (vegetative stage)	0.23	0.55	0.09
December (vegetative stage)	0.36	0.13	0.002
January (reproductive stage)	0.47	0.22	0.00002
March (reproductive stage)	0.51	0.26	0.00012

There were noticeably poor correlations between actual maize, MSI and Max temperature in all four months. The p-values were significant in December, January and March (Table 4.4). The small p-values showed that the predictors (Max temp and NDVI) were a meaningful addition to the regression model.

NDVI values in December were similar to November NDVI values; they varied from 0.16 to 0.22 (Table 4.1). The R^2 values were very low (Table 4.2). SAVI values were also similar to November SAVI values ranging from 0.23 to 0.30 (Table 4.1) with low R^2 value, R^2 = 0.07, p = 0.012 (Table 4.3). MSI values did not show much change too; they varied from 1.3 to 1.5 (see table 4.1) with R^2 = 0.13 and p =0.002 (Table 4.4).

There was a noticeable change in NDVI and SAVI values in January; they varied from 0.2 to 0.3 and from 0.3 to 0.4, respectively (Table 4.4). The regression models showed better correlations, R^2 = 0.54, p = 0.000 (Table 4.4) and SAVI regression results gave R^2 = 0.52

and p = 0.00 (Table 5) see table 5. MSI values showed a slight increase in January varied from 1.2 to 1.4 (Table 4.1). MSI regression analysis results showed poor correlation with R^2 =0.22 and p = 0.00012 (Table 4.4).

There was a high increase in NDVI and SAVI values in March; NDVI values varied from 0.3 to 0.6 and SAVI values varied from 0.4 to 0.8 (Table 4.1) and there was poor correlation with R^2 value of 0.40 and p-values of 0.000 for NDVI (table 4.2). R^2 = 0.53 with p=0.0000 for SAVI regression analysis results (Table 4.3). MSI values also showed increase; they were from 1.1 to 1.9 (Table 4.1), with regression correlation (R^2 = 0.26) and a small p-value of 0.00012 (Table 4.4).

Considering the R^2 values of each regression analysis performed per month, NDVI, SAVI and Maximum temperature were identified as better predictors to estimate maize yield in January (reproductive stage) with R^2 = 0.54 and 52, respectively. There was good relationship between MSI index and meteorological data in November (vegetative stage). Therefore, this index is suitable to estimate maize grain yield at vegetative growth stage. The results were significant in all four months judging from p-values obtained. This means that maximum temperature has impacts on vegetation indices. Based on the results obtained in this study, the combination of different vegetation indices was relevant. The reason for this is, the indices managed to estimate maize grain yields at different growth stages.

4.2 Testing goodness of fit of the model

Results obtained when testing the performance of the model with NDVI and temperature as variables in four months of 2013/2014 season are shown in Table 4.5.

Table 4.5: Depicts the values of Root Mean Square Error (RMSE) obtained in four months of 2013/2014 growing season for NDVI and temperature

Month	RMSE in t/ha
November (vegetative stage)	1.62
December (vegetative stage)	1.68
January (reproductive stage)	1.17
March (reproductive stage)	1.19

In all the four months (November, December, January and March), the models showed poor fit when using NDVI and maximum temperatures as grain yield predictors. This is evidenced by the large values of RMSE in these months (4.5). The models over-predicted the yields in these months.

Results obtained when testing the performance of the model with SAVI and temperature as variables in four months of 2013/2014 season are shown in Table 4.6.

Table 4.6: Depicts the values of Root Mean Square Error (RMSE) obtained in four months of 2013/2014 growing season for SAVI and temperature

Month	RMSE in t/ha
November	1.62
December	1.63
January	1.13
March	1.21

The SAVI vegetation index showed similar model fitness properties as NDVI in November, December, January and March, the values of RMSE were large in these months (Table 4.6) Results obtained when testing the performance of the model with MSI and temperature as variables in four months of 2013/2014 season are shown in Table 4.7.

Table 4.7: Depicts values of Root Mean Square Error (RMSE) obtained in four months of 2013/2014 growing season for MSI and temperature

Month	RMSE in t/ha
November	1.17
December	1.62
January	1.54
March	1.00

Model with MSI combined with maximum temperature showed poor fit in all the four months (November, December, January and March); this is evidenced by large values of RMSE obtained in these months (Table 4.7).

The different combination of variables were used to perform regression analysis to see if they could improve the fit of the model. For each month five different combinations of variables were performed. In November (vegetative stage) 2013, the results were as follows:

- $\boldsymbol{Yield = NDVI}$, results showed R^2 value of 0.029, p-value for was 0.10 and RMSE was 1.71.
- $\boldsymbol{Yield = Max\ temp + rainfall}$; R^2 =0.30, p-value =0.09 and RMSE=0.63.
- $\boldsymbol{Yield = Rainfall}$; R^2 =0.19, p-value =0.00002 and RMSE was 1.57.
- $\boldsymbol{Yield\ = MSI}$; R^2 =0.08, P-value =0.008 and RMSE=1.67.
- $\boldsymbol{Yield\ =\ rainfall\ +\ Min\ temp}$; R^2 =0.41, p-value =0.45 and RMSE =1.33.
- $\boldsymbol{Yield = NDVI + Avg\ temp}$; R^2 = 0.04, p = 0.17 and RMSE = 1.68

From the results obtained above, only one model showed better correlation. This model is Yield =Min temp + rainfall with R^2 = 041. However, the model results are significant judging from p-values, except one model.

In December (vegetative stage) the results were:

- $\boldsymbol{Yield} = \boldsymbol{NDVI}$, results showed R^2 value of 0.01, p-value was 0.29 and RMSE was 1.73.
- $\boldsymbol{Yield} = \boldsymbol{Max\ temp} + \boldsymbol{rainfall}$; R^2 =0.52, p-value =0.002 and RMSE=1.20.
- $\boldsymbol{Yield} = \boldsymbol{Rainfall}$; R^2 =0.46, p-value =0.007 and RMSE was 1.27.
- $\boldsymbol{Yield} = \boldsymbol{MSI}$; R^2 =0.10, P-value =0.001 and RMSE=1.64.
- $\boldsymbol{Yield} = \boldsymbol{rainfall} + \boldsymbol{Min\ temp}$; R^2 =0.68, p-value =0.006 and RMSE =0.98
- $\boldsymbol{Yield} = \boldsymbol{NDVI} + \boldsymbol{Avg\ temp}$; R^2 = 0.09, p = 0.01 and RMSE = 1.59.

Considering values of R^2, three models (Yield =Max temp + rainfall, Yield = rainfall and Yield = rainfall + Min temp) showed better correlations with R^2 of 0.52 and 0.46, 0.68, respectively. However, these models showed poor performances based on RMSE values. The small p-values mean that the results were significant.

In January (reproductive stage), the following results were obtained:

- $\boldsymbol{Yield} = \boldsymbol{NDV}I$, results showed R^2 value of 0.04, p-value=0.07 and RMSE was 1.70.
- $\boldsymbol{Yield} = \boldsymbol{Max\ temp} + \boldsymbol{rainfall}$; R^2 = 0.22, p-value= 0.00002 and RMSE=1.53.
- $\mathbf{Yield} = \boldsymbol{Rainfall}$; R^2 =0.04, p-value =0.07 and RMSE was 1.70.
- $\boldsymbol{Yield} = \boldsymbol{MSI}$; R^2 =0.07, P-value =0,009 and RMSE=1,67.
- $\boldsymbol{Yield} = \boldsymbol{rainfall} + \boldsymbol{Min\ temp}$; R^2 =0.04, p-value =0.16 and RMSE =1.70
- $\boldsymbol{Yield} = \boldsymbol{NDVI} + \boldsymbol{Avg\ temp}$; R^2 = 0.05, p = 0.09 and RMSE = 1.69

From above obtained results in January, none of the models showed a good correlation. In March (reproductive stage) the same model were repeated and the results were as follows:

- $\boldsymbol{Yield} = \boldsymbol{NDVI}$, results showed R^2 value of 0.05, p-value was 0.04 and RMSE was 1.69.
- $\boldsymbol{Yield} = \boldsymbol{Max\ temp} + \boldsymbol{rainfall}$; R^2 =0.22, p-value =0.008 and RMSE=1.53.
- $\boldsymbol{Yield} = \boldsymbol{Rainfall}$; R^2 =0.04, p-value =0.71 and RMSE was 1.70.

- $\boldsymbol{Yield} = \boldsymbol{MSI}$; R^2 =0.15, P-value =0.0002 and RMSE=1.60.
- $\boldsymbol{Yield} = \boldsymbol{rainfall} + \boldsymbol{Min\ temp}$; R^2 =0.04, p-value =0.16 and RMSE =1.70.
- $\boldsymbol{Yield} = \boldsymbol{NDVI} + \boldsymbol{Avg\ temp}$; R^2 = 0.12, p = 0008 and RMSE = 1.54.

In March (reproductive stage), none of the models showed good relationship, but p-values showed that the results were significant.

4.3 Comparison between ground-based (actual) yields and predicted yields

Comparisons of predicted (model-based) and observed yields arise frequently in agricultural research. This section presents the results of simulation models predicting maize grain yield from meteorological and remotely sensed data compared with actual maize yield measurements to assess the model's accuracy. Testing models predictions are a critical step in science. The purposes of these comparisons are to assess models predictive accuracy, to inform preferences among several competing models, to inform among various possible measurements serving as model inputs, and to define a range of conditions over which a model is applicable or reliable. The prediction is accurate if the difference between the predicted and actual yields is within a small range. Difference between ground-based and predicted yields obtained using NDVI and temperature as model variables in November 2013 are shown in Table 4.8.

Table 4.8: Difference between ground-based and predicted maize yields in November 2013 for models with NDVI and temperature as variables

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	4,24
4,37	4,29
2,61	5,64
4,37	5.02
6,45	5,36
8,05	5,82

T-Test statistics, results of Table 4.8 are; ground-based yield mean=5. 065, predicted yield mean=5. 062, F statistic=7. 97, t-value= 0.004045 and p-value=0. 99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p > 0.05$).

Difference between ground-based and predicted yields obtained using SAVI and temperature as model variables in November 2013 are shown in Table 4.9.

Table 4.9: Difference between ground-based and predicted maize yields in November 2013 for models with SAVI and temperature as variables

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,37
4,37	5,59
2,61	3,99
4,37	3,93
6,45	5,92
8,05	7,58

T-Test statistics, results of Table 4.9 are; ground-based yield mean = 5. 065, predicted yield mean = 5. 062, F statistic = 7. 97, t-value = 0.004045 and p-value = 0. 99. The results mean that the difference between ground-based yield and predicted yield is not significant ($p>0.05$).

Table 4.10: Difference between ground-based and predicted yields in November 2013 for models with MSI and temperature as variables.

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,76
4,37	4,10
2,61	3,66
4,37	5,79
6,45	7,03
8,05	6,04

T-Test statistics, results of Table 4.10 are; ground-based yield mean = 5. 065, predicted yield mean = 5. 063, F statistic = 1. 82, t-value = 0.001724 and p-value = 0. 99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$).

Difference between ground-based and predicted yields obtained using NDVI and temperature as model variables in December 2013 are shown in Table 4.11.

Table 4.11: Difference between ground-based and predicted maize yields in December 2013 for models with NDVI and temperature as yield variables

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	4,12
4,37	5,47
2,61	3,75
4,37	5,72
6,45	6,27
8,05	5,07

T-Test statistics results of Table 4.11 are; ground-based yield mean=5.065, predicted yield mean = 5.067, F statistic = 3.88, t-value = -0.001913 and p-value = 0.99. The results mean that the difference between ground-based yield and predicted yield is not significant ($p>0.05$). Difference between ground-based and predicted yields obtained using SAVI and temperature as model variables in December 2013 are shown in Table 4.12.

Table 4.12: Difference between ground-based and predicted maize yields in December 2013 for models with SAVI and temperature as yield predictors

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	4.12
4,37	5.47
2,61	3.75
4,37	5.72
6,45	6.27
8,05	5.07

T-Test statistics results of Table 4.12 are; ground-based yield mean = 5.065, predicted yield mean = 5.067, F statistic = 3.88, t-value = -0.001913 and p-value = 0.99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$). Difference between ground-based and predicted yields obtained using MSI and temperature as model variables in December 2013 are shown in Table 4.13.

Table 4.13: Difference between ground-based and predicted maize yields in December 2013 for models with MSI and temperature as yield estimators

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	4,71
4,37	4,69
2,61	4,29
4,37	6,26
6,45	5,09
8,05	5,34

T-Test statistics results of Table 4.13 are; ground-based yield mean = 5.065, predicted yield mean = 5.067, F statistic = 3.88, t-value = -0.001913 and p-value = 0.99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$).

In November 2013 NDVI, SAVI and MSI were used as components of maize yield estimates compared with the observed/ground-based yields. Results showed that the difference between observed and predicted yield varied from -3.02 tons per hector (t/ha) to 2.24; from -3.02 to 2.24 t/ha and from -1.64 to 3.05 t/ha for NDVI, SAVI and MSI yield estimators, respectively (Tables 4.9, 4.10 and 4.11). In the same year different date (December), the same indices were used to estimate maize yield, the results showed that the residuals ranged from -1.35 to 2.98 t/ha; -1.35 to 2.98 t/ha and -1.63 to 2.88 t/ha for NDVI, SAVI and MSI, respectively (see tables 4.12, 4.13 and 4.15. Difference between ground-based and predicted yields obtained using NDVI and temperature as model variables in January 2014 are depicted in Table 4.14.

Table 4.14: Difference between ground-based and predicted yields in January 2014 for models with NDVI and temperature as variables

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,16
4,37	4,71
2,61	4,58
4,37	5,18
6,45	5,28
8,05	7,48

T-Test statistics results of Table 4.14 are; ground-based yield mean = 5.065, predicted yield mean = 5.065, F statistic = 7.63, t-value = 0.00 and p-value = 1.00. The results mean that the difference between ground-based yield and predicted yield is no significant (p>0.05). Difference between ground-based and predicted yields obtained using SAVI and temperature as model variables in January 2014 are shown in Table 4.15.

Table 4.15: Difference between ground-based and predicted maize yields in January 2014 for models with SAVI and temperature as yield estimators

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,16
4,37	4.71
2,61	4.58
4,37	4,18
6,45	5.28
8,05	7,48

T-Test statistics results of Table 4.15 are; ground-based yield mean = 5.065, predicted yield mean = 5.065, F statistic =7.63, t-value = 0.00 and p-value = 1.00. The results mean that the difference between ground-based yield and predicted yield is no significant (p>0.05). Difference between ground-based and predicted yields obtained using MSI and temperature as model variables in January 2014 are shown in Table 4.16.

Table 4.16: Difference between ground-based and predicted maize yields in January 2014 for models with MSI and temperature

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,77
4,37	4,31
2,61	5,12
4,37	5,42
6,45	6,32
8,05	5,56

T-Test statistics results of Table 4.16 are; ground-based yield mean =5.065, predicted yield mean = 5.068, F statistic = 4.55, t-value = -0.003886 and p-value = 0.99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$). Difference between ground-based and predicted yields obtained using NDVI and temperature as model variables in March 2014 are shown in Table 4.17.

Table 4.17: Difference between ground-based and predicted maize yields in March 2014 for models with NDVI and temperature as yield estimators

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,71
4,37	3,58
2,61	3,79
4,37	5,94
6,45	6,25
8,05	7,12

T-Test statistics results of Table 4.17 are; ground-based yield mean = 5.065, predicted yield mean = 5.065, F statistic = 1.50, t-value = 0.00 and p-value = 1.00. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$). Difference between ground-based and predicted yields obtained using SAVI and temperature as model variables in March 2014 are shown in Table 4.18.

Table 4.18: Difference between ground-based and predicted maize yields in March 2014 for models with SAVI and temperature as variables

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3.71
4,37	3.58
2,61	3.79
4,37	5,94
6,45	6.25
8,05	7.12

T-Test statistics results of Table 4.18 are; ground-based yield mean = 5.065, predicted yield mean = 5.065, F statistic = 1.50, t-value = 0.00 and p-value=1.00. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$). Difference between ground-based and predicted yields obtained using MSI and temperature as model variables in November 2013 are shown in Table 4.19

Table 4.19: Difference between ground-based and predicted maize yields in March 2014 for models with MSI and temperature as yield predictors

Ground-based yield (t/ha)	Predicted (yield t/ha)
4,54	3,86
4,37	3,37
2,61	4,36
4,37	5,53
6,45	5,76
8,05	7,49

T-Test statistics results of Table 4.19 are; ground-based yield mean = 5.065, predicted yield mean = 5.062, F statistic = 1.59, t-value = 0.00 and p-value=0.99. The results mean that the difference between ground-based yield and predicted yield is no significant ($p>0.05$).

The following year in January 2014, NDVI, SAVI and MSI were also used to estimate maize yield. The results showed that the difference between ground-based and predicted yields varied from -0.82 to 0.82 t/ha when using NDVI and maximum temperature, varied from -0.82 to 0.82 t/ha for SAVI index and ranged from -2.22 to 2.75 t/ha when MSI was used to estimate yield (Tables 4.14, 4.15 and 4.16). In March the same year, the difference between observed and estimated yields was observed using the same indices i.e. NDVI, SAVI and MSI. The results showed that the differences were from –1.57 to 1.16

t/ha for NDVI, from -1.57 to 1.16 t/ha for SAVI and varied from -1.64 to 3.05 t/ha for MSI (see table 4.17, 4.18 and 4.19).

From the above obtained results there were small differences between observed and predicted maize yields in all the months (November, December, January and March). The p-values obtained in t-Test analysis between observed and predicted yields of all four months, were large ($p>0.05$). This means that there was no significant difference between observed and predicted yields. Therefore, vegetative indices and meteorological (temperatures and rainfall) parameters can be used to reliably estimate maize grain yield before harvest.

CHAPTER 5: DISCUSSION AND CONCLUSION

5.1 Discussion.

The main goal of the study was to assess the capability of satellite data (obtained at different crop growth stages) in predicting maize final yield before harvest. This was achieved by performing a regression analysis between observed grain yield, meteorological data and three satellite vegetation indices, i.e. Normalized Difference Vegetative Index (NDVI), Soil Adjusted Vegetative Index (SAVI) and Moisture Stress Index (MSI) obtained at different maize growth stages (vegetative and reproductive). The results indicated that up to 55% of maize grain yield can be predicted using a combination of satellite indices and meteorological data.

The study obtained small values of NDVI and SAVI during vegetative growth stages (November 2013 and December 2013). At reproductive (flowering) stage (January 2014) the values showed slight increase and in March 2014 (reproductive stage) NDVI and SAVI values were high. The MSI values were moderate to high from November 2013 through March 2014.

Small values of NDVI and SAVI in November 2013 and December 2013 meant that maize was at an early (vegetative) stage during these months because these indices increase with an increase in the crop canopy (Sawasawa, 2003). The slight increase of NDVI and SAVI in January 2014 indicated that maize was changing from low-level growth stage (vegetative) to reproductive (flowering) stage. Therefore, maize was at flowering stage in January 2014. The high values of vegetation indices (NDVI and SAVI) obtained in March showed that maize was at reproductive stage (grain filling). The grain filling stage is the most important stage of maize and excess rainfall or wet day during this stage can severely deteriorate the yield quality of maize. Moderate to high values of MSI obtained throughout the growing season indicated that the area in which the research took place did not experience water problems in 2013/2014 growing season.

NDVI and SAVI results obtained in this study concur with the results found by Jackson et al., (1991) when interpreting different vegetative indices of different crops, including the maize crop in Swaziland.

In the early stages of the maize crop (November and December), coefficient of determination (R^2) values of regression analysis between maximum temperature and two vegetation indices, i.e. NDVI and SAVI were low $R^2 = 0.13$ in November for both NDVI and SAVI, $R^2 = 0.09$ in December for both NDVI and SAVI. This means that NDVI and SAVI are not good yield predictors at early stages of maize growth. The R^2 values increased in January, $R^2 = 0.55$ for both NDVI and SAVI regression results. This suggests that at a high level of maize crop canopy, NDVI and SAVI are better yield predictors. Therefore, the best stages that can be used to predict maize grain yield using NDVI and SAVI are reproductive stages. These results agree with John et al., (2001) when estimating corn grain yield using remote sensing imagery in California.

The study also found that NDVI alone is not significant when predicting maize yield. This is confirmed by big p-values in each model that included only NDVI as the independent variable. The combination of NDVI with meteorological data in a model showed significant results. When the temperatures were very high (November and December) the relationship between maize yield, NDVI and temperature was very poor. The temperatures dropped in January, the relationship was better ($R^2 =0.55$) as mentioned above. This meant that temperature has an impact on the increase and decrease of NDVI values, thus, it has effects on the yield of maize.

MSI regression coefficient differed from the regression coefficient of NDVI and SAVI, MSI regression results had high values during vegetative stage (November, $R^2 = 0.55$). This means that, when MSI is regressed with maximum temperature can predict maize grain yield at the vegetative stage.

The differences in the correlations and explaining ability to yield are due to the quality of data being used and derived models (Muthy et al., 1994). Mohd et al., (1994) used yield from highly controlled research and found good correlation ($R^2 = 0.87$). From the results obtained in this study, it is evident that the quality of data may have a significant effect on the degree of the relationship between remotely sensed vegetation indices and the maize yield. The findings of this study showed that a combination of vegetation indices, i.e. Normalized Difference Vegetative Index (NDVI), Soil Adjusted Vegetative Index (SAVI) and Moisture Stress Index (MSI) and meteorological data can improve maize yield prediction at different growth stages above use of vegetation indices alone.

The results obtained in this study are in agreement with field observations that suggested that vegetation indices during vegetative and reproductive stages can be used to detect variations in maize grain yield (Gundin-Garcia, 2010). The results also confirm previous studies that suggested a close relationship between maize grain yields with vegetation indices during reproductive stage at field level (Tollenar and Aguilera, 1992; Rajcan and Tollenar, 1999a; Tollenar et al., 2004). This study established that there is a significant positive relationship between remotely sensed vegetation indices and observed maize field. Sawasawa (2003) found a positive relationship between remotely sensed NDVI and rice yield at field level ($R^2 = 0.52$, $p<0.05$).

Water shortage has a significant impact on maize grain yield. The current study used MSI to determine the impacts of water on maize yield and the results were positive in November ($R^2 = 0.54$), this means there was enough water during these months. The study also showed that the use of other vegetation indices without combining them with meteorological data to predict yield did not offer any significant improvement in explaining the yield. This suggests that the use of NDVI with meteorological data for crop growth monitoring and yield estimation is valid as reported by previous authors (Riad et al., 2006. Gat et al., (2000), also noted the correlations between vegetation indices and linear transformed, e.g. SAVI could not perform any better than the original vegetation indices, in this case NDVI and MSI and he proposed to use the original vegetation indices without any transformations.
There was no significant difference between observed and predicted maize grain yields. This suggests that the used vegetation indices in the prediction of maize yield are suitable

to explain maize yield during different growth stages. However, the models did not perform well, this is evidenced by large values of Root Mean Square Error (RMSE), that varied from 1.00 to 1.70 t/ha.

Previous studies (Teal et al., 2006; Martin et al., 2007; Solari et al., 2008) related maize yield with vegetation indices during vegetative stages. Most of the previous studies that reported a correlation between vegetation indices and maize grain final yields during vegetative stage related chlorophyll meter reading with vegetation indices, whereas this study did not consider chlorophyll readings. Previous studies also reported good correlation between remote sensing data and maize yield at reproductive stages using satellite sensors evaluating nearly entire growing season (Shanahan et al., 2001; Mkhabela et al., 2005; Baez et al., 2005). The high correlation obtained in this study was during the reproductive stage, this means that the study is similar to the previous studies.

5.2 Conclusion.

Remote Sensing and Geographic Information Systems (GIS) can be used as useful tools to predict maize grain yield at a regional level. Being intended for use by decision-makers these techniques were designed to be simple and based on readily available data. The study proved that maize grain yield can be predicted with high accuracy using regression models and information on weather (temperature and rainfall) data. The models showed high accuracy in predicting maize yield before harvest.

Remote sensing approach is an important technique for early maize yield estimation because it is based on key crop growth factors at the optimum development stage. Regression models used in this study allows delivering early maize yield forecasts in a fast and cheap way, it can be considered as a promising complement to the ground-based yield assessment.

The best time for making an accurate maize yield prediction was found to be reproductive stage (January to March). Maize harvesting in the Free State Province, South Africa, generally takes place from April to May; therefore, yield predictions can be made 1-3 months prior to harvest, thus giving the Government, NGO's, grain handlers and other food security stakeholders enough time to plan for imports in case of a deficit or exports in case of surplus. In conclusion the results mean that regression models performed on vegetation indices values and meteorological data are capable of accurately estimate maize yield at different growth stages.

CHAPTER 6: RECOMMENDATIONS

- It is recommended that the high-resolution imagery with less cloud cover is used to investigate crop yield because in some cases there are mixed-crop farms. In these cases, high-resolution imagery assists in accurately identifying individual crop types.
- In the analysis, it has been shown that other vegetation indices that takes into account soil reflectance e.g. SAVI did not perform better than the NDVI. Nevertheless, in literature these indices have been claimed to perform better than vegetation indices that do not take into account soil influences on reflectance. In view of this it is suggested that there is need to establish specific soil reflectance in the area, and apply the actual soil reflectance when dealing with Soil adjusted vegetative indices rather than using the generally applied factor of 0.5 for all the soils, and at any vegetative density.
- It is recommended that the study similar to this should use land management practices (e.g. fertilizers applied), which may have an effect on crop growth and production. It is important to assess this and incorporate into the model if found to be significant.
- It is recommended that ground truth data can be used in similar studies as ancillary data source to contribute in verifying the vegetation index values obtained from satellite images.
- Based on the results, it is recommended that the regression models must be developed for other geographical areas in South Africa, if the careful testing of the data and model assumptions is observed.

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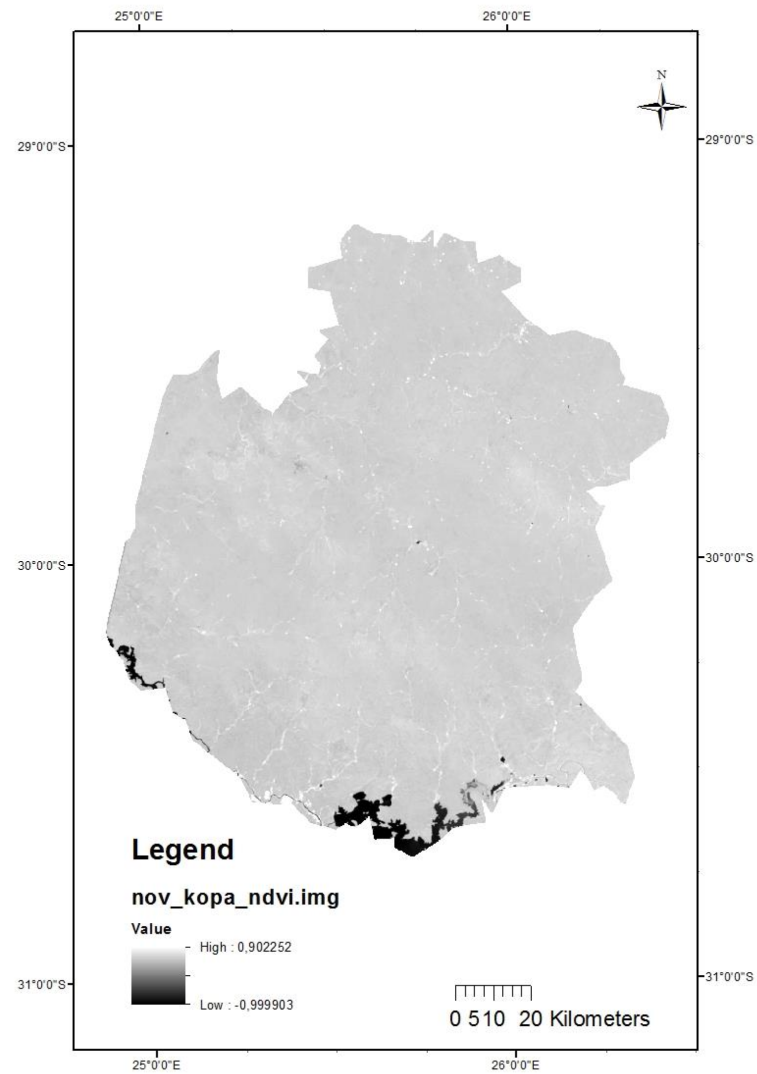
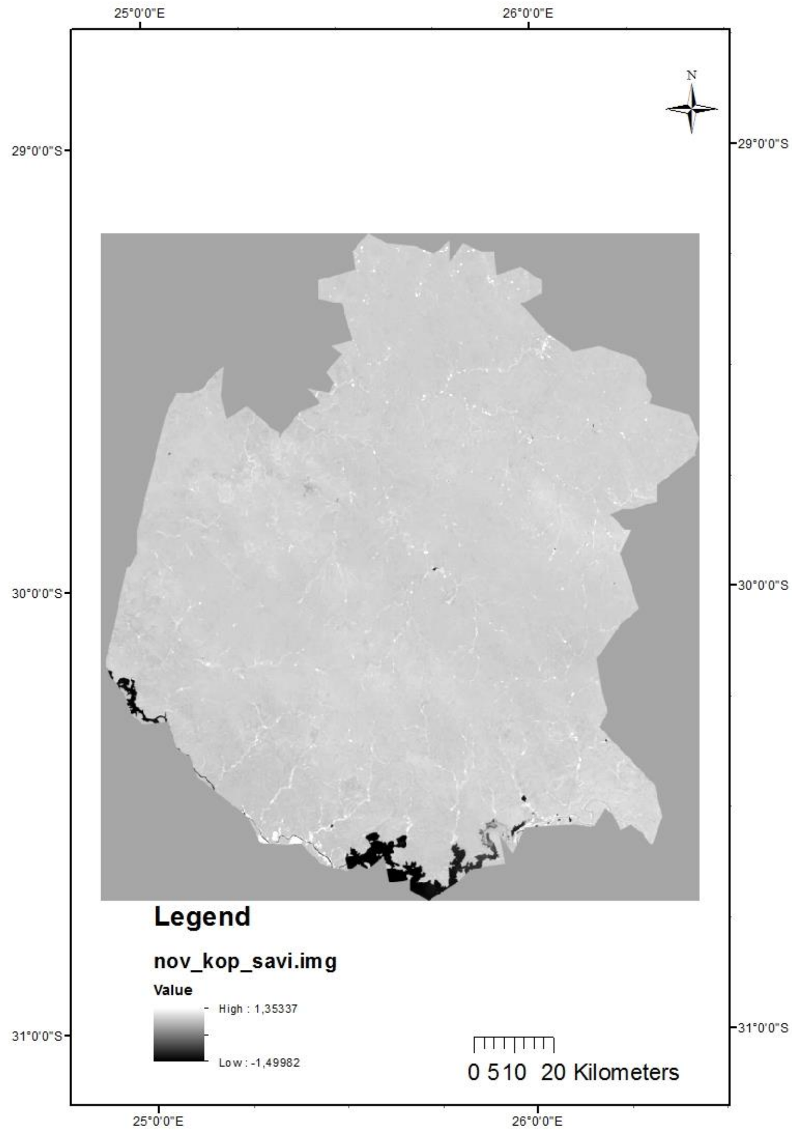
APPENDICES

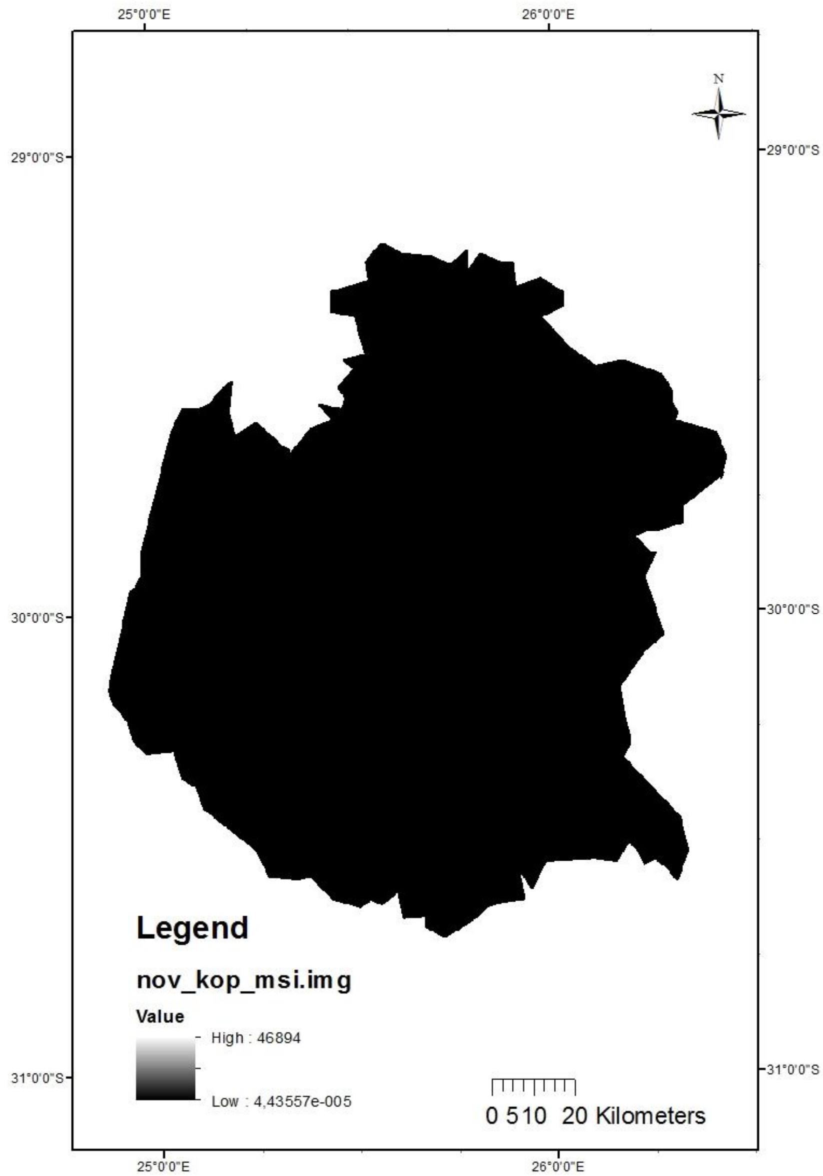
Appendix 1. November NDVI image.



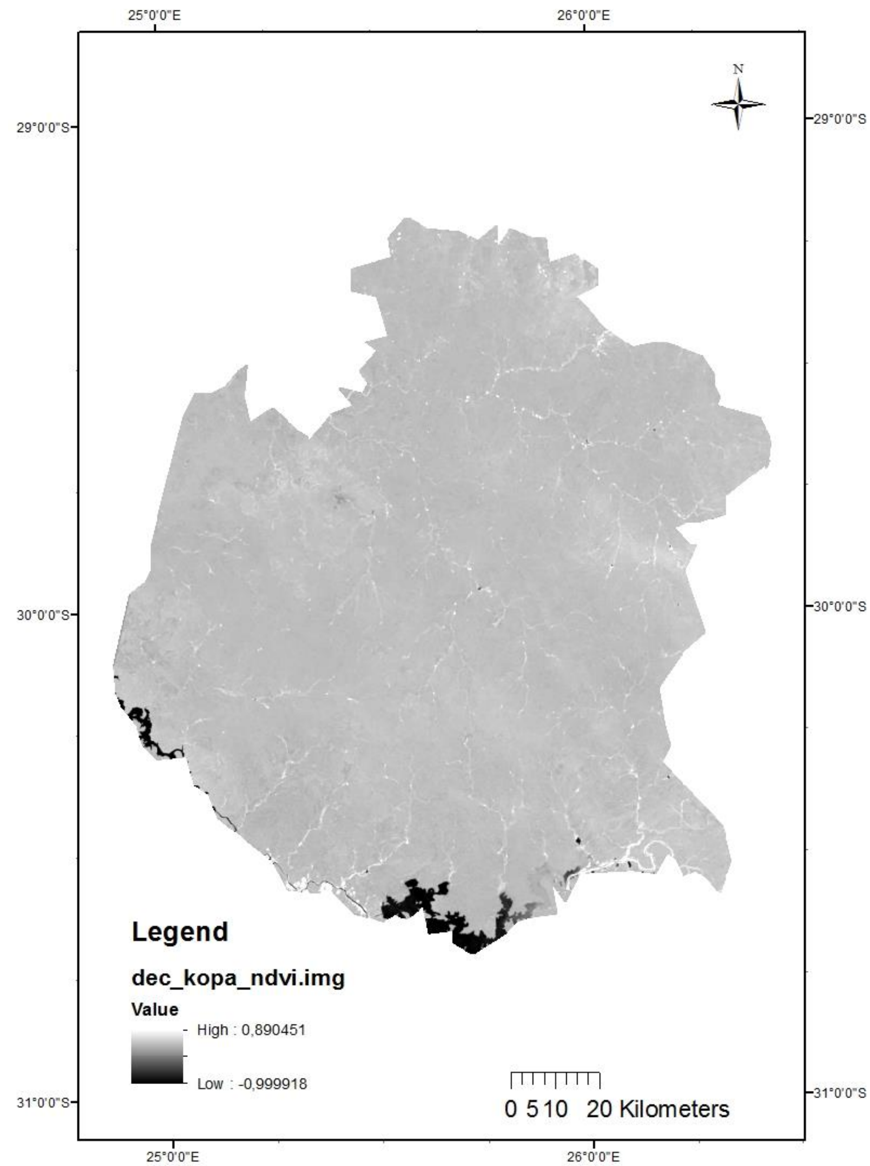
Appendix 2. November SAVI image.



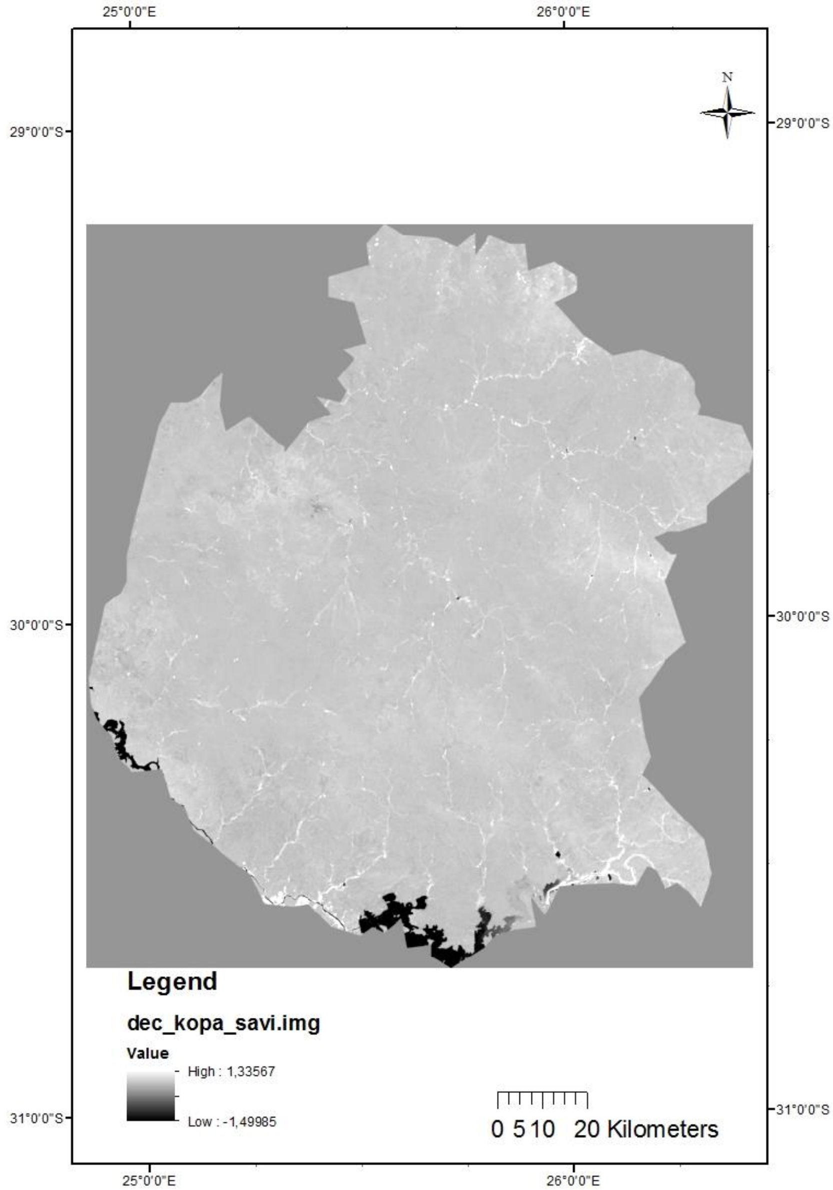
Appendix 3. November MSI image



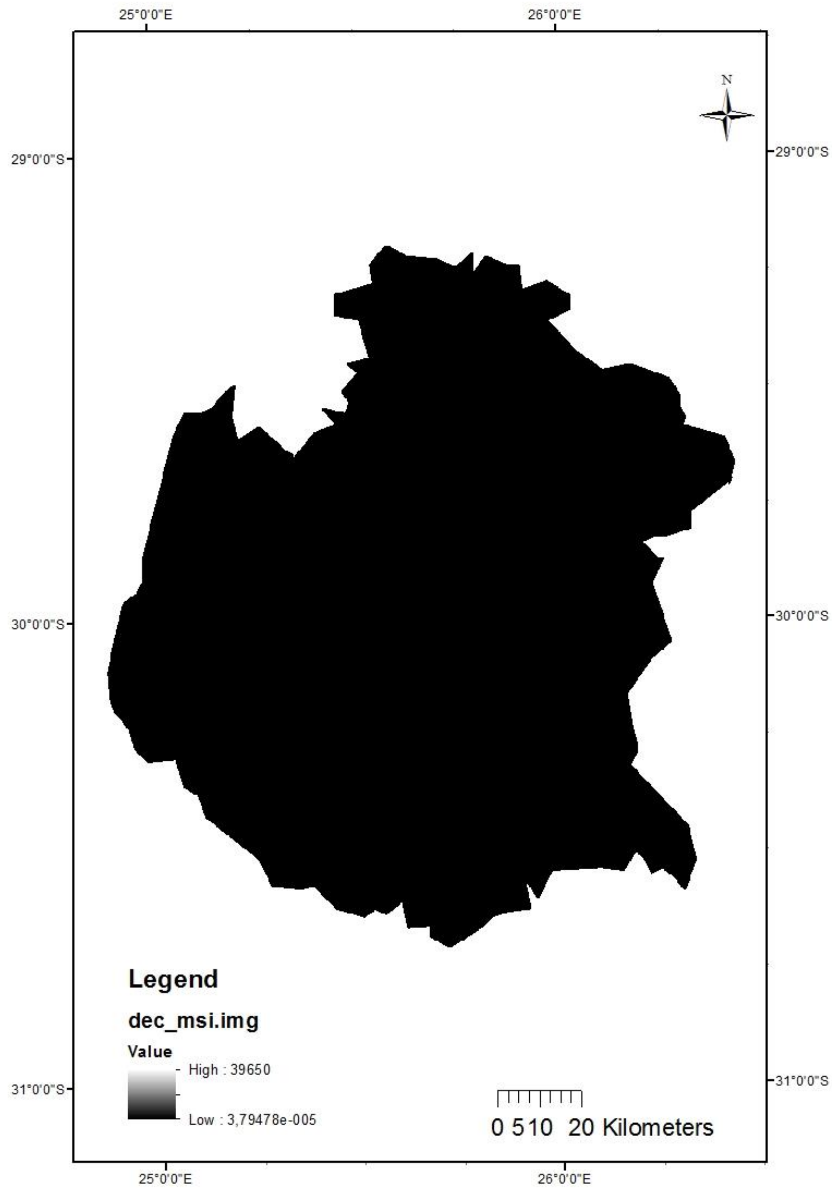
Appendix 4. December NDVI image



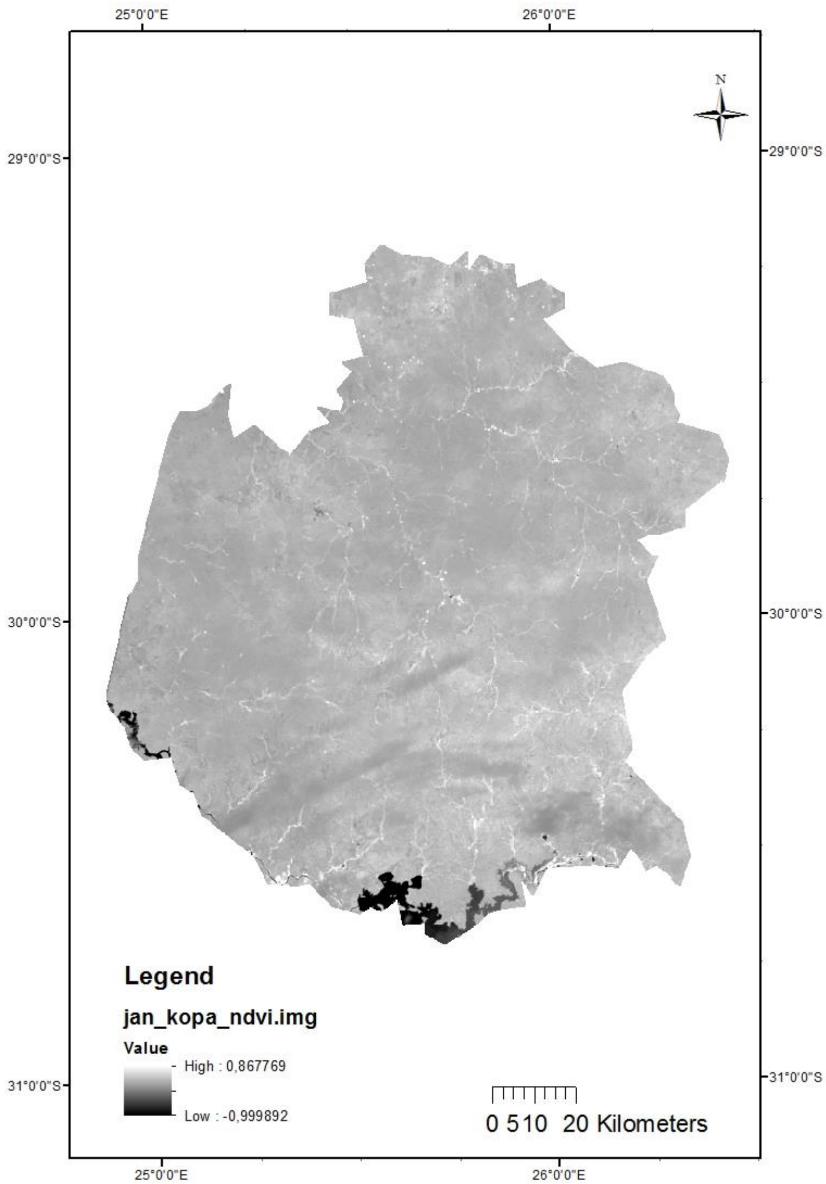
Appendix 5. December SAVI image



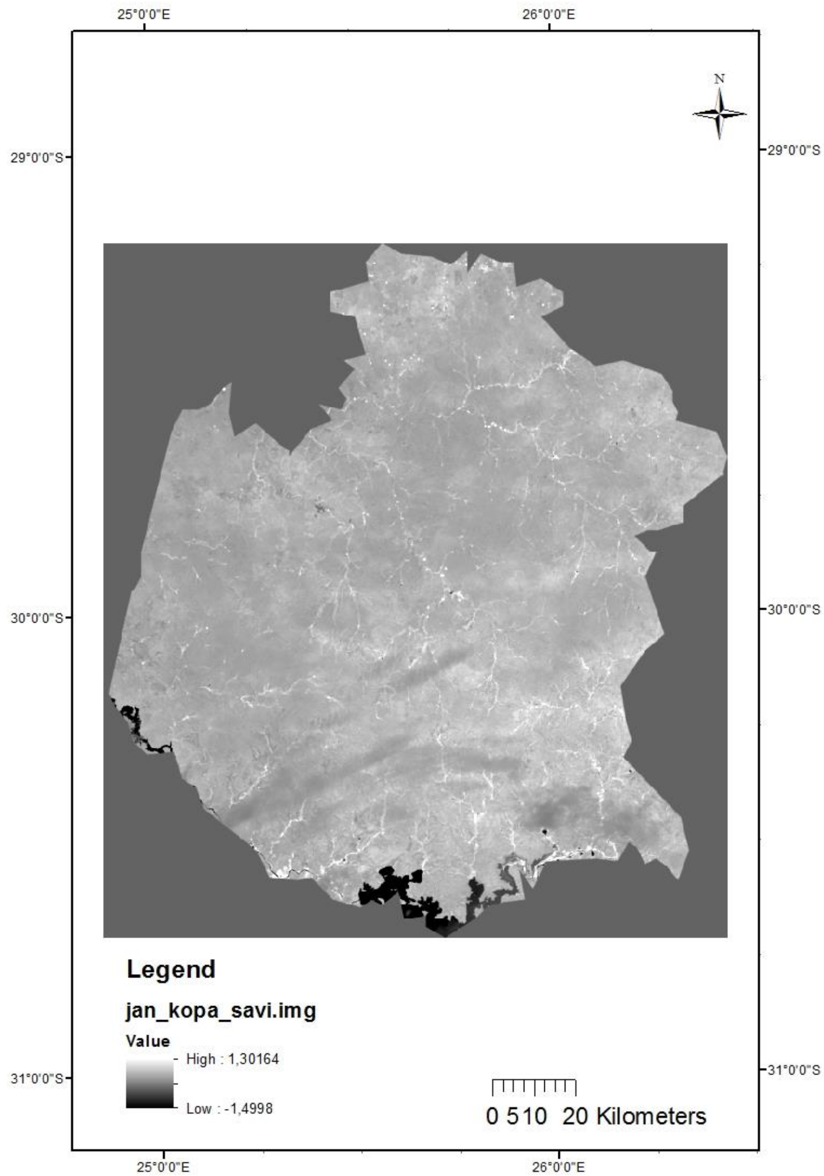
Appendix 6. December MSI image



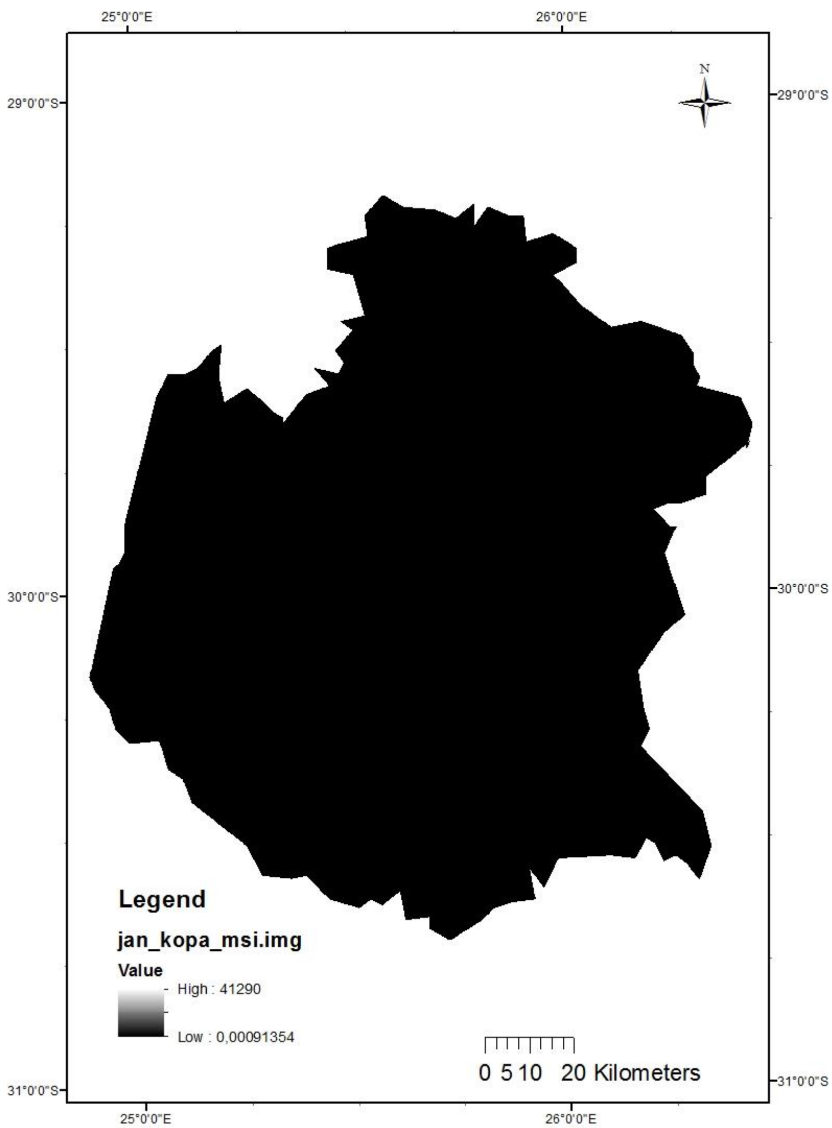
Appendix 7. January NDVI image



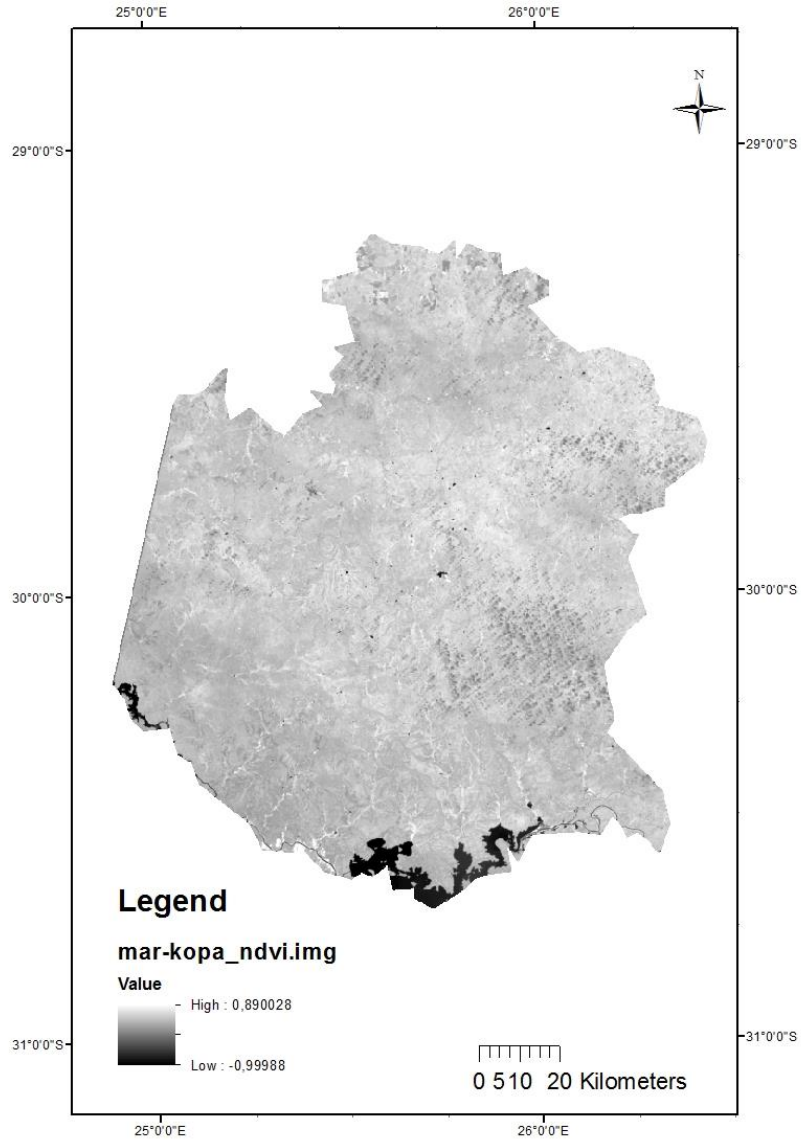
Appendix 8. January SAVI image



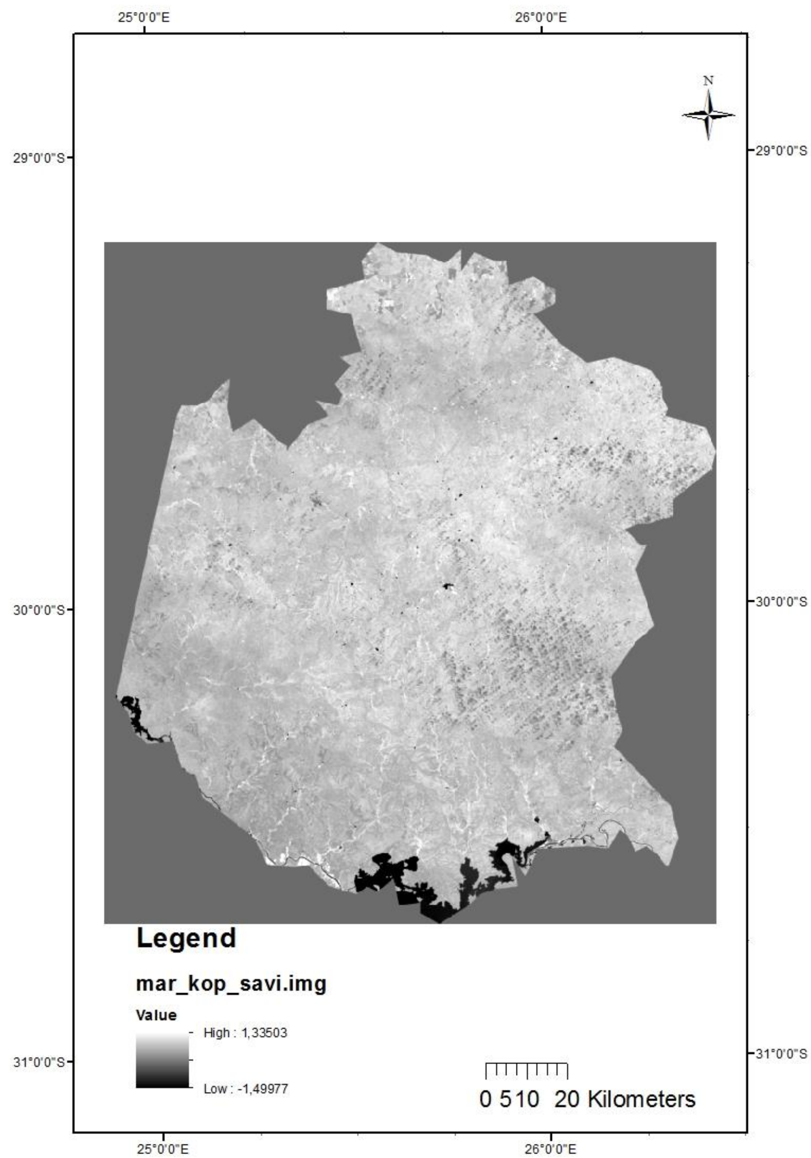
Appendix 9. January MSI image



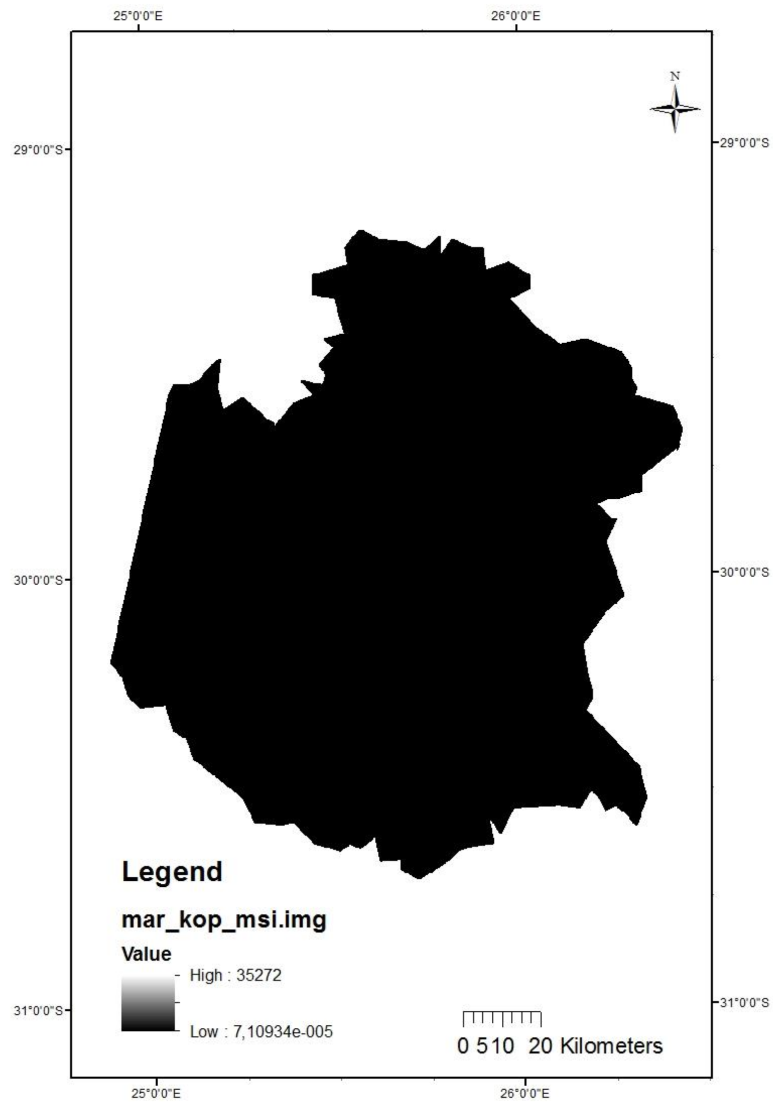
Appendix 10. March NDVI image



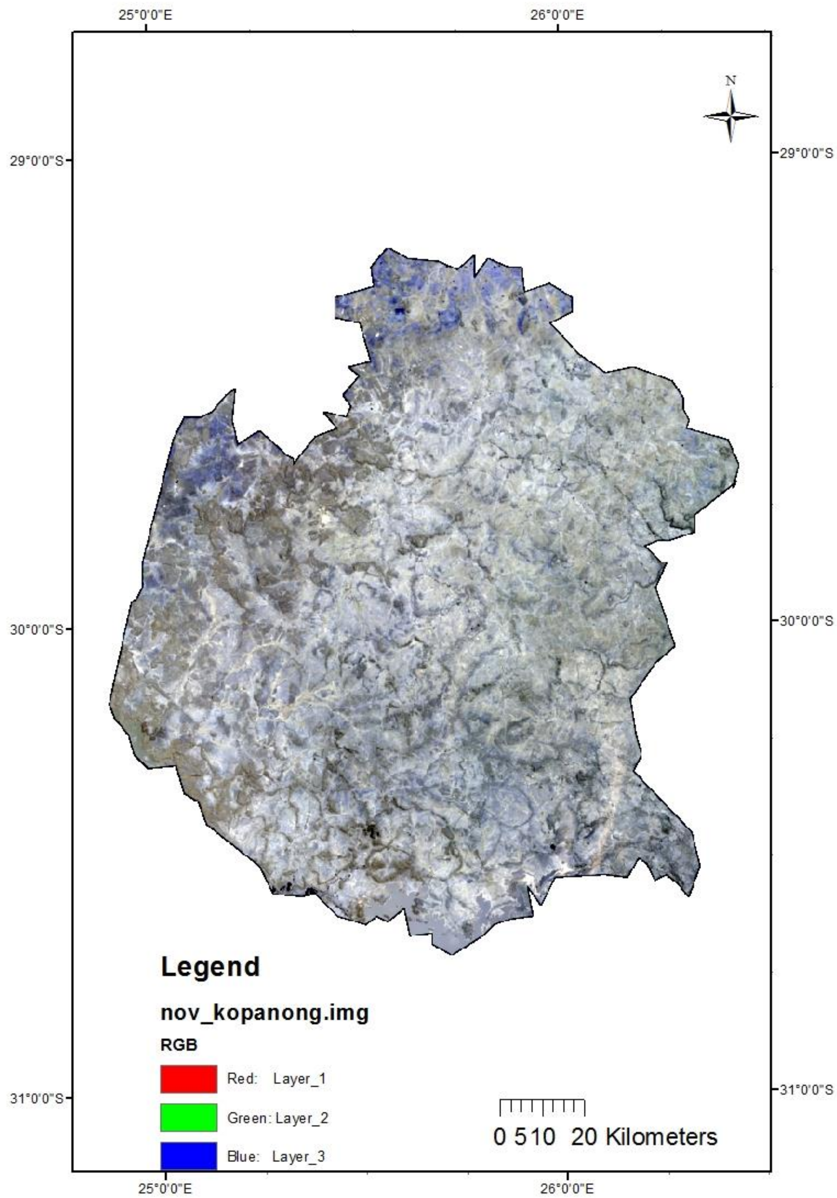
Appendix 11. March SAVI image



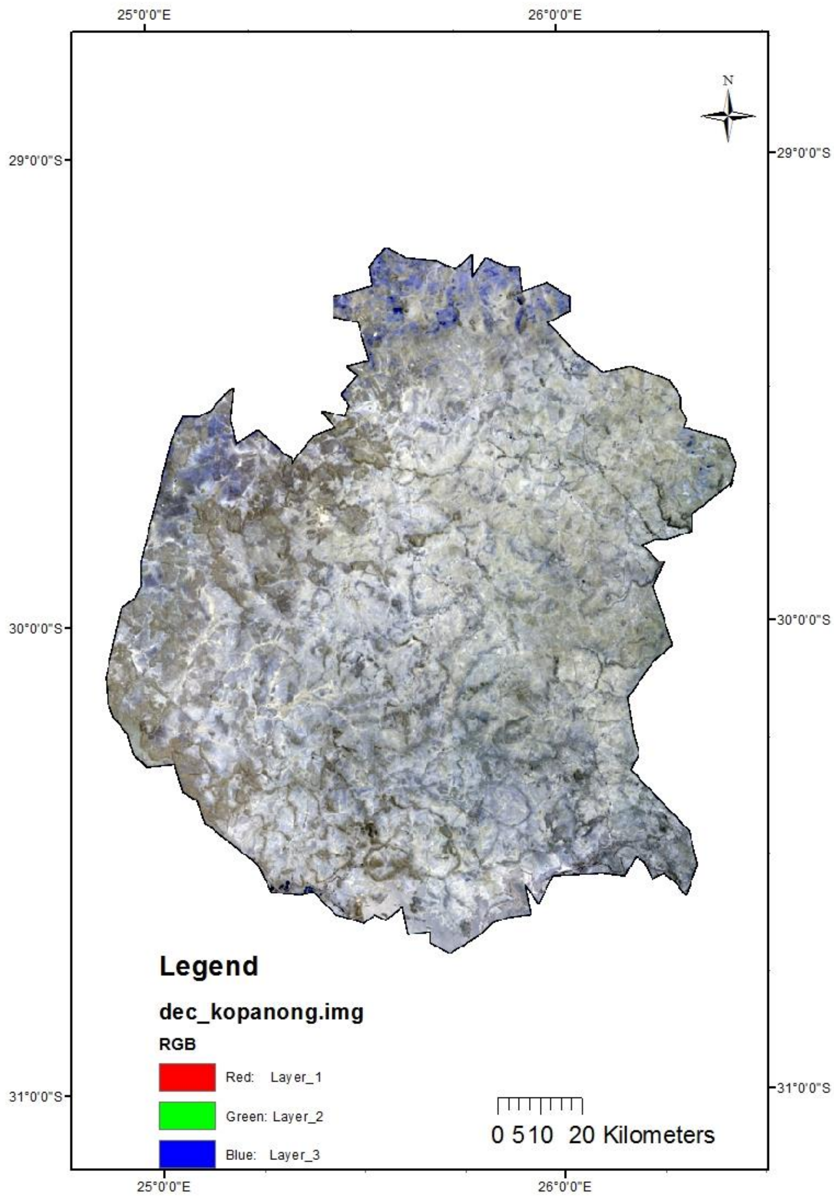
Appendix 12. March MSI image



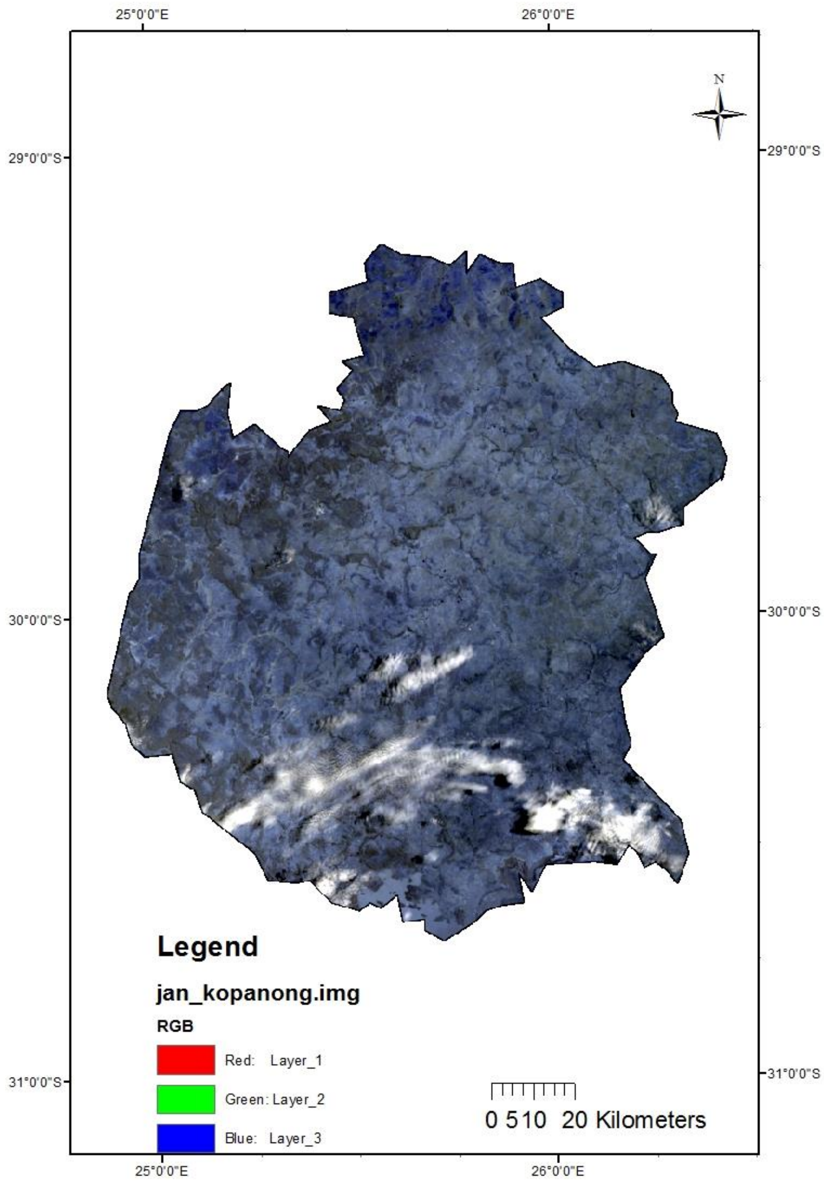
Appendix 13. 04/11/2013 image



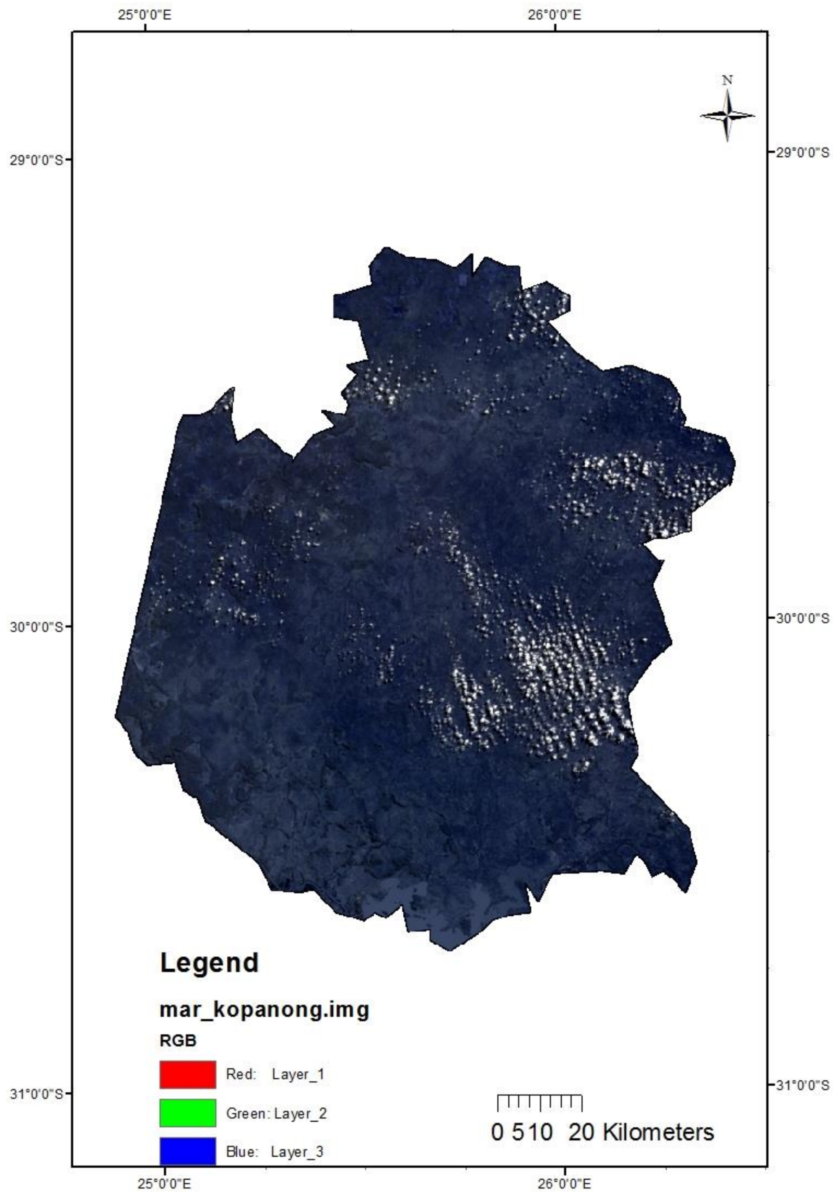
Appendix 14. 06/12/2013 image



Appendix 15. 23/01/2014 image



Appendix 16. 28/03/2014 image



Appendix 1- 16.

Nov_kopa_ndvi.img: November Kopanong NDVI image.

Nov_kop_savi.img: November Kopanong Soil Adjusted Vegetation Index (SAVI) image.

Nov_kop_msi.img: November Kopanong Moisture Stress Index (MSI) image.

Dec_kopa_ndvi.img: December Kopanong NDVI image.

Dec_kopa_savi.img: December Kopanong SAVI image.

Dec-kopa-msi.img: December Kopanong MSI image

Jan_kopa_ndvi.img: January Kopanong NDVI image.

Jan_kopa_savi.img: January Kopanong SAVI image.
Jan_kopa_msi.img: January Kopanong MSI image.
Mar_kopa_ndvi.img: March Kopanong NDVI image
Mar-kopa_savi.img: March Kopanong SAVI image.
Mar_kopa_msi.img: March Kopanong MSI image.
Nov_kopanong.img: November Kopanong satellite image.
Dec-kopanong.img: December Kopanong satellite image.
Jan_kopanong.img: January Kopanong satellite image.
Mar_kopanong.img: March Kopanong satellite image.

Appendix 2: Approval of Ethics Clearance certificate

The certificate below is issued by the research office of the UFH -GMRDC providing for full ethics clearance certificate for the research entitled “Estimating maize grain yield from crop growth stages using remote sensing and GIS in the Free State Province, South Africa”.

This research study was undertaken in the Local Municipality of Kopanang in the Free State Province, South Africa.