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SPECTRO AGROMETEREOLOGICAL MAIZE YIELD FORECAST MODEL USING REMOTE SENSING AND GIS IN SOUTH TIGRAY ZONE, ETHIOPIA

BY

ABIY WOGDERES ZINNA

A Thesis Submitted to the School of Earth Sciences Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in Remote Sensing and Geographic Information Systems (GIS)

Addis Ababa University
Addis Ababa, Ethiopia
May, 2014

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This is to certify that the thesis prepared by ABIY WOGDERES ZINNA, entitled: *SPECTRO AGROMETEREOLOGICAL MAIZE YIELD FORECAST MODEL USING REMOTE SENSING AND GIS IN SOUTH TIGRAY ZONE, ETHIOPIA* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and GIS complies with the regulations of the university and meets the accepted standards with respect to the originality and quality.

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List of Abbreviations

AGRISTARS – Agriculture and Resource Inventory Surveys through Aerospace Remote Sensing

AMSU - Advanced Microwave Sounding Unit

asl - Above Sea level

AVHRR – Advanced Very High Resolution Radiometer

CPSZ – Crop Production System Zone

CSWB - Crop Specific Water Balance

CV- Coefficient of Variation

CYMFS- Crop Yield Monitoring and Forecasting System

ECMWF- European Center for Medium Range Weather Forecast

ETA- Actual Evapotranspiration

fAPAR – Fraction of Absorbed Photo synthetically Active Radiation

FAO – Food and Agriculture Organization

FAS – Foreign Agriculture Service

FEWSNET – Famine Early Warning System

GAC – Global Area Coverage

GDP- Gross Domestic Product

GIS – Geographic Information System

GLAM – Global Agriculture Monitoring

IFPRI – International Food Policy Research Institute

LAC – Local Area Coverage

LACIE – Large Area Crop Inventory Experiment

MERIS - Medium Resolution Imaging Spectrometer

MIR – Middle Infrared

MODIS - Moderate Resolution Imaging Spectroradiometer

MSS- Multi Spectral Scanner

MVC- Maximum Value Composite

NASA - National Aeronautics and Space Administration

NDVI- Normalized Difference Vegetation Index

NMA- National Meteorological Agency

NOAA – National Oceanic and Atmospheric Administration

NWP – Numerical Weather Prediction

PET – Potential Evapotranspiration

P Value – Probability Value

Qt/ha - Quintal per Hectare

RFE – Rainfall Estimate

RMSE – Root Mean Square Error

RVI – Ratio of Vegetation Index

USAID - United States Developmental Aid

WRSI – Water Requirement Satisfaction Index

ABSTRACT

For a country like Ethiopia whose economy is strongly dependent on rainfed agriculture; reliable, accurate and timely information on types of crops grown, their acreage, crop growth and Yield forecast are vital components for planning efficient management of resources. Remote-sensing data acquired by satellite have a wide scope for agricultural applications owing to their synoptic and repetitive coverage. This study reports the development of an operational spectro-agrometeorological yield model for maize crop derived from time series data of SPOTVEGETATION, actual and potential evapotranspiration, rainfall estimate satellite data for the years 2003-2012 which were utilized as input data for the indices while official grain yield data produced by the Central statistical Agency of Ethiopia was used to validate the strength of indices in explaining yield (quintal per hectare). One obstacle to successful modeling and prediction of crop yields using remotely sensed imagery is the identification of image masks. This process allows to consider only information pertaining to the crop of interest. Therefore crop masking at crop land area was applied and further refined by using agro ecological zone suitable for crop of interest(maize).Correlation analyses were used to determine associations between crop yield, spectral indices and agrometeorological variables for the maize crop of the longest rainy season (Meher). Indices with high correlation with maize yield were identified and were ready for further analysis, accordingly rainfall and average Normalized Difference Vegetation Index (NDVIa) have high correlation with yield (85% and 80% respectively). Many studies reported that linear regression modeling is the most common method to produce yield predictions by using remote sensing derived indicators together with bio climatic information. Statistical multiple linear regression model has been developed using variables which have high correlation with yield. Accordingly, NDVIa and rainfall were bring to the regression and lastly a regression model with P-value of less than 0.05 at 95 % confidence level were developed. The developed spectro-agrometerological yield model was validated by comparing the predicted Zone level yields (quintal per hectare) with those estimated by CSA(quintal per hectare). Very encouraging results were obtained by the model (r^2 0.88 , RMSE 1.4 quintal/ ha and 21% CV). From this study we found that crop yield forecasting is possible using remote sensing and GIS in the fragmented agricultural lands of south Tigray. Since the data range we used for analysis was small we recommend application of the model after testing by newly appeared data with a long range of time series data before using for operational purposes.

Key Words: Remote Sensing, Yield Prediction, NDVI, Maize Yield

CHAPTER ONE

1 INTRODUCTION

1.1 Background

Agriculture is the backbone of the Ethiopian economy, contributing about 45 % of the country's Gross Domestic Product (GDP), a livelihood to about 84 % of the population and 86% of its export earnings (FDRE, 2013). It is thus, crucial for a country like Ethiopia whose economy is strongly dependent on rainfed agriculture; reliable ,accurate and timely information on types of crops grown, their acreage, crop growth and yield forecast are vital components in planning efficient management of resources.

Forecasting crop yield before harvest is therefore crucial especially in regions characterized by climatic uncertainties like Ethiopia. This enables planners and decision makers to predict how much to import in case of short fall or optionally to export in case of surplus. It also enables governments to put in place strategic contingency plans for redistribution of food during times of famine (Sawasawa, 2003).

In Ethiopia, there are two methods of monitoring and forecasting crop yield in advance of harvest. The first is Crop Yield Monitoring and Forecasting System(CYMFS) run by the Ethiopian National Meteorological Agency (NMA) in conjunction with the European Union (EU) Joint Research Council (JRC) and the Food and Agricultural Organization(FAO). This system relies on empirical Crop Specific Water Balance (CSWB) model of Food and Agriculture Organization (FAO) rather than processed based crop simulation model. The CSWB, which is less likely to capture complex nonlinear interaction between crop and climate is considered as shortcoming of the CYMFS system (Greatrex, 2012).

The second method involves collecting data on crop yield based on stakeholders assessment of the crop field compared to the previous year yield estimation as collected by CSA. The result of this method is used by the Ethiopian government as an official statistics and considered as conventional technique. Beyene and Meissner (2010) concluded that the procedure which CSA uses to forecast yield is highly subjective and dependent on the agenda of the stakeholders since the data is collected from the stakeholder's discussion but this data is widely used by the decision makers of the country (Greatrex, 2012).

The introduction of remote sensing and the derived vegetation indices in the early 80's was considered a potential tool to improve simulations in real-time. NDVI has been used as an indicator of the vigor of vegetative activity as represented by indirectly observable chlorophyll activity. Remote sensing products alone have been used in different parts of the world to estimate crop yield (Hastings and Emery, 1992).

Potdar *et al*. (1999) as cited in Rojas (2006) observed for some cereal crops grown in rain-fed conditions that rainfall distribution parameters in space and time need to be incorporated into crop yield models in addition to vegetation indices deduced from remote sensing data. Such hybrid models show higher correlation and predictive capability than the simple models. The agro-meteorological models introduce information about solar radiation, temperature, air humidity and soil water availability while the spectral component introduces information about crop management, varieties and stresses not taken into consideration by the agro-meteorological models.

A large range of satellite sensors provide us regularly with data covering a wide spectral range (from optical through microwave) and these data are acquired from various orbits and in different spatial and temporal resolutions namely high resolution and low resolution imagery (Rembold *et al*., 2013).

The large number of existing studies carried out throughout the world prove the relevance of low resolution satellite images for crop monitoring and yield prediction at the regional level and under different environmental circumstances. The relatively lower costs generally associated with the acquisition of low resolution satellite images makes them an attractive instrument for crop monitoring and yield forecasting (Rembold *et al*., 2013).

In Ethiopia, field survey for the conventional method of forecast is proved by researchers as subjective; it is worth while investigating cheaper and more timely methods to substitute it using remote sensing and GIS.

Therefore this research tries to adress the development of an operational spectro-agrometeorological yield model for maize in South Tigray zone of Tigray regional state using a spectral index; the Normalized Difference Vegetation Index (NDVI) derived from SPOT-VEGETATION, meteorological data obtained from Rainfall estimate (RFE 2.0) model and Official figures produced by the Government of Ethiopia, which is CSA yield data.

Maize is selected to be analyzed because it continues to be a significant contributor to the economic and social development of Ethiopia. As the crop with the largest smallholder coverage at 8 million holders (compared to 5.8 million for teff and 4.2 million for wheat), maize is critical to smallholder livelihoods in Ethiopia (IFPRI, 2010).

1.2 Statement of the problem

Crop yield forecast in many countries is based on conventional techniques of data collection for crop and yield estimation based on ground based field visits and reports. These reports are often subjective, costly, time consuming and are prone to large errors due to incomplete ground observation leading to poor crop yield assessment and also in most countries the data become available too late for appropriate actions to be taken (Greatrex, 2012).

In contrast, remote sensing can provide accurate and timeliness of the crop production statistics hence most studies have established that there is correlation between Normalized Difference Vegetation Index (NDVI), agro meteorological data and the green biomass and yield (Rojas, 2006).

In Ethiopia, these studies were mostly done at regional / national level covering large areas using low-resolution imagery and few studies have been conducted at lower administrative level. This study, therefore, forecast crop yield at zonal level using remote sensing and GIS.

The research problem has been identified by the researcher practical concern on the area and personal communication with CSA officials on June 2013 to supplement the existing approach with remote sensing technology and serve as spring board of relatively accurate and timely agricultural forecast.

1.3 Objectives

The general objective of the research is to develop a maize yield forecast model for Southern zone of Tigray region using remote sensing and GIS techniques.

Specific objectives are:-

- To test the efficiency of remote sensing in crop yield forecast.
- To Evaluate the applicability of the method in Ethiopian condition.
- To prepare maize yield forecast map of the year 2013.

1.4 Significance of the study

The research output is important in improving the agricultural forecast of CSA by laying ground, to shift from conventional approach which is proofed by researchers as subjective, time consuming and costly to remote sensing supported approach. This exercise would also serve as a spring board to Central Statistical Agency future plan for modeling of crop forecast using remote sensing and GIS. In the academic arena, it will serve as a reference for further research on crop forecast modeling of different crops since each crop needs its own model to be forecasted.

1.5 Limitation of the study

The limitation of the study were lack of sufficient related research works on crop yield forecast using remote sensing and GIS in Ethiopia, absence of better resolution satellite imageries especially for rainfall estimation and crop mask data derivation. Limited software's available for time series image analysis (difficulty to shift when it fails to compute) was also the major limitation encountered during implementation of this research.

1.6 Organization of the study

Including this introductory chapter, the study is organized into six chapters. Each chapter has its own heading and subheadings. Chapter one gives background information about the study. Chapter two presents a review of literature where theoretical and related literatures were reviewed. Chapter three, deals in detail, description of the study area, data acquisition and software packages and data processing and analysis methods. Chapter four presents results of the study and here correlation of different indices with maize yield and a multivariate regression model for yield forecast were presented Chapter five deals with discussion of the result, here results were discussed in relation with related research outputs. The final chapter (Chapter six) presents conclusion and possible recommendations of the research result.

CHAPTER TWO

2 LITERATURE REVIEW

2.1 Theoretical framework

Remote sensing is defined as the science of acquiring information about an object through the analysis of data obtained by a device that is not in contact with the object. The instruments used for measuring electromagnetic radiation are called sensors. These sensors record the reflected radiation from the surface of the earth and will be used for many analyses; one of these is agricultural analysis (Leiliesand and Kiefer, 1994).

As it is indicated in George and Hanuschak (2010) agricultural analysis using remote sensing data requires knowledge about plants photosynthesis activity. Green plants have a unique spectral reflectance influenced by their structure and composition. The proportion of radiation reflected in different parts of the spectrum depends on the state, structure and composition of the plant. In the visible portion of the spectrum (0.4um – 0.7 um), plants absorb light in the blue (0.45 um) and red (0.6 um) regions and reflect relatively more in the green portion of the spectrum due to the presence of chlorophyll. Chlorophyll does not absorb all wave length of sunlight; it absorbs the blue and the red wave lengths while green light is reflected. The reflection of visible radiation is mainly a function of leaf pigments, whereas the Near Infrared (NIR) is reflected by the internal mesophyll structure of the leaf. In cases where plants are subjected to moisture stress or other conditions that hinder their growth, the chlorophyll production decreases. This in turn leads to less absorption in the blue and red bands. As the leaves dry out or as the plant ripens or senescence or become diseased or cells die, there is reduction in chlorophyll pigment. This results in general increase in reflectance in the visible spectrum and a reduction in a reflectance in the middle infrared (MIR) portion of the spectrum due to cell deterioration. Thus, the spectral response of a crop canopy is influenced by the plant health, percentage of groundcover, growth stage, stress condition and canopy structure.

These reflected wave lengths may be detected by a sensor positioned above the crop. As a result of the above mechanism, healthy vegetation will show high value of reflectance in the NIR and low values in the visible spectrum. In the visible region, leaf reflectance is lower than soil reflectance whereas in the NIR leaf reflectance is higher than soil reflectance. This behavior is useful for explaining the utility of these reflectance measurements in agricultural applications and for the separation of crops from soil (George and Hanuschak, 2010).

2.1.1 Satellite imagery for agricultural application

Already in the early 80s, it was shown by Tucker and co-workers (1980, as cited in Atzberger, 2013) that green vegetation can be monitored through its spectral reflectance properties. Today, a large range of satellite sensors provide us regularly with data covering a wide spectral range (from optical through microwave) and these data are acquired from various orbits and in different spatial and temporal resolutions.

2.1.1.1 High spatial resolution satellite imagery

The analysis of satellite imagery for identifying crop variability has been exploited since the availability of Landsat MSS/TM data in the mid 1970's which is characterized by high spatial resolution and relatively low temporal resolution hence their revisit time is long. With the advent of today's high-performance commercial satellites, beginning with the 1999 launch of Space Imaging's IKONOS satellite, imagery of the highest spatial and radiometric fidelity is now available throughout the world. This imagery is ideal for time-critical analysis of cropland. The analyzed image and information derived from it can then be seamlessly brought into a Geographical Information System (GIS) as part of the crop management decision support structure. When the high-resolution imagery is combined with microclimate weather data, powerful agronomic modeling and assessment tools can be developed for improved field and sub field-management (Esri, 2013).

2.1.1.2 Low spatial resolution satellite imagery

Low resolution satellite images essentially refers to a spatial resolution between 250 meters and several kilometers. Most of the early studies (e.g., from the 80s and the 90s) relate to the use of different sensors of the NOAA AVHRR series. These images were typically available at the national and multinational level with a 1 km resolution (LAC or Local Area Coverage) and, at the continental and global level, with a 4 - 6 km resolution (GAC or GLOBAL Area Coverage) or below. It was only at the end of the 90s that the French–Belgian–Swedish satellite, SPOT, was equipped with a 1-km resolution sensor for vegetation monitoring at the global scale called VEGETATION. In addition, several so-called medium resolution sensors (maximum 250 m) have become operational since the year 2000; amongst the best known are the Moderate Resolution Imaging Spectro radiometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS) sensors belonging to the TERRA/AQUA and ENVISAT platforms, respectively. All the low and medium resolution sensors that have proven their validity for land surface observation and vegetation analysis normally also find their applications in agriculture (Rembold *et al*.,2013).

Low resolution satellite imagery has been extensively used for crop monitoring and yield forecasting for over 30 years and plays an important role in a growing number of operational systems. The relationship between the spectral properties of crops and their biomass/yield has been recognized since the first spectrometric field experiments (Rembold *et al*., 2013).

2.1.2 Remote sensing derived variables for agricultural application

For deriving information from remote sensing data for agricultural application, a large number of spectral analysis have been developed. Besides the spectral signature, useful information can also be retrieved by analyzing the temporal signature properties of vegetation. Further useful information can also be retrieved from the spatial arrangement of the pixels, *i.e.*, the texture of the image, even at coarse resolution (FAO, 2010). It is worthwhile to investigate the relationship between different indices and yield from different literatures in order to apply for this research.

2.1.2.1 Vegetation index(VI)

Tucker and co-workers (1980) as cited in Atzberger (2013) indicated that arithmetic combinations of vegetation reflectance in the red and near infrared (so called “vegetation indices” or VI) are particularly useful for vegetation characterization. Vegetation Indices (VIs) are mathematical combinations or ratios of mainly red, green and infrared spectral bands; they are designed to find the functional relationships between crop characteristics and remote sensing observations. Vegetation indices are strongly modulated by the interaction of solar radiation with crop photosynthesis and thus are indicative of the dynamics of biophysical properties related to crop status. But at early crop development stages the effects of soil reflectance influence the values of some vegetation indices for the detection of crop stress (FAO, 2010). The most commonly used vegetation index include ratio vegetation index (RVI) and Normalized difference vegetation index (NDVI).

Ratio Vegetation Index (RVI) is the simplest form of ratio based vegetation indices calculated through the use of infrared and the red band of the electromagnetic spectrum. It is calculated as follows; RVI=IR/R where IR is infrared and R is Red band of the electromagnetic spectrum.

Normalized Difference Vegetation Index (NDVI) is another form of ratio based vegetation index but here the difference between IR and Red band as a ratio of the summation of the two bands (Fig 2.1). Thus, it is computed as follows:

NDVI= IR-R/IR+R

Out of all VIs, NDVI stands out and is regarded as an all-purpose index. This vegetation index is the most widely used and well understood vegetation index (Sawasawa, 2003).

The well-known NDVI was proposed in 1978 by Deering. The index became, subsequently, the most popular indicator for studying vegetation health and crop production. The success of the NDVI stems from its close relation to the canopy Leaf Area Index (LAI) and fAPAR (fraction of Absorbed Photo synthetically Active Radiation). Due to its almost linear relation with fAPAR, the NDVI can be readily used as an indirect measure of primary productivity (Atzberger, 2013).

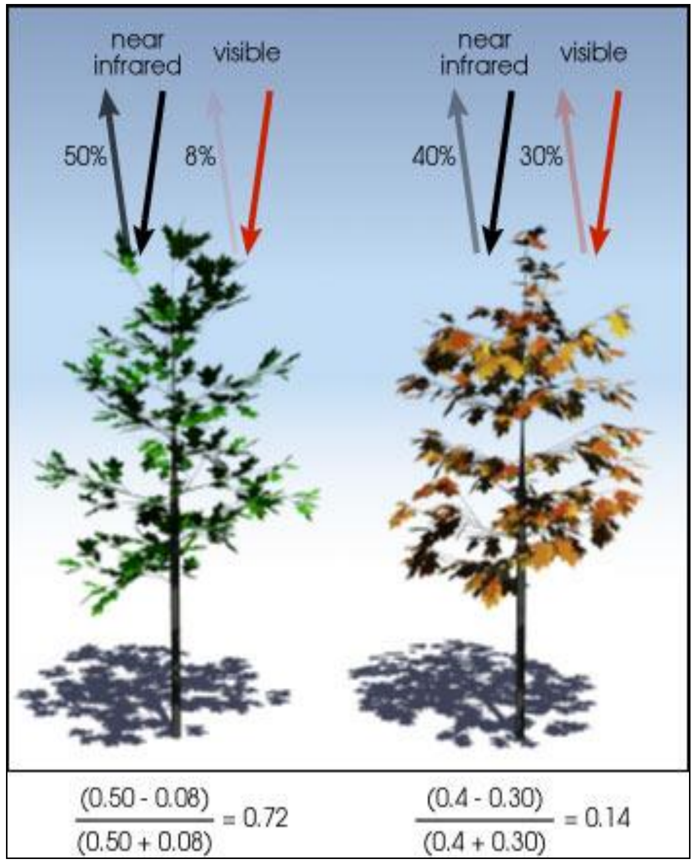

Figure 2.1 Computation of NDVI.

Source: Fewsnet (2007)

2.1.2.2 Water requirement satisfaction index (WRSI)

Water Requirement Satisfaction Index (WRSI) is a geospatial model that was developed by Food and Agricultural Organization (FAO) for use with satellite data to monitor water supply and demand for rainfed crop throughout the growing season. It is also a crop performance index based on the availability of water in the soil (Legesse and Suryabhagavan, 2014).

Currently, crop moisture stress on grain crop can be monitored using WRSI which is satellite based crop performance index. This index indicates the extent to which the water requirement of the crop has been satisfied in the growing season (Tewlde Yideg, 2012). Technically, WRSI is the ratio of seasonal actual crop evapotranspiration (ETac) to the seasonal crop water requirement, which is the same as the potential crop evapotranspiration (PETc). Originally developed by FAO, the WRSI has been adapted and extended by USGS in a geospatial application to support FEWS NET monitoring requirements. As a monitoring tool, the crop performance indicator can be assessed at the end of every 10-day period during the growing season (Geo WRSI v2.0 manual).

2.1.2.3 Weather variables

The most important weather variables affecting crop yield are solar radiation, temperature and rainfall, although as these weather phenomena are in extricable interlinked and is often difficult to observe individual effects in the field.

Solar radiation is one of the most important indicators of the relationship between crop and weather. This radiation is directly used by crop photosynthesis. In the tropics, if a crop is not water limited, yields will be higher in cloudless season than in wet season. The effect of temperature is primarily on the development of the crop. In addition plants are often sensitive to heat stress during certain development stage (Greatrex, 2012).

According to Osborne (2004) as cited in Greatrex (2012) Rainfall is also another indicator of relationship between crop and weather. Rainfall is expressed by a crop as a slower frequency variation in soil moisture. If a plant is water stressed, then it will limit transpiration through restricting photosynthesis resulting in less growth and smaller yields. Although rainfall is generally beneficial, high intensity of rainfall can negatively affect a crop through erosive runoff or flooding.

Timely and accurate rainfall estimation is of great importance when forecasting crop yields and real time rainfall observations. Rain gauge networks have traditionally provided a simple and in expensive method for daily and dekedal rainfall estimation. In recent years, these have been complemented by the development of precipitation radar networks, satellite rainfall estimates ($SRFE_s$) and output from numerical weather prediction (NWP) models, which have been particularly successful in increasing the temporal and spatial resolution of the estimates (Novella and Thiae, 2012).

Rainfall estimate (RFE) are produced specifically with the aim of monitoring African drought and rainfall. The algorithm uses a mix of panchromatic and infrared sensors plus daily rainfall observations to produce daily rainfall estimate at a scale of 0.1^{o}. The RFE 2.0 is a combination of three satellite rainfall datasets and one rain gauge rainfall data inputs. The inputs are GOES precipitation index (GPI) which is 4 km and half hours of spatial and temporal resolution respectively, special sensor microwave imagery (SSN/I) with15 km spatial and 4 times per day (6 hour) temporal resolution and Advanced Microwave Sounding Unit (AMSU) is also 1/3 degree (37 km) spatial 5 day temporal resolution of satellite derived rainfall data sets and the Global Telecommunication Station (GTS). GTS is a station rainfall data with un even spatial and from minute to daily temporal resolutions rainfall datasets (Novella and Thiae, 2012).

There has been a limited attempt to validate or compare satellite products over Africa. Jobard *et al*. (2011) as cited in Greatrex (2012) compared and validated all of the satellite products at a 10 day time scale over the Sahel and found that the regionally calibrated TAMSAT and RFE 2.0 had higher skill.

2.2 Crop yield forecast in the world

The objective of the yield forecast is to give a precise, scientific, sound and independent forecast of crop yield as early as possible during the growing season by considering the effect of weather and climate. The difference between forecast and estimate are in the time of the release. Forecasts are made before the entire crop has been harvested whereas estimates are made after the crop has been harvested (Sawasawa, 2003).

According to Reynolds *et al*. (2000) as cited in Greatrex (2012) there are several methods of yield forecasting. The traditional method of yield forecasting is the evaluation of crop status by experts. Observations and measurements are made throughout the growing season such as tiller number, spikelet number and their fertility percentage, percentage of damage from pests and fungi etc. From the data obtained in this way yield can be forecasted using regression method. These reports are often subjective, costly, time consuming and are prone to large errors due to incomplete ground observation, leading to poor crop yield assessment and crop area estimation. In most countries the data become available too late for appropriate actions to be taken to avert food shortage. Other methods used to forecast crop yield are the use of remote sensing and crop simulation models.

In the first method, with the development of satellites, remote sensing images provide access to spatial information at global scale; and of features and phenomena on earth on an almost real time basis. They have the potential not only identifying crop classes but also of estimating crop yield. As outlined by Becker Reshef *et al*.(2010); preliminary research and development on satellite monitoring of Agriculture started with the landsat 1 system (ERTS) in the early 1970s, stated that unanticipated severe wheat shortage in Russia drew attention to the importance of timely and accurate prediction of world food supplies. As a result, in 1974, the United States Developmental Aid (USAiD) together with NASA and NOAA initiated the Large Area Crop Inventory Experiment (LACIE). The goal of this experiment was to improve domestic and international crop forecasting methods.

With enhancement that become available from the NOAA-AVHRR sensor (Advanced Very High Resolution Radiometer) allowing for daily global monitoring, the AGRISTARS (Agriculture and Resource Inventory Surveys through Aerospace Remote Sensing) program was initiated in the early 1980s. One of the most recent efforts that NASA and the USDA Foreign Agriculture Service (FAS) have initiated is the Global Agriculture Monitoring (GLAM) project. Besides GLAM system, there are currently several other regional to global operational agricultural monitoring systems providing critical agriculture information at a range of scales like USAID Famine Early Warning System (FEWS NET), UNFAO Global Information and Early Warning System(GIEWS). However, the USDA FAS with its GLAM system is currently the only provider of regular, timely, objective crop production forecasts at a global scale (Atzberger, 2013).

The second method is yield forecast using agro meteorological inputs in to a statistical regression which is used in many yield forecasts research. In general a simple statistical model is build using matrix with historic yield and several agro meteorological parameters. Then a regression equation is derived between yields as function of one or more agro meteorological parameters. The meteorological models used for forecasting yield are mainly based on two variables temperature and precipitation because they are related to crop yields and can be easily obtained from meteorological stations or satellite measurements. In rainfed agricultural regions taking rainfall is the most important factor affecting crop growth and yield (George and Hanuschak, 2010).

According to Rudorff and Batista (1990, as cited in George and Hanuschak, 2010), when such models are applied at regional level they cannot fully simulate the different crop growing conditions within the region. The application of agro meteorological models is more common when it is integrated with remote sensing.

There were researches carried out throughout the world on the use of remote sensing and crop simulation models. The methodology and their results were presented as follows.

Benedetti and Rossini (1993) used the AVHRR satellite derived NDVI data for wheat forecast in a region of Italy. They derived a simple linear regression model for wheat yield estimates and forecast based on NDVI images during the grain season. They validated their results against official data and found good correlation between the two.

In Mediterranean African countries, Rembold and Maseli (2004) used the NDVI derived from the AVHRR platform to estimate cereal production and found a good result too. However, it has been argued that remote sensing might not be suitable in developing countries because of their stratified agricultural system and very small farm sizes. Meanwhile the increased availability of high spatial resolution makes this technique a possible and interesting alternative for yield forecast.

Many studies showed that yield forecasting can be obtained by the use of NDVI data of specific periods which depend on the climatic conditions of the area and the type of crop grown. One important limitation of the yield /NDVI regression is that most of the fore mentioned studies are linked to the environmental characteristics of specific geographic areas or are limited by the availability of large and homogeneous datasets of low resolution data and it is the difficult in extending locally calibrated forecasting methods to other areas or to other scale (Rembold *et al*., 2013).

According to Rembold *et al*.(2013) it should be noted that where the crop area is not known the NDVI /yield relationship does not provide information on final crop production and also this relation makes use of under specific conditions such as stable crop area over the observed period. In many cases the predictive power of remotely sensed indicators can be improved by adding independent meteorological (bio climatic) variables in the regression model. Several bio climatic and remote sensing based indicators have proven to be highly correlated with yield for certain crops in specific areas. These variables can be either measured directly (like rainfall coming from synoptic station) or by satellites (such as rainfall estimates) or can be the result of other models like ETa (actual evapotranspiration) or soil moisture.

For crop forecasting, Satellite derived point specific rainfall estimates were input in to a crop water balance model to calculate WRSI. When these WRSI values were regressed with historical yield data, the results showed that relatively high skill yield forecasts can be made even when the crops are at their early stages of growth (Sawasawa, 2003). According to Victor (1988, as cited in Senay and Verdin, 2003), rainfed based crop performance can be assessed using water requirement satisfaction index (WRSI).The bioclimatic variables introduce information about solar radiation, temperature, air humidity and soil water availability while spectral component introduce information about crop management, varieties and stresses not taken in to consideration by the agro meteorological models. Such hybrid models show higher correlation and prediction capability than the models using remote sensing indicators only.

Rojas (2006) in his research entitled "crop yield model development in eastern Africa. Study case of Kenya using spectro agro meteorological model" concluded that it is possible to conduct operational maize yield forecasts using CNDVI derived from SPOT VEGETATION and ETa from the FAO CSWB model. CNDVI showed to improve the spectral signal of the maize crop areas when compared with the simple spatially averaged NDVI using the general crop mask. CNDVI proved to be a simple and valid method for NDVI extraction with low resolution satellite images and highly fragmented high resolution land cover classes. Due to this prediction capability it is possible to obtain an early forecast using the CNDVI and ETa accumulated from planting decade to the end of the flowering phonological phase. A more accurate estimate will be possible when the maize crop cycle reaches the end using the CNDVI and ETA accumulated for the whole length of the maize crop cycle. The result reveals that it is possible to have reliable predictions 3 to 4 months earlier than the official estimates provided by national authorities and based on traditional field sampling surveys. As the time-series of the yield data was limited, some reservations for the model must be made, until a longer series of yield data will become available. The simplicity of the proposed regression yield model should allow an operational implementation in developing countries. He recommended that based on these encouraging results, regression models could be developed for other geographical areas in Eastern Africa.

2.3 Crop yield forecast in Ethiopia

Many countries in sub-Saharan Africa are highly dependent on rainfed agriculture. When combined with a lack of coping mechanisms and crop management options, climate shocks can have a disproportionate effect on food security. This is particularly apparent in Ethiopia, which has an economy strongly linked to rainfed agriculture and where it can be difficult to forecast, monitor or measure crop yield in time for regional food security assessments. It would be extremely useful for policy makers to be able to forecast regional crop yield either at the time of harvest or at the beginning of the season, as it would allow advance planning in the event of crop surplus or failure. Of equal importance is to be able to assign a measure of uncertainty to the forecast (Greatrex, 2012).

Ethiopia currently has two methods of monitoring and forecasting crop yield in advance of harvest. The first is CYMFS run by the Ethiopian Meteorological Agency (NMA) in conjunction with the European Union Joint Research Council (JRC) and the Food and Agricultural Organization (FAO). It works by combining a geographic information system (GIS) the FAO crop specific water balance (CSWB) model, the JRC crop production system zones database and meteorological information from the European Center for Medium Range Weather Forecasts (ECMWF). Additional and independent real-time Normalized Difference Vegetation Index (NDVI) satellite data from SPOT VEGETATION is also incorporated, using a specific crop mask to concentrate the analysis only on agricultural areas. This approach has several potential shortcomings according to Gretrix (2012). The first is its reliance on an empirical CSWB model rather than a processed based crop simulation model. Empirical crop simulation models are less likely to capture complex non-linear interactions between crop and climate (Greatrex, 2012).

Teo (2006) as cited in Greatrex (2012) concluded that a CSWB model performed less well than a process based model when forecasting groundnut yield over the Gambia and also ECMWF model shows some exaggeration in rainfall estimation in east Africa.

The second method involves collecting data on crop yield based on stakeholder's assessment of the crop field compared to the previous year yield estimation as collected by CSA. This method is used by the Ethiopian Authorities to monitor crop yield as an official statistics. At the time of harvest for either cropping season, CSA invites key stakeholders such as farmers unions, NGOs & external organizations (FAO) to a meeting to discuss on how the season has developed. These stakeholders are asked to agree on a percentage change in perceived crop yield from the previous season in the prepared questionnaire at the field. For example, it might be decided that the crop yield in Tigray during 2009 is 80 % of the crop yield in Tigray during 2008. This number is then multiplied by the previous year's yield to give a 'pre-harvest estimate' (Beyene and Meissner, 2010).

Another software called Livelihood Early Assessment Protection (LEAP) developed by World Food Program (WFP) has also used in Ethiopia for crop yield forecast in addition to the two mainly known approaches. According to Hoefsloot (2008) as cited in Tewlde yideg (2012) now days in Ethiopia crop yields are predicted by the amount of available water as compared to the crop water requirement for the growing season using LEAP software developed specifically for Ethiopian Context. One of the goals of LEAP is to serve as a platform for calculation of weather based indices starting out with the calculation of a crop water balance indicator, WRSI. In addition, it uses relevant soil information from FAO digital soil map and topographical parameters derived from the GTOPO30 Digital Elevation Model (DEM) (Legesse and Suryabhagavan, 2014).

Greatrex (2012) carried out research on Ethiopia using the crop simulation model called the General Large Area Model for annual crops (GLAM). GLAM is a process based model designed to simulate tropical crop production in regions where there is an observed relationship between climate and crop yield and has been shown in studies to capture the crop/weather relationship at large scales and found that this model was shown to exhibit the correct sensitivity to climate and to perform reasonably when compared with observed crop yields. The limitations of the approach with the current calibration dataset are, Ethiopian agriculture is extremely complex with many different varieties of maize used by farmers to adapt to their climate, thus the use of a single cultivar in GLAM MAIZE led to unrealistic results in some high altitude locations and the time a plant takes to develop to maturity is one of the most important determinants of final yield and strongly dependent on growing season temperature. In turn, temperature is highly dependent on altitude, thus maize grown at a high altitudes will experience lower growing season temperatures, resulting in longer development times and higher yields. In the study, GLAMMAIZE was run using a single lowland maize cultivar that needs relatively high temperatures in order to develop. This means that for high altitude, low temperature pixels, GLAMMAIZE took an excessively and unrealistically long time to develop and results in an unrealistic pattern. Lastly she recommended that an operational crop yield forecasting system needs to be able to work at a regional scale if it is to be of use to policy makers in order to substitute the existing conventional method which was proofed as subjective, time consuming, un reliable and have also a problem of timeliness.

2.4 Introduction to maize crop

Maize (Zeamays) has long been a part of agricultural systems. It was first documented in 7000 B.C. in the Andean region of Central America and now, along with wheat and rice forms one of the world's most important staple crops (Dereje and Eshetu, 2011).

Currently, maize is the preferred staple for over 900 million poor consumers and is widely regarded as the most important staple food crop in Africa. The importance of maize in developing countries can be seen clearly from the analysis done by the International Maize and Wheat Improvement Center (CIMMYT) for the maize global mega Programme (Greatrex, 2012).

Among cereals, maize accounts for the largest share in total production and the total number of farm holdings involved in Ethiopia. In 2010/11, maize accounted for 28 percent of the total cereal production, compared to 20 percent for teff and 22 percent for sorghum, the second and third most cultivated crops. About 8 million smallholders were involved in maize production in 2010/11, compared to 6.2 million for teff and 5.1 million for sorghum. It should be noted that in Ethiopia, smallholder farms account for 95 percent of the total agricultural production, with large farms contributing to only 5 percent of total production and to only 2.6 percent of cereal production in particular. The average farm size is less than one hectare, with 40 percent of the farmers cultivating less than 0.52 hectares. Maize is the largest and most productive crop in Ethiopia. The fastest growth rates in area cultivated, production and yield were also recorded in the case of maize: between 2003/04 and 2007/08, maize production expanded by 103 percent; and area under maize increased by 51 percent while yield increased by 32 percent. The share of maize in total area has increased by 6 percent between 2003/04 and 2007/08. According to the data obtained from FAOSTAT, Ethiopia is the second largest producer of maize in Eastern and Southern Africa, following South Africa. Between 2000 and 2010, it accounted for 12.3 percent of the total maize production in the region, compared to 36.3 percent for South Africa (Demeke, 2012).

2.5 Agricultural periods in Ethiopia

Ethiopia is one of the most climatically complex countries in Africa. This is in part due to its topography, and also because of the country's placement with respect to large scale weather patterns. There is a large amount of spatio-temporal complexity in Ethiopia's seasonal rainfall cycle, which is in general defined by the progression of the Inter-Tropical Convergence Zone (ITCZ). The North and Mid-West of Ethiopia have a single longest rainy season (*Meher)* with its maximum in late July (Fig 2.2). The rest of the country has a bimodal seasonal distribution made up of the shortest rainy season (*Belg)* and longest rainy season (*Meher)* rains (MOA, 2007).

Generally speaking, there are two main agricultural seasons in Ethiopia namely short rainy season (*Belg)* and longest rainy seasons (*Meher)*. Shortest rainy season (Belg) season occurs primarily during February, March and April. It generally consists of short season crops and out of the six staple food crops, short cycle maize is considered the most important. Although Short rainy season (*Belg)* season is important as a hunger breaker, it accounts for only 3% of total production. Longest rainy season (*Meher)* season is the main agricultural season in Ethiopia and is dominated by teff and maize grown during the summer rains (Greatrex, 2012).

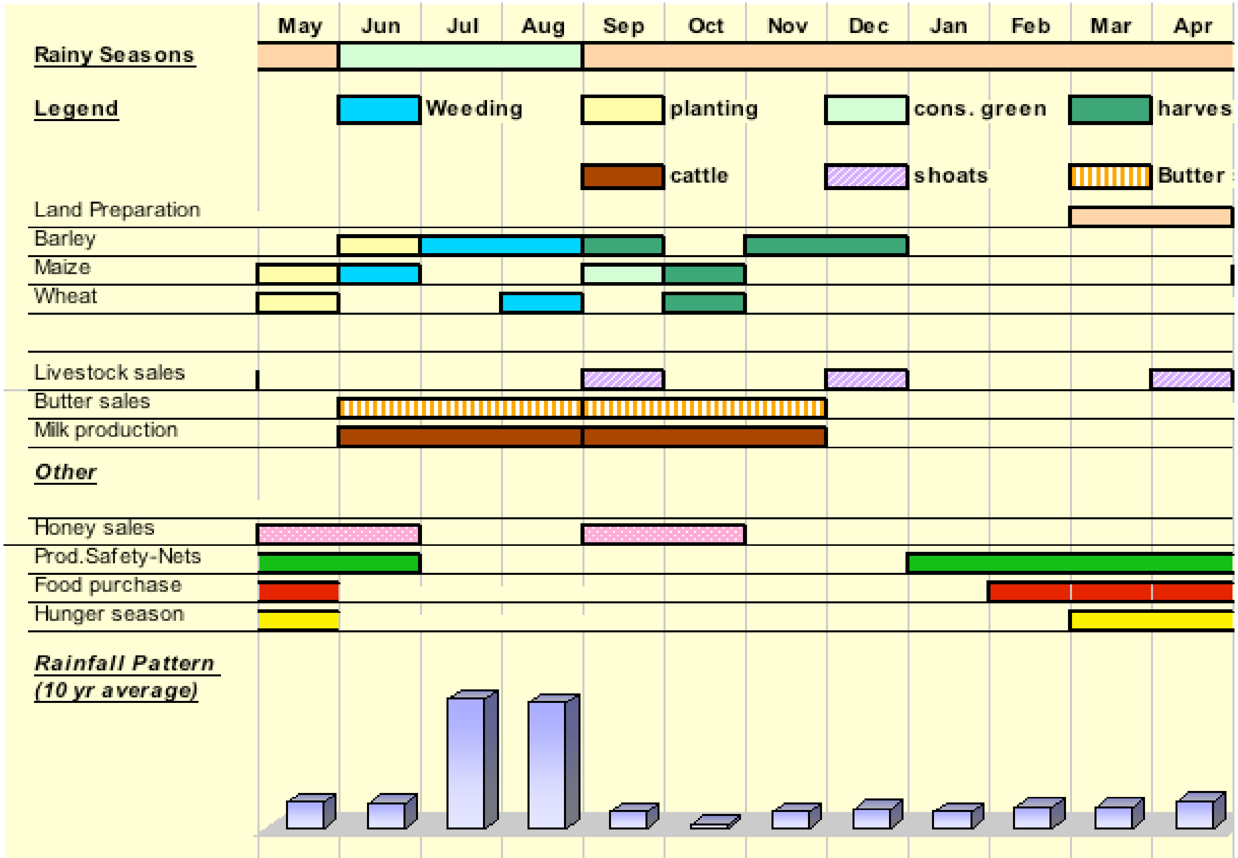

Figure 2.2 Seasonal calendars of crops.
Source: Livelihood profile for Tigray (2007)

CHAPTER THREE

3 MATERIALS AND METHODS

3.1 Description of the study area

The study is conducted in south Tigray zone, Tigray Regional State of Ethiopia. Geographically it is situated, latitude 12^{o}15′16″N–13^{o}38′45″N and longitude 38^{o}59′33″E – 39^{o}53′20″E covering a total area of about 9432 km^2 (Fig 3.1).The altitude of the study area ranges from 1156 to 3671 m asl.

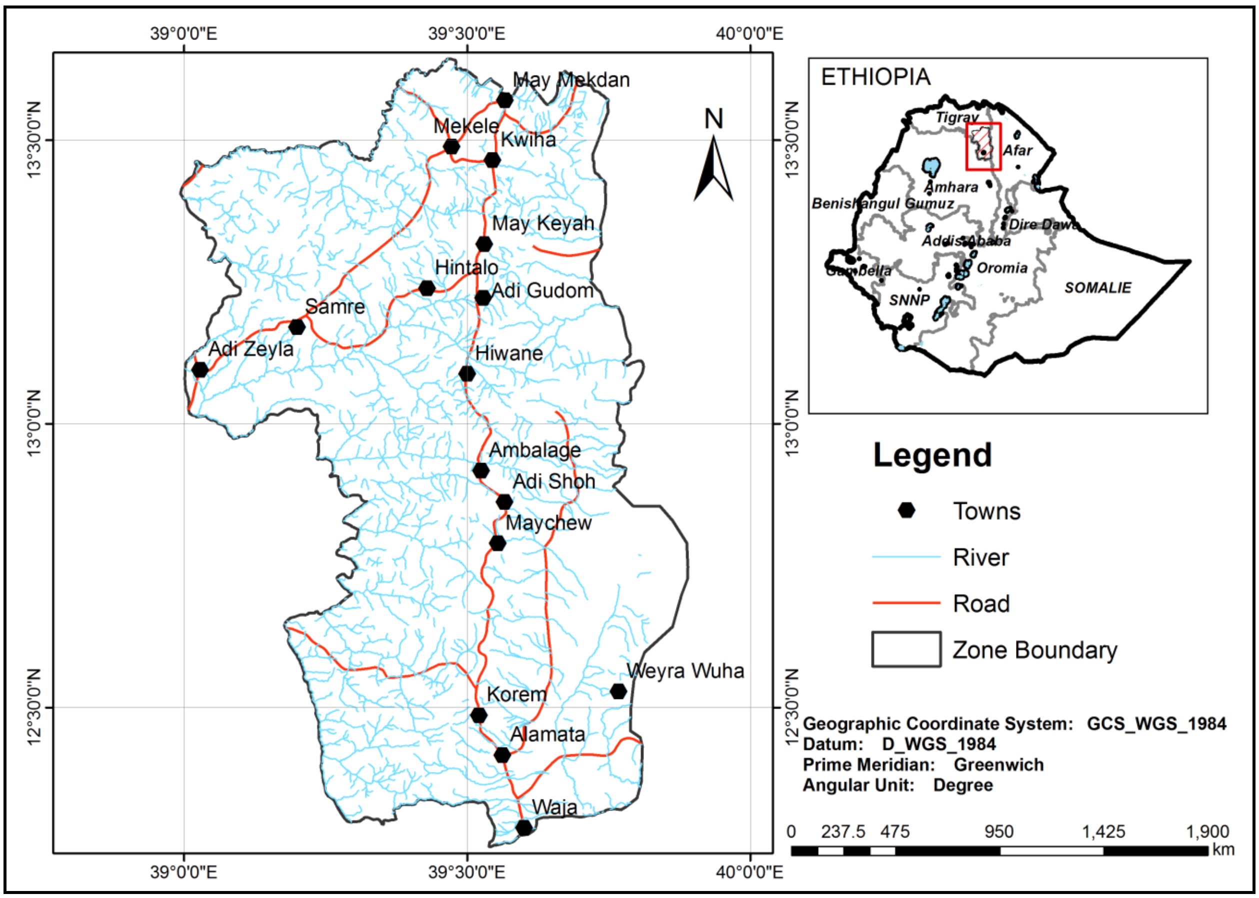

Figure 3.1 Location map of the study area.

3.1.1 Population

Based on the 2007 Census conducted by the Central Statistical Agency of Ethiopia (CSA), South Tigray Zone has a total population of 1,006,504, of which 497,280 are men and 509,224 women; and according to a projection conducted after 5 years the total population of the zone is 1,166,578 of which 575,797 are men and 590,781 are women.

The density of the population of the zone is 61 persons per square kilometer according to CSA Abstract of 2012 (CSA, 2012).

3.1.2 Temperature

The climatic variables of the study area are highly governed by the topography of the area mainly by its altitude. The monthly maximum temperature of the zone ranges from 24.5°C in January to 29.5°C in June and its minimum temperature ranges from 10.2°C in December to 14.8°C in June according to NMA as reconstructed from station observations and remote sensing and other proxies for the years from 1981 up to 2010 (Fig 3.2 and 3.3).

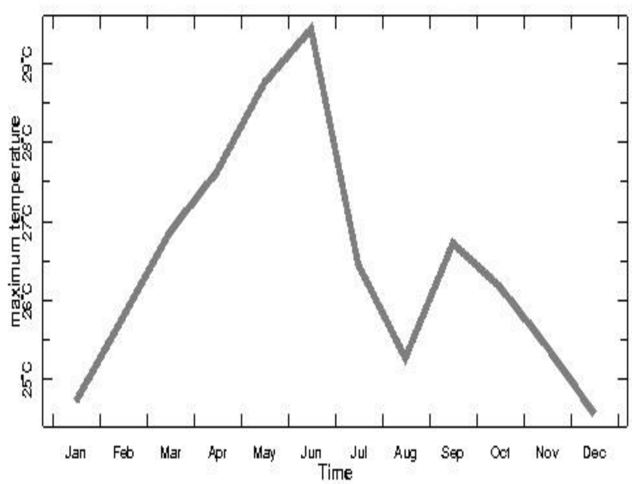

Figure 3.2 Maximum temperature of the study area (1981-2010)

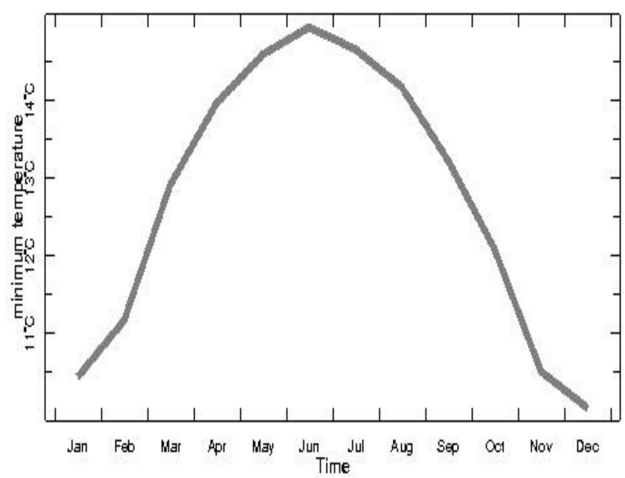

Figure 3.3 Minimum temperature of the study area (1981-2010)

3.1.3 Rainfall

The area is characterized by a bimodal rainfall pattern with a short rainy season "*Belg*" from March to April and a long rainy season "*Meher*" from June to September with a peak in August. The annual mean rainfall varies from 10 mm in November to 210 mm in August as shown in figure 3.4.

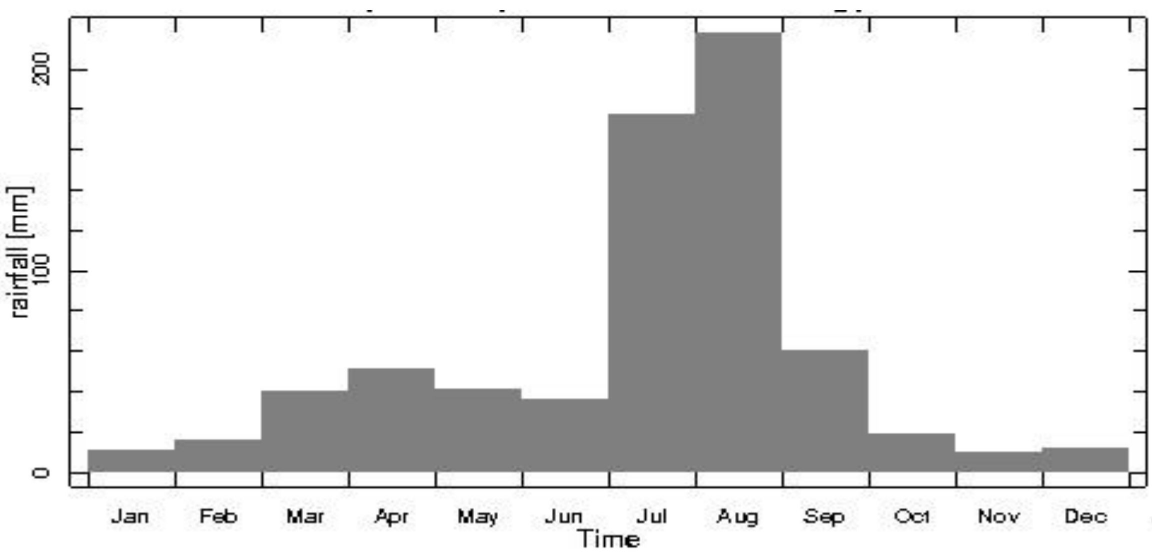

Figure 3.4 Mean monthly rainfall for the year 1983 - 2010

3.1.4 Cropping condition

The planting or sowing time of different crops varies depending on the onset and continuity of the rainfall. There are two distinctly known (Bi-modal) and traditionally used cropping seasons. Short cropping season (*Belg*) is the one, which starts as soon as the last harvest of the previous long rainy *(Meher)* season crop is over. Successful short rainy season crops are meant to leave the land for the second crop season and hence will be harvested around May, allowing enough time for land preparation and sowing of the longest rainy season (*Meher*) crops. The second cropping season is the long rainy season as it is practiced in most parts of the country and the study area. As shown in table 3.1, cereal crops grown in the study area include teff, wheat, maize, barley and sorghum (Dagnew Belay, 2007).

Table 3.1 Area, Production and yield of cereal crops for private peasant holding for meher season 2012/13.

Cereal Crop	Area in Hectare	Production in quintal	Yield quintal /hectare
Teff	41,618.97	520,805.5	12.51
Barley	44,428.61	804,621.08	18.11
Wheat	49,241.73	948,781.03	19.27

Cereal Crop	Area in Hectare	Production in quintal	Yield quintal /hectare
Maize	7,330.77	89,978.33	12.27
Sorghum	42,667.35	798,592.24	18.72

(Source: CSA, 2013 agricultural report).

3.1.5 Soil

The soil type of the study area is dominantly Leptosol followed by Vertisols ,Cambisols and Calcisols (Fig 3.5). Leptosols are by far the most extensive group of soils in the world. They are found mainly in mountainous regions and in areas where soil has been eroded to the extent that hard rock comes near to the surface. Other (minor) occurrences are along rivers where gravely deposits have accumulated without substantial admixture of fine earth material (ISRIC, 2013)[1].

Vertisols are clay-rich soils that shrink and swell with changes in moisture content. During dry periods, the soil volume shrinks, and deep wide cracks form. The soil volume then expands as it wets up. This shrink/swell action creates serious engineering problems and generally prevents formation of distinct, well-developed horizons in these soils (Soil Taxonomy, 2013)[2].

Cambisol type of soil is also dominant type of soil which is characterized by the absence of a layer of accumulated clay, humus, soluble salts, or iron and aluminum oxides. They differ from un weathered parent material in their aggregate structure, color, clay content, carbonate content, or other properties that give some evidence of soil-forming processes. Because of their favorable aggregate structure and high content of weather able minerals, they usually can be exploited for agriculture subject to the limitations of terrain and climate. Cambisols are the second most extensive soil group on earth (Cambisol, 2013)[3].

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[1] http://www.isric.org/about-soils/world-soil-distribution/leptosolsaccessed on 11/18/2013

[2] http://www.cals.uidaho.edu/soilorders/vertisols.htm accessed on 11/18/2013.

[3] http://www.britannica.com/EBchecked/topic/707510/Cambisol accessed on 11/18/2013.

Calcisols type of soil occurs in regions with distinct dry seasons, as well as in dry areas where carbonate-rich groundwater comes near the surface. Soils having a (petro-)calcic horizon (horizon with accumulation of secondary calcium carbonates). In addition, they have no diagnostic horizons other than an ochric or cambic horizon, a calcareous argic horizon, or a gypsic horizon beneath a petrocalcic horizon (ISRIC, 2013)[4].

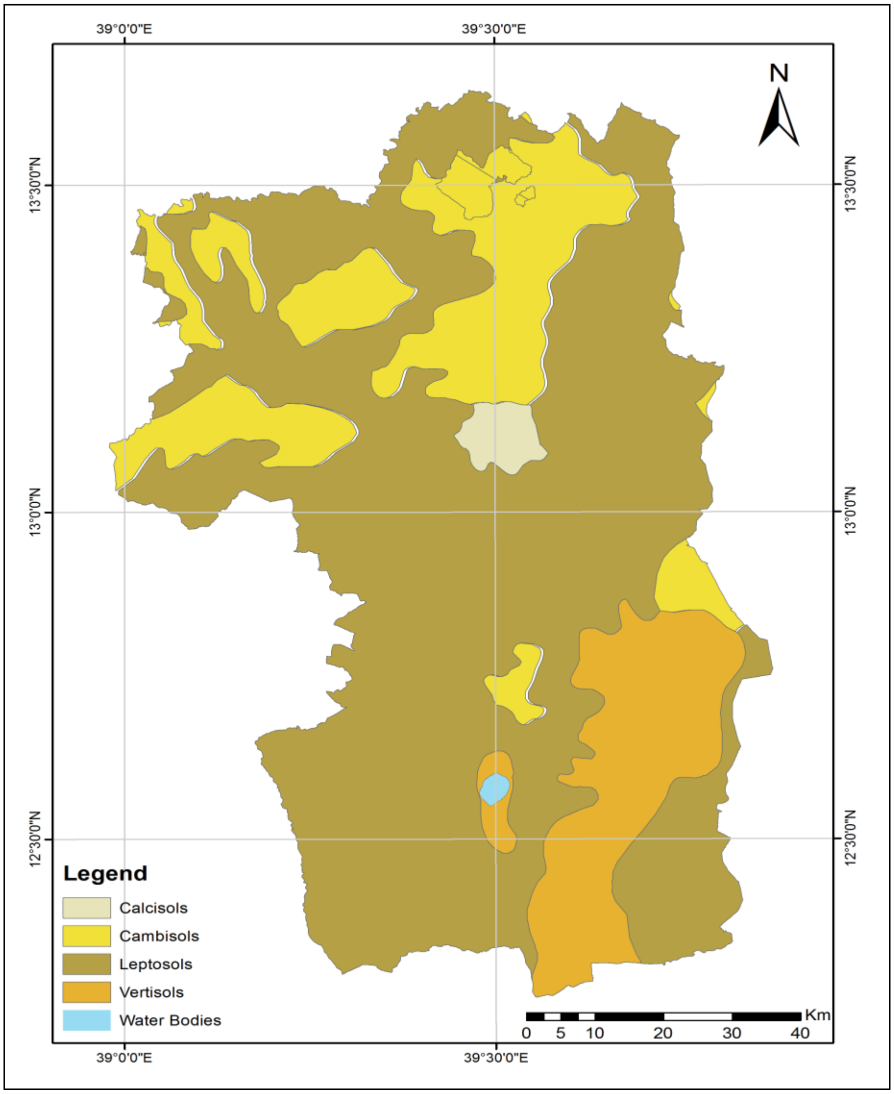


Figure 3.5 Soil map of the study area.
(Source: FAO soil map of 1998)

[4] http://www.isric.org/about-soils/world-soil-distribution/calcisols accessed on 11/18/2013.

3.2 Data acquisition and software packages

The data used in this study were collected both from primary and secondary sources. Primary data comprised of information captured from satellite imagery and field observations. Secondary data sources include published and unpublished materials such as books, topographic and thematic layers, journals, reports of Meteorological Agency and Central Statistical Agency as well as other publications and scientific works. To manipulate these data sets, different software's were also used for the analysis. Details of the methodology are presented in Figure 3.7.

3.2.1 Satellite imagery, available models and ancillary data

In this study different satellite imageries and models were collected from different sources in order to apply them for the analysis. Among them; rainfall estimates, SPOT VEGETATION, WRSI and pan sharpened SPOT 5 imagery were the major ones.

3.2.1.1 Rainfall estimate (RFE 2.0)

According to Helen (2012) rain gauge, radar and numerical weather prediction (NWP) networks are inadequate and insufficient for use in crop yield forecasting in Ethiopia therefore the forecast should be based on satellite rainfall estimation. Washington *et al*. (2006) described that satellite rainfall data have the potential to be used as inputs to crop yield prediction models due to the good spatial coverage and high temporal resolution of the satellite information. This is particularly relevant for Africa where the ground based observational network is often sparse and not always well maintained. Based on these findings, the researcher looks for metrological satellites rather than synoptic information to derive meteorological data. Accordingly the rainfall data used in this study was derived from RFE which is a rainfall estimate product of NOAA's climate prediction center currently used by FEWSNET and several UN agencies such as FAO and WFP for agricultural monitoring in large number of African countries. There exists two RFE versions (RFE 1.0 and RFE 2.0) produced with different methodologies. RFE 1.0 uses an interpolation method to combine Meteosat and Global Telecommunication system data and it is available for the period 1995-2000. RFE 2.0 uses additional techniques to better estimate precipitation while continuing to cold cloud duration (CCD) and station rainfall.

The data is available from 2001. Compared to other rainfall data like ECMWF, RFE shows a better estimation (Rijks *et al*., 2007).

For RFE 2.0 World meteorological organization (WMO) Global Telecommunication System (GTS) data from ~1000 stations provide station rain gauge totals, and are taken to be the true rainfall within 15-km radii of each station. Two new satellite rainfall estimation instruments are incorporated into RFE 2.0, namely, the Special Sensor Microwave/Imager (SSM/I) on board Defense Meteorological Satellite Program satellites, and the Advanced Microwave Sounding Unit (AMSU) on board NOAA satellites. SSM/I estimate are acquired at 6-hour intervals, while AMSU rainfall estimates are available every 12 hours with 8 km resolution. RFE 2.0 obtains the final daily rainfall estimation using a two part merging process. All satellite data are first combined using the maximum likelihood estimation method, then GTS station data are used to remove bias. This RFE 2.0 satellite rainfall estimate was used and can be freely down loaded from http://earlywarning.usgs.gov/fews/africa/web/dwndailyrfe.php(Eerens *et al*., 2014).

3.2.1.2 SPOT VEGETATION (VGT)

The SPOT VEGETATION(VGT) which was launched in March 1998 on board of the SPOT 4 satellite, to monitor surface parameters with a frequency of about once a day on a global basis at a spatial resolution of 1 km is selected for NDVI derivation. Compared with the existing instruments of the same kind, in particular NOAA AVHRR, SPOT VEGETATION provides an enhanced radiometric resolution and above all a limited local distortion of about 0.3 km (Rojas *et al*., 2005; Sawasawa, 2003).

When a set of multi-temporal images is processed, a high geometric accuracy is absolutely critical. The same pixel, taken from images relative to different dates, must represent the same ground area, with a minimum shift. This was not the case for the NOAA-AVHRR images under this aspect the new SPOT-VGT images are much better (Rijks *et al*., 2007).

SPOT VEGETATION which is synthesized for Decadal (S10) images became regularly available from the first of January 2003 therefore can be used for this research for NDVI analysis (2003-2013). Here software called Spirit was used to analyze time series imagery. Daily synthesis (S1) or ten-day synthesis (S10); these are mosaics of acquired image segments, respectively for 24h periods and for the last 10 days. A Maximum Value Composite (MVC) synthesis can be delivered with several spatial resolutions. These three products are called S10 for 1 km^2 data, S10.4 for 4 km^2, and S10.8 for a resolution of 8 km^2 (Eerens *et al*., 2014).

3.2.1.3 Water requirement satisfaction model

Originally developed by FAO, the WRSI has been adapted and extended by USGS in a geospatial application to support FEWSNET monitoring requirements. USGS/FEWSNET recently uses Geospatial Water Requirement Satisfaction Index (WRSI) crop model, which allows for localized crop modeling, monitoring and forecasting at sub national level, using locally available datasets as model inputs. The result of this model was also selected as one parameter in order to develop a maize forecast model.

WRSI for a season is based on the water supply and demand a crop experiences during a growing season. It is calculated as the ratio of seasonal actual evapotranspiration (ETa) to the seasonal crop water requirement (WR):

WRSI = (AET / WR) * 100.

WR is calculated from the Penman-Monteith potential evapotranspiration (PET) using the crop coefficient (Kc) to adjust for the growth stage of the crop:

WR = PET * Kc.

AET represents the actual (as opposed to the potential) amount of water withdrawn from the soil water reservoir ("bucket"). Whenever the soil water content is above the maximum allowable depletion (MAD) level (based on crop type), the AET will remain the same as WR, i.e., no water stress. But when the soil water level is below the MAD level, the AET will be lower than WR in proportion to the remaining soil water content (Tinebeb, 2012).

3.2.1.4 Pansharpened spot 5 imagery

Pansharpening is a technique that merges high resolution panchromatic data with medium resolution multi spectral data to create a multi spectral image with higher resolution features. Pan sharpening allows using panchromatic (pan) and multispectral (MS) images from different sources and sensors to produce pansharpened color images.

A multi spectral image is an image that contains more than one spectral band. It is formed by a sensor which is capable of separating light reflected from the earth in to discrete spectral bands while a panchromatic image contains only one wide band of reflectance data. The data is usually representative of a range of ‘n’ bands and wavelength, such as visible or thermal infrared, that is, it combines many colors so it is “pan” chromatic.

A multi spectral image contains a higher degree of spectral resolution than a panchromatic image, while often a panchromatic image will have a higher spatial resolution than a multi spectral image. Therefore this study uses a pansharpened image which represents a sensor fusion between the multi spectral Landsat image and panchromatic image of SPOT which gives the best of both image types i.e high spectral and spatial resolution of SPOT 5 meter panchromatic image for crop masking generation (Leiliesand and kiefer, 1998).

3.2.1.5 Ancillary dataset

There are other relevant data sets that are obtained from CSA, like shapefile which is developed for 2007 population and housing census. These shapefiles were used to restrict the study area boundary and helped much for field visit especially for accuracy assessment by identifying accessible areas. Toposheets from EMA were also used to check the geometric correction of the satellite imageries.

3.2.1.6 Official yield statistics

The production of quantitatively yield estimates needs the calibration of the model with historical crop yield statistics. A specific attention must be paid on the spatial level at which these data are available to be able to consider homogenous areas as well as on the length of the time series of the statistics (Rijks *et al*., 2007). Accordingly, historical grain yield data (2004-2012) which is available at zonal level was collected from Central Statistical Agency (CSA). The agricultural department of CSA provided the archive of maize grain yield estimate (Fig 3.6). The yield statistics were obtained from ground sample survey based on list frame approach (see CSA annual agricultural report of 2013 for detail).

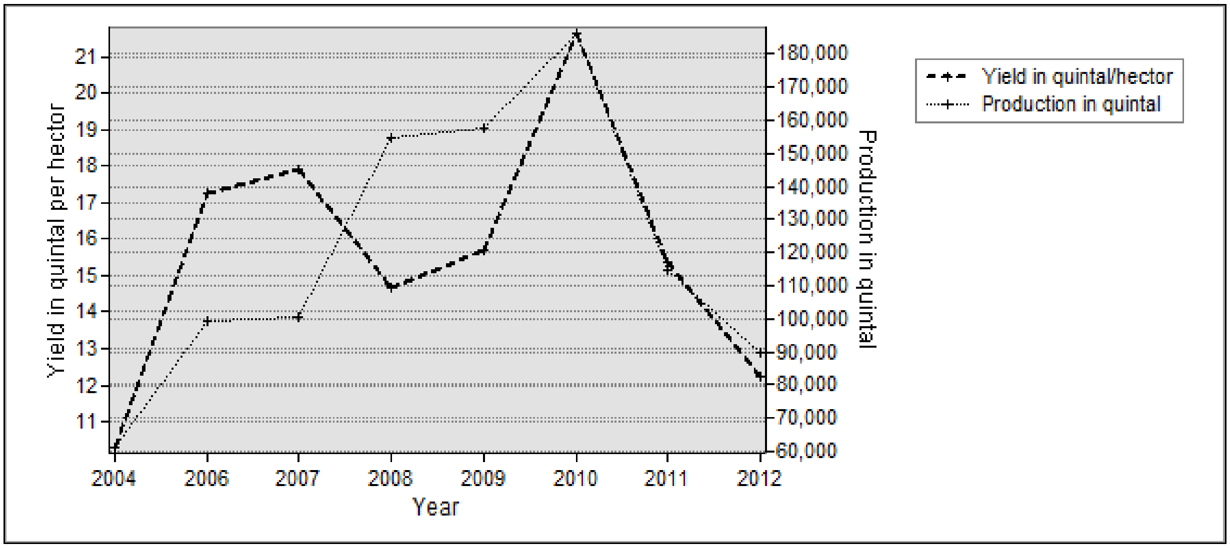


Figure 3.6 Trend of Maize crop yield (2004 – 2012) in south Tigray Zone.

Source: CSA annual agricultural report.

3.2.1.7 Materials

Table 3.2 presents the materials and software's used in the study in line with their sources and purposes.

Table 3.2 Summary of equipment and materials used for data collection and analysis.

No	Equipment	Source	Purpose
1	Satellite Images	SPOT VEGETATION(1 km resolution)	For NDVI derivation
		SPOT 5 Image PanSharpened (5 m resolution)	For land cover analysis
		RFE 2.0 (8 km)	To derive rainfall
		ETa (1 km)	To derive Evapotranspiration
		PET(1 degree)	To derive Potential Evapotranspiration

No	Equipment	Source	Purpose
2	Toposheet - 1338 B_4,D_2,D_4 - 1339 A_3,A_4,B_3,B4 C_1,C_2,C_3,C_4 D_1,D_2,D_3,D_4 -1340 A_3,C_1,C_3 - 1238 B_2,B_4,D_2 - 1239 A_1,A_2,A_3,A_4 B_1,B_2,B_3,B_4 C_1,C_2,D_1,D_2 -1240 A_1,A_3,C_1	EMA	Geo- referencing
3	GPS(Global Positioning System)	CSA	Positioning and receiving data from satellites
4	Erdas Imagine 9.2, ArcMap10,Spirit, MadCAT 3.3, VGT extract, LEAP 2.7.1, JMP statistical tool, e- cognition 8.2		GIS & statistical software for image and vector processing and data analysis.
5	Administrative Boundaries	Central Statistical Agency(2007 population census)	For subseting study area

3.2.1.7.1 SPIRIT software

Most of the available GIS and image processing software packages do not provide a complete range of built in functionalities to handle time series of images, and are not optimized for the needs of the crop monitoring community. They generally do not offer a flexible image processing environment that can be used by technicians and involved institutions to adapt the data analysis steps and generate additional and customized outputs. Therefore, we can conclude that none of the existing systems provides in one package the highly specific set of time series processing functions to assess crop and vegetation status, including temporal smoothing, computation of long term averages and anomalies, classification based on vegetation seasonal performance, and production of the outputs traditionally used in crop monitoring bulletins (statistics, maps, graphs). For this reason, a flexible and user-friendly interface, targeting both national and international agriculture and food security experts, is highly desirable (Eerens *et al*., 2014).

SPIRITS is an integrated, modular software platform that aims at answering the requirements outlined above. The software is extensively documented and distributed freely for non-commercial use. SPIRITS works with 2D-flat binary image files. “2D-flat” means that the layers of a multi-spectral or multi-temporal set are stored as separate files. The ancillary information (“metadata”) must be present in an additional ASCII-file with the same name as the image but with extension “.hdr”. For the latter, the rules of the ENVI software are followed, although new keywords have been added to provide more information on the image values, their scaling to physical units, the presence of flags (i.e. codes to label special features such as sea, clouds, snow), acquisition date and periodicity (at the moment only daily, ten daily, monthly and annual images are allowed) (Eerens *et al*., 2014).

3.2.1.7.2 JMP statistical software

JMP combines powerful statistics with dynamic graphics, in memory and on the desktop. Its interactive and visual paradigm enables JMP to reveal insights that are impossible to gain from raw tables of numbers or static graphs. For statistical data analysis and model building JMP statistical discovery software from SAS would enable user to produce vibrant statistical analysis (Allbed *et al*., 2014).

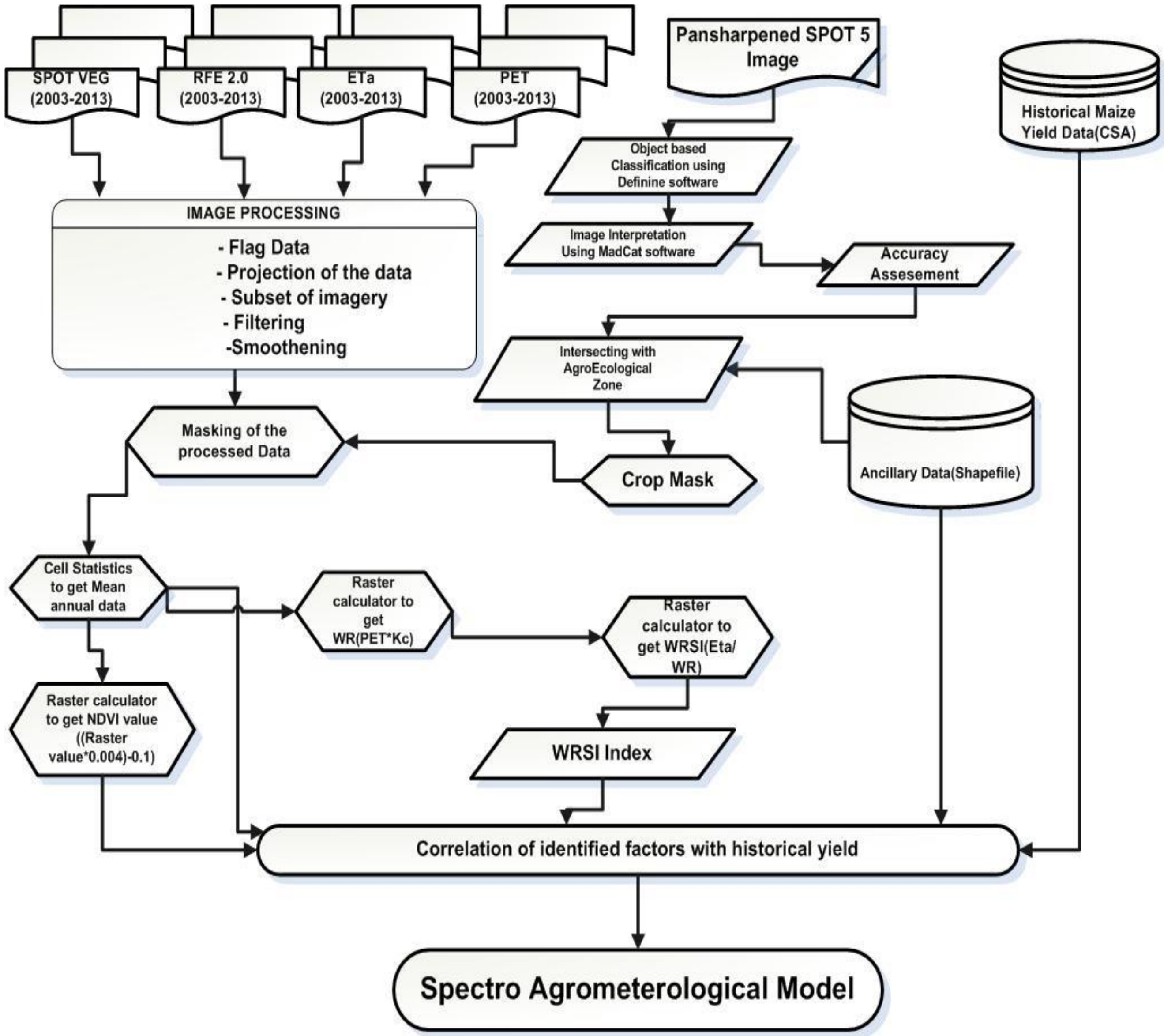


Figure 3.7 Methodological flow chart of spectro-agrometerological model.

3.3 Data processing and analysis methods

There are two approaches of quantifying yield production using remote sensing. These are purely remote sensing approach (direct approach) and mixed approach where additional bio climatic predictor variables are used. In many cases, the predictive power of remotely sensed indicators can be improved by adding independent meteorological (bio climatic) variables in the regression models but in an area where there is stable crop area over the observed period and homogenously large area a direct NDVI / production regression can be applied (Rembold *et al*., 2013).

Potdar *et al*. (1999) as cited in Rembold *et al*. (2013) observed that the spatiotemporal rainfall distribution needs to be incorporated in to crop yield models, in addition to vegetation indices deduced from remote sensing data, to predict crop yield of different cereal crops grown in rainfed condition. Such hybrid models show higher correlation and predictive capabilities than the models using remote sensing indicators only as input variables. Therefore, due to these advantages this research uses the mixed approach which is also refereed as spectro-agro meteorological approach.

In the spectro-agro meteorological approach, the spectral component introduces information about crop management, varieties and stresses while bio climatic variables introduce information about solar radiation, temperature, air humidity and soil water availability (Rembold *et al*., 2013).

3.3.1 Selection of date of satellite imagery and acquiring the time series imagery

The choice of the date of the image is made based on the analysis of the information given by the farmers on the date of transplanting and date of harvesting. The choice of date was in such a way that the image should coincide with the peak vegetation period of the farmers field (Rembold *et al*., 2013).

Accordingly the study area planting date is found to be from middle of May and this is also cross checked with the zone livelihood profile which also states that May is planting date for maize crop in the study area. Generally maize crop in southern Tigray zone is planted in May, growth in biomass occurs from June to July and flowering in September based on the information found from the interview with the local farmers.

Following this, SPOT-VGT NDVI Decadal images is freely downloaded from the website http://www.vito-eodata.be/PDF/portal/Application.html from the month May up to September starting from 2003 to 2012 (ten years' time series data).

After acquiring the data (which consists of several HDF layers joined in one ZIP file), the following steps were performed:

1. Extraction of the NDVI product and the so-called 'Status Map' using VGT Extract software. This software is freely available for download on www.agricab.info.

2. Applying the Status Map on the NDVI image in SPIRITS software using the 'Flag VGT NDVI' tool.

After the above two processes were carried out, 150 decadal (S-10) images of SPOT VGT NDVI (Fig 3.8)were ready for further analysis with raster value ranging from 0 to 255.

In the same manner, RFE 2.0 satellite rainfall estimates which are found in dekedal at http://earlywarning.usgs.gov/fews/downloads/index.php?regionIDwerefreely downloaded from the month May up to September starting from 2003 to 2012(ten years' time series data) with rainfall estimate ranging from 0 up to the maximum rainfall estimated (Fig 3.9).

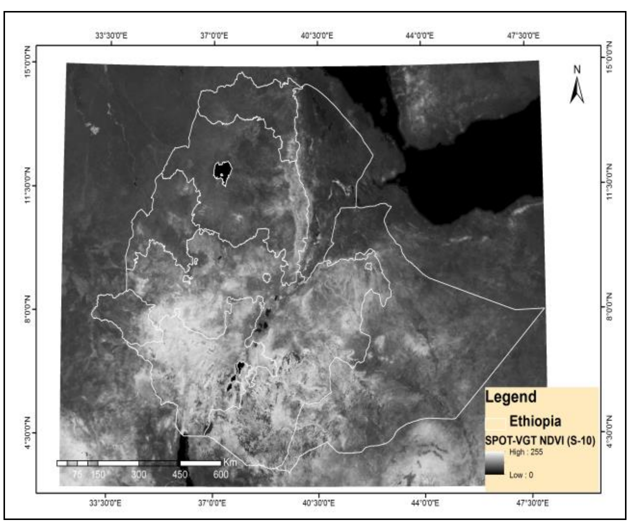


Figure 3.8 SPOT VGT image of Ethiopia,1st Decade of May 2003.

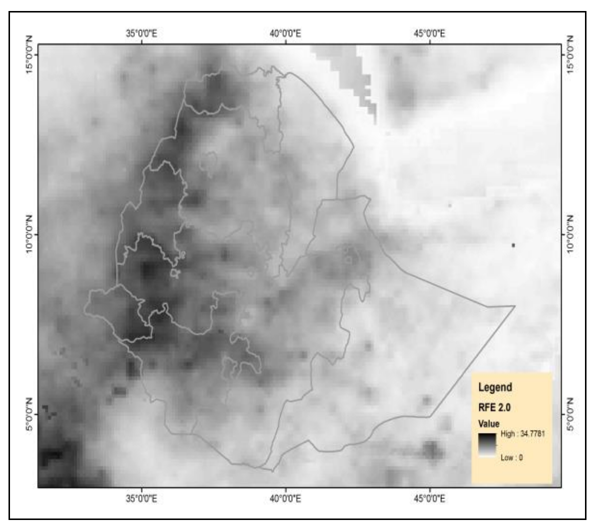
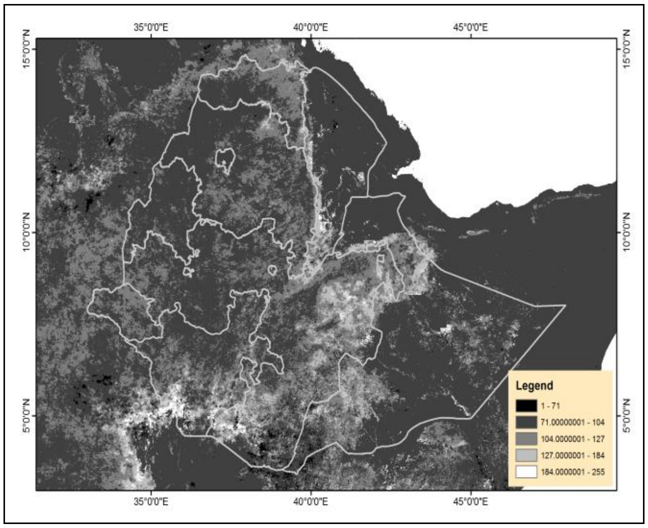


Figure 3.9 RFE 2.0 image of Ethiopia, Mean of 2003 (May - September).

Actual Evapotranspiration (ETa) and Potential evapotranspiration (PET) are another input for the model computation which were downloaded freely from FEWSNET http://earlywarning.usgs.gov/fews/downloads/index.php? at monthly and annual level from May up to September of year 2003 up to 2012 respectively (Fig 3.10 and 3.11).



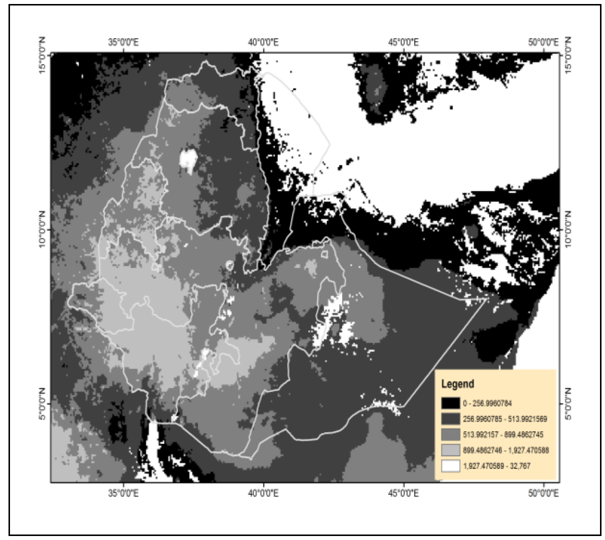


Figure 3.10 ETa imagery of September, 2010.

Figure 3.11 PET imagery (2003 mean annual).

3.3.2 Preprocessing of satellite images

A prerequisite for using time series of remote sensing data for agricultural application is atmospheric correction and geometric rectification of the dataset. In this study, the S-10 images were used. The S-10 images represent maximum S-1 values with in a ten day period to minimize the effects of clouds and atmospheric optical depth. Atmospheric corrections for ozone are done on the images before they are delivered to users (Sawasawa, 2003).

The products of SPOT VEGETATION acquired by MARS are 10-day NDVI synthesis (S10) images, obtained through Maximum Value Compositing (MVC). The images are corrected for radiometry, geometry and atmospheric effects and the same is carried out for RFE 2.0 results (Rojas *et al*., 2005). However other preprocesses were carried out such as projecting the layers, extracting region of interest, smoothening and filtering.

3.3.2.1 Projection of the data

All data used in this study including satellite imageries of different source, topographic maps, thematic layers like road, towns were projected to the geographic coordinate system GCS_WGS_1984 and datum of World geodetic system 84 (WGS 84), ensuring consistency between datasets. Here topographic maps were used to check the geometric rectification of the satellite imageries.

3.3.2.2 Extracting region of interest

The first step which is necessary for the preprocessing is extracting of all the available raster data with the shapefile of the study area. This extraction of region of interest allows running any process in a relatively short time. The process is performed in one go for all images using SPIRITS software.

3.3.2.3 Filtering of the study area

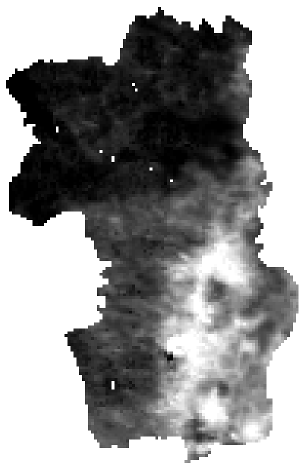
In a filter operation the values of each pixel is changed according to its value in the original image and the value of neighboring pixels. Some examples of applications when filtering is used are noise removal or for the visual enhancement of the image. The filter tool applies a user defined kernel to calculate new values for the central pixel using a mathematical operation on the original cell value and its neighbors.

The software which I have used for the analysis of time series data (SPIRITS) includes a low pass filter tool which is designed to emphasize larger, homogenous areas of similar tone and reduce the smaller detail in an image (Eerens *et al*.,2014).

3.3.2.4 Smoothening of the study area

Since raw series of SPOT VEG/RFE 2.0 are quite irregular, they must be pre-processed, filling unexpected and unreliably low values caused by local dampness/mist or partial cloudiness and simulating reasonable values for cloudy pixels. This is done for all 150 dekedal images in one go on the series of all pixels, using a particular option of the SPIRIT Software program.

A good way of looking at time series at pixel level is the Z-profile tool of ENVI. In order to export time series to ENVI, MTA (meta) files were created to visualize the time profile of smoothed and non-smoothed images. Figures from 3.12 – 3.15 explains the difference between the smoothed and unsmoothed images and how smoothening corrects values to the normal situation by avoiding outliers (Spirit manual, 2013).



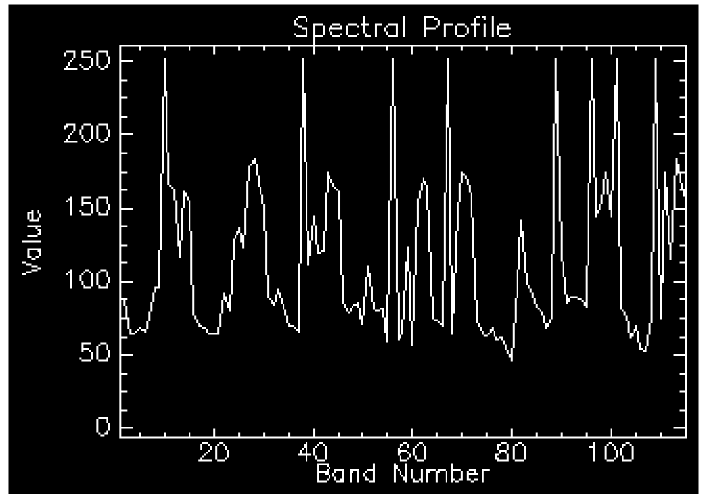


Figure 3.12 UnSmoothed S10s time series

Figure 3.13 Spectral profile of unsmoothed data

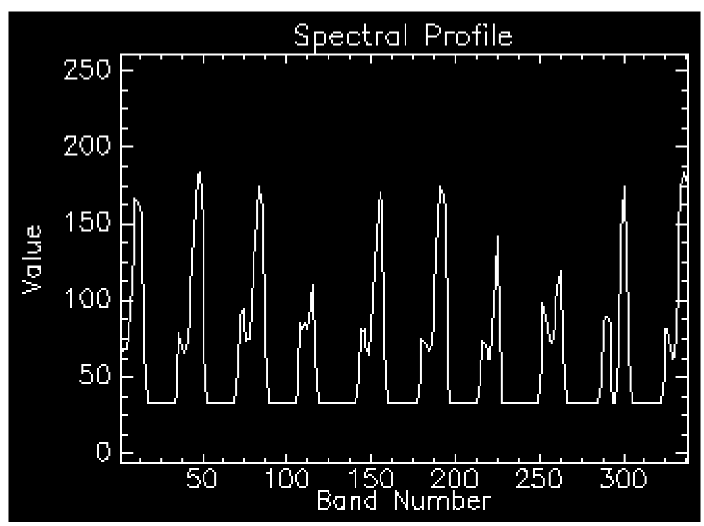


Figure 3.14 Smoothed S10s time series

Figure 3.15 Spectral profile of smoothed data

3.3.3 Maize crop masking

One obstacle to successful modeling and prediction of crop yields using remotely sensed imagery is the identification of image masks. Image masking involves restricting an analysis to a subset of a crop land masking where all sufficiently cropped pixels are included in the mask but the ideal approach would be to use crop specific masks. This would allow one to consider only information pertaining to the crop of interest. However, this approach is not applicable to areas such as, the one being studied by the researcher where there is crop rotation. Therefore, crop masking at crop land area is acceptable for such areas (Rijks,2007). For this reason, pan-sharpened SPOT 5 imagery is used in order to carryout land cover classification for the study area.

3.3.3.1 Image interpretation

Image interpretation is defined as the extraction of qualitative and quantitative information in the form of a map, about the shape, location, structure, function, quality, condition by using human knowledge or experience. Image interpretation in satellite remote sensing can be made using a single scene of satellite imagery (Kindu *et al*., 2013).

Pansharpened SPOT 5 image of 2006 was acquired from CSA and used for image classification using visual image interpretation (Fig 3.16). The pansharpened SPOT 5 image is then processed in Definien software for object based classification.

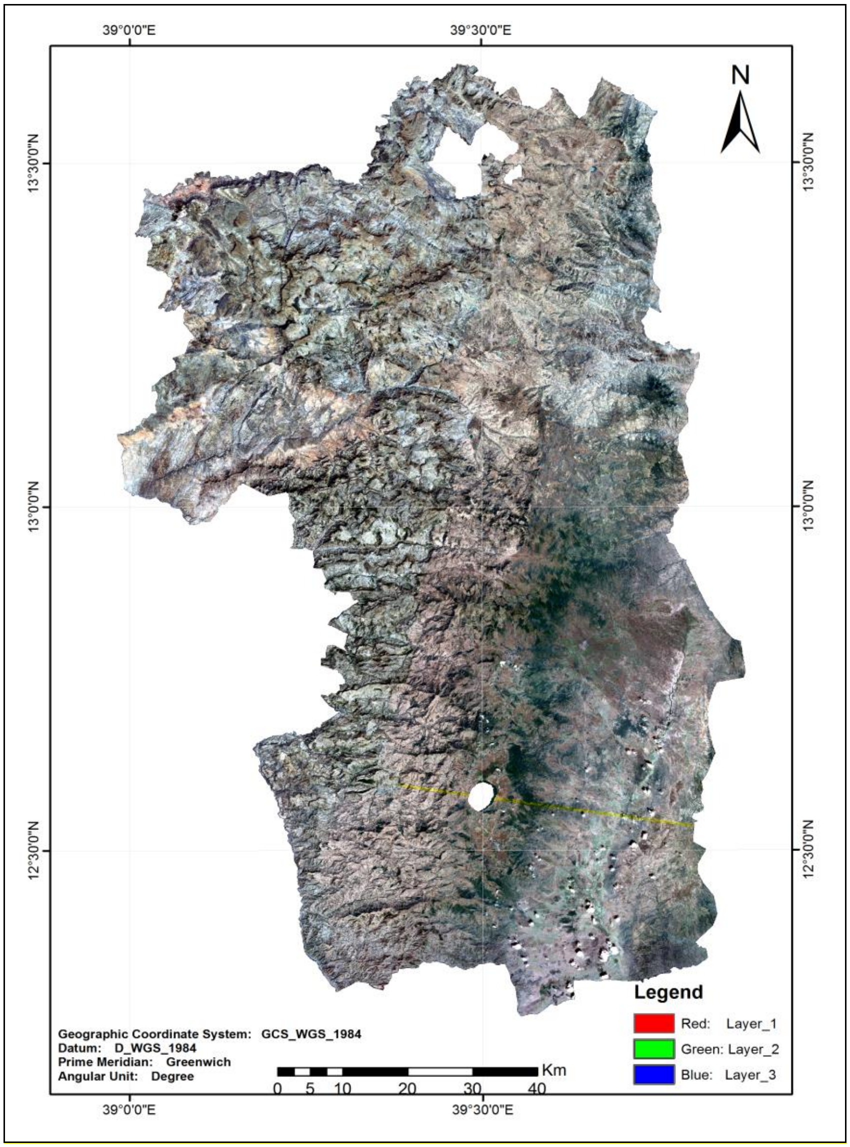


Figure 3.16 SPOT image of the study area.

Object based image analysis requires the creation of objects or separated regions in an image. One established way to do so is image segmentation. Depending on its application, different approaches exist for image segmentation ranging from very simple to highly sophisticated algorithm (Kindu *et al*., 2013).

Multi resolution segmentation (MS) which is available in e-cognition developer 8.0 software is used for image segmentation. The MS algorithm is bottom up region merging technique starting with a single image object of one pixel and repeatedly merging them in several loops in pairs to larger units. It also optimizes the procedure that minimizes the average heterogeneity for a given number of objects and maximizes their homogeneity based on defined parameters. These parameters are scale, shape and compactness and defined through trial and error to successfully segment objects in an image (Kindu *et al*., 2013).

Using identified target LULC classes object based classification was applied to a segmented image in order to assign a class to each of the segments using MaDCAT software and the technique followed was visual interpretation. This approach attempts to assign objects that are generated through image segmentation in to a specific class of interest, in our case agriculture and non-agriculture class (Fig 3.17).

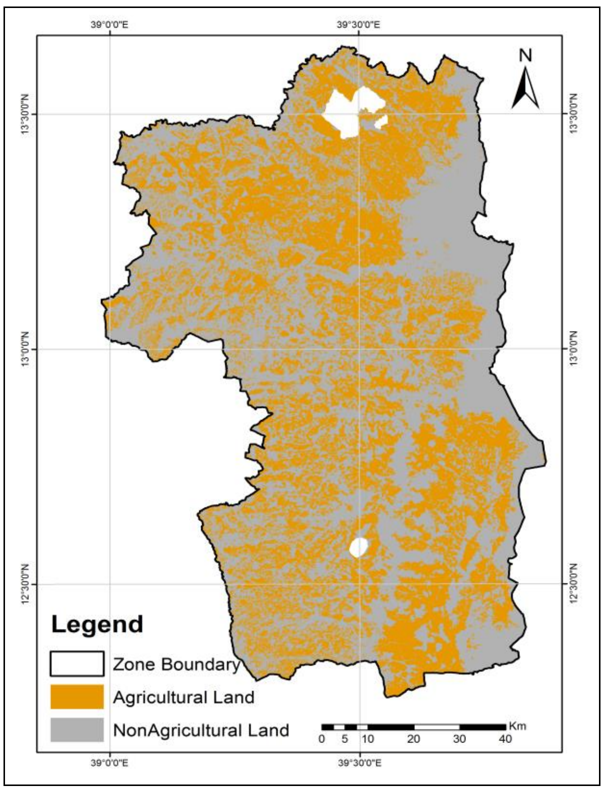


Figure3.17Interpreted image of the study area.

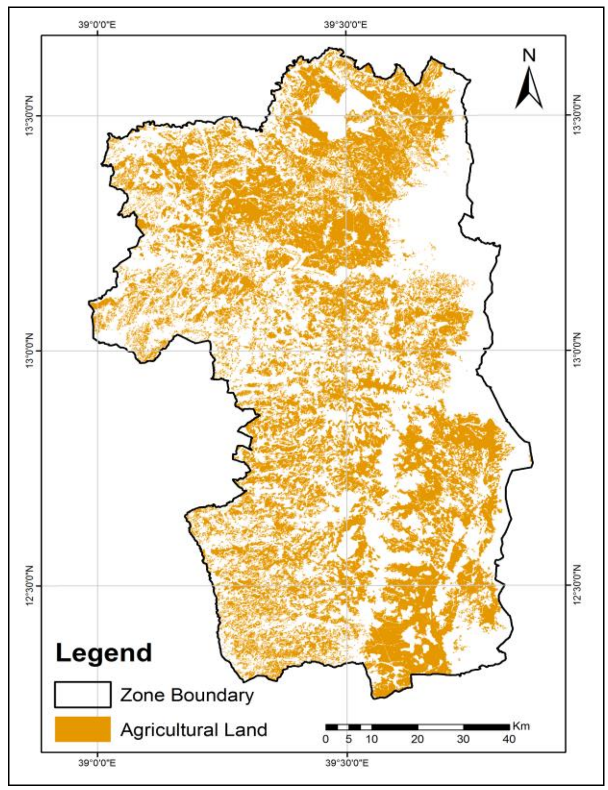


Figure 3.18Agricultural land of the study area.

3.3.3.2. Accuracy assessment

Land cover accuracy is commonly defined as the degree to which the derived classification agrees with reality and the accuracy of the map in a larger part determines the usefulness of the map (Ashenafi Burqa, 2008).

Accuracy assessment is critical for a map generated from any remote sensing data. Error matrix is the most common way to present the accuracy of the classification results. Overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off diagonal elements of the error matrices and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance.

For an accuracy assessment of a map being produced by object based image analysis (OBIA) the units to be tested are the image objects. Therefore, the OBIA classification is validated with the representation of the whole polygon majority class. Accordingly, the above interpreted classes (i.e. agriculture and non-agriculture) were equally represented.

The enough number of samples that represent the thematic classes and ensure good distribution across the map is important to test the attribute accuracy. Rule of thumb is 50 samples per map class or can be derived using the formula devised by Grenier *et al.* (2008).

$$n = \frac{B\pi(1-\pi)}{b2}$$

Where' n' is total sample, 'B' is determined from a chi square table with 1 degree of freedom multiplied by $1 - \frac{\alpha}{k}$ where k is the number of classes ,

'α' is the precision error tolerance,

'b' is absolute precision of each cell ,

'π' is the proportion of the class.

Accordingly the sample size for the accuracy assessment is found to be 288 and 144 sample points were generated for each class. Then these points were randomly generated for each class and their GPS reading was up loaded to GPS for the field accuracy assessment (Fig 3.19).

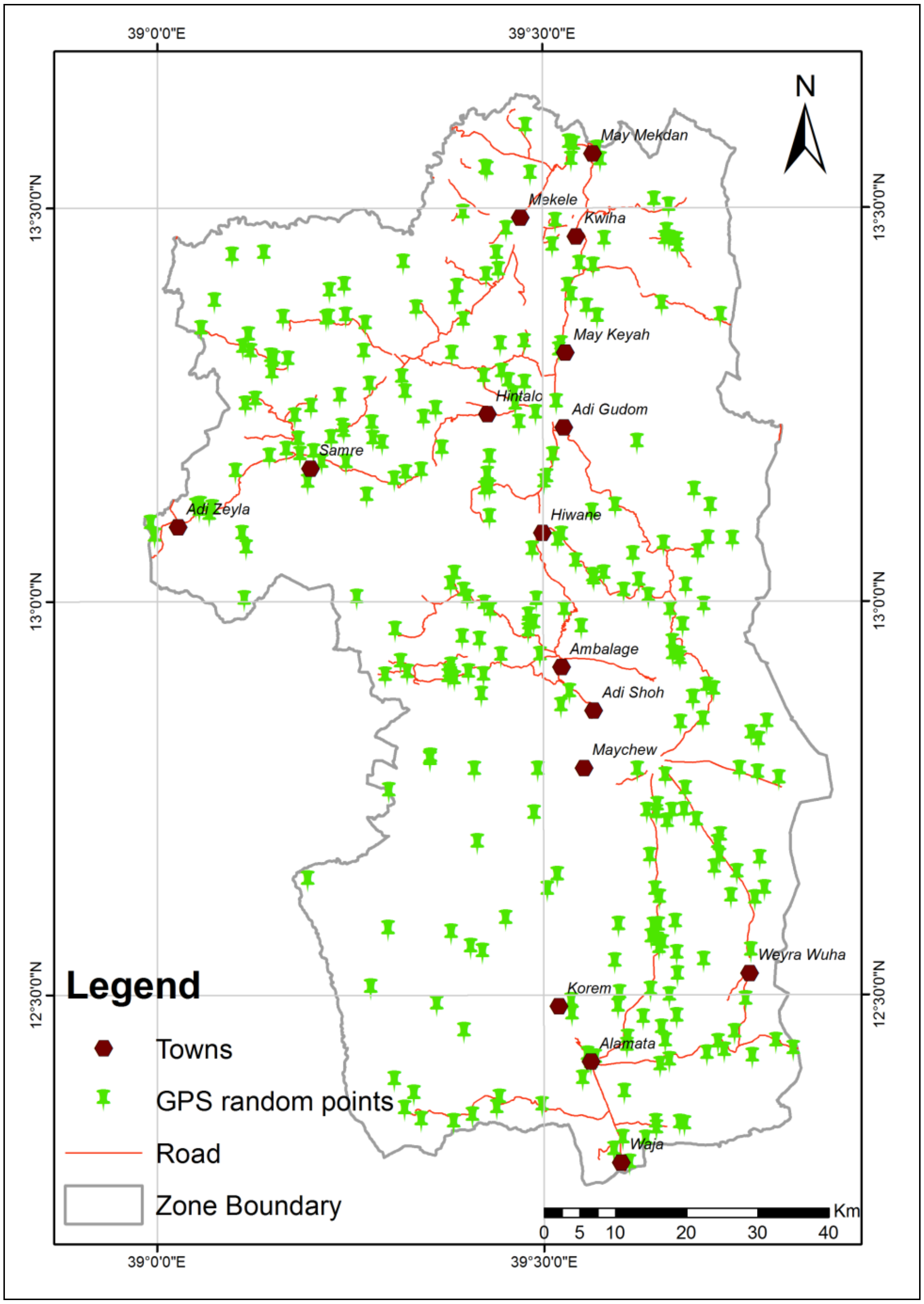


Figure 3.19 Random points generated for accuracy assessment.

These points were checked in two ways; those that are accessible were observed in the field and the second means was using Google Earth as a reference. Accordingly the following error matrix (Table 3.3) for the 288 sample points is presented as follows.

Table 3.3 Accuracy assessment table

	Ground Truth data				
		Agriculture	**Non Agriculture**	**Total**	**User Accuracy**
Map Data	**Agriculture**	***130***	**14**	**144**	**90.28**
	Non Agriculture	**23**	***121***	**144**	**84.03**
	Total	**153**	**135**	***288***	
	Producer Accuracy	**84.97**	**89.63**		

The overall accuracy and kappa analysis were used to perform a classification accuracy assessment and accordingly over all accuracy of the data is 87% and kappa coefficient was computed which is 0.74 and from the result the interpretation can be taken as accurate result for further analysis. Detail calculation of user and producer accuracy and sample photos can be referred from the Appendix 2 and 3.

3.3.3.3. Crop mask data derivation

Another input for the masking of the crop data is crop agro ecology of the study area. This data is then selected using an optimum elevation which is suitable for maize growth according to Dereje and Eshetu (2011) that is between elevations of l500 and 2200 meters.

The interpretation result of land cover which have only Agriculture land area was intersected by Crop agro ecological zone suitable for maize crop to refine the interpretation (Fig 3.20) and to reach to a more crop specific mask data for the study area (Rijks *et al*.,2007).

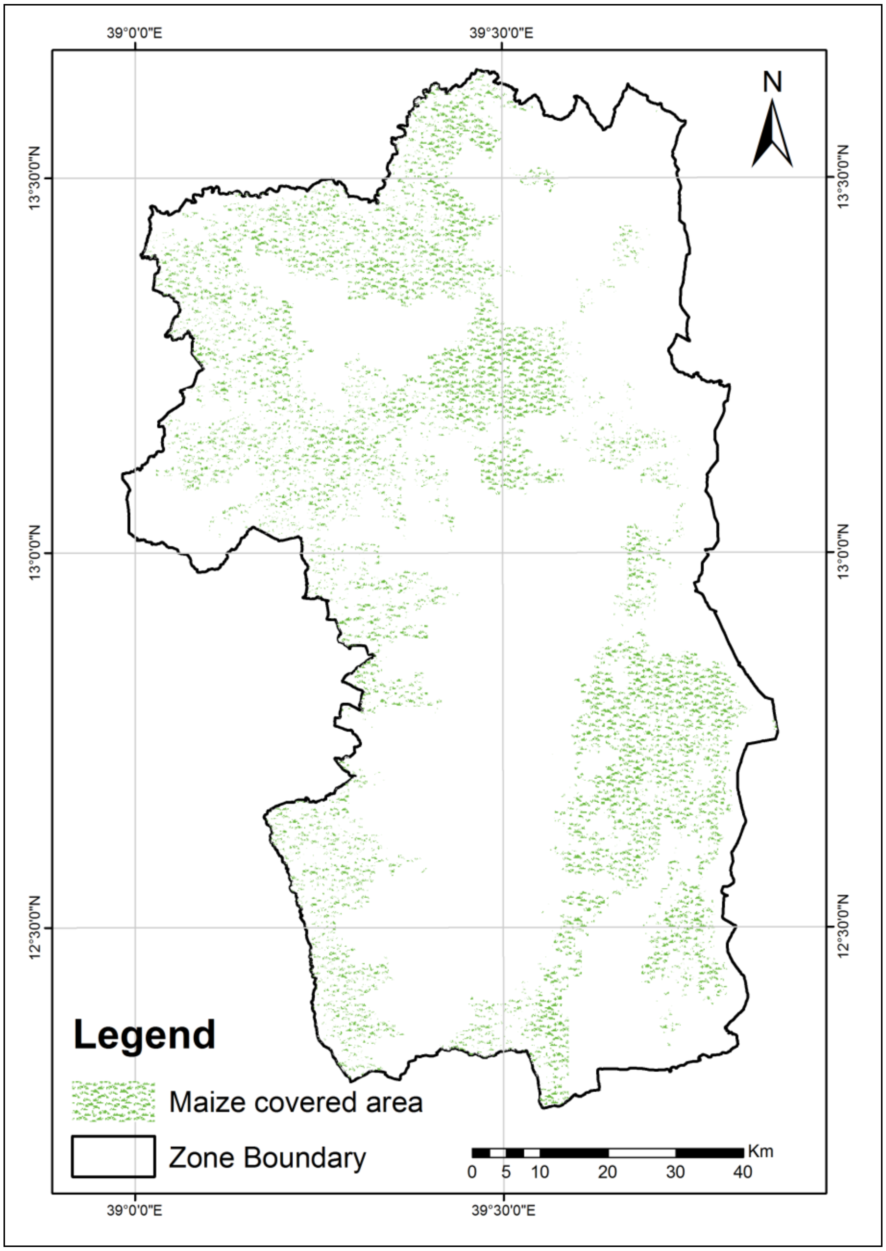


Figure 3.20 Crop mask data for maize.

3.3.4. Preparing independent variables using mask data

To determine the predictive capability of the independent variables, all variables are extracted with crop mask data for further correlation analysis and to identify highly correlated ones with the dependent variable which is maize yield.

The time series data (150 dekedal) of NDVI which have passed through image preprocesses in one go were ready for monthly maximum value compositing (MVC) and 50 monthly composited NDVI images were prepared. These monthly NDVI images were then extracted using the crop mask data to focus only on crop of interest then average NDVI, cumulated NDVI and Maximum NDVI value for each year was computed. The calculated value is in raster value which ranges from 0 to 255 and needed to be changed to NDVI value. Thus, the formula, NDVI = (RAW*0.004) - 0.1, is run and the result were ready for correlation with maize yield (Fig 3.22) (Eerens and Haesen, 2013).

RFE 2.0 time series data of Decadal image was also composited at monthly level using MVC and were extracted with crop mask data and yearly average was computed from the extracted results for further analysis (Fig 3.25).

The WRSI model which is a ratio of seasonal actual crop evapotranspiration (ETac) to the seasonal crop water requirement, which is the same as the potential crop evapotranspiration (PETc). Here maize crop coefficient from LEAP software was adopted (fig 3.21) for the phonological stage and accordingly;

May and June – 0.3

July – 0.75

August – 1.2

September – 0.6

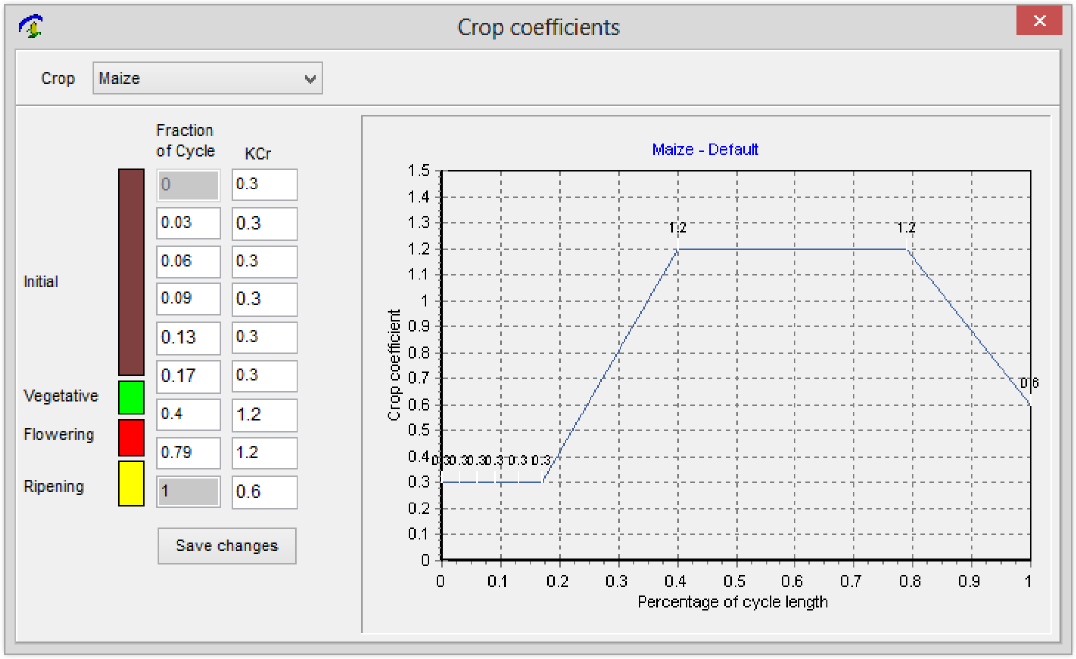
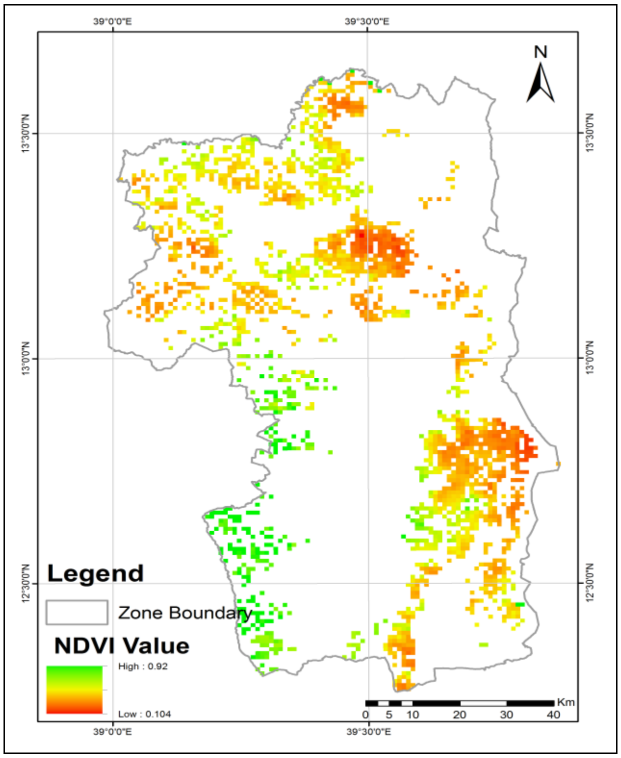


Figure 3.21 Crop coefficient of maize in different stage(Planting-Flowering).

(Source: LEAP software)

Monthly ETa were multiplied by their respective coefficient and extracted using crop mask data and averaged in order to give ETac for each year. The same procedure is followed for water requirement and resulted in PETc. The ratio of ETac with PETc will give the WRSI and prepared for further analysis (Fig 3.23 and 3.24).



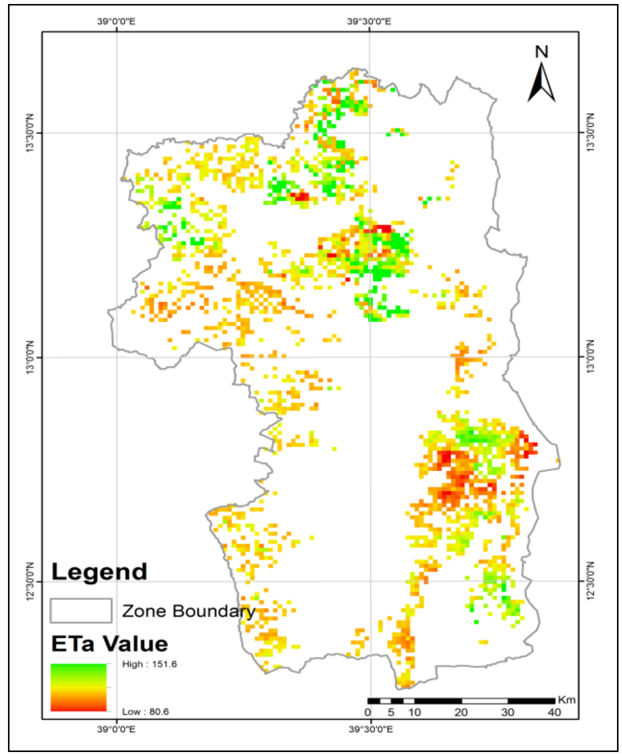
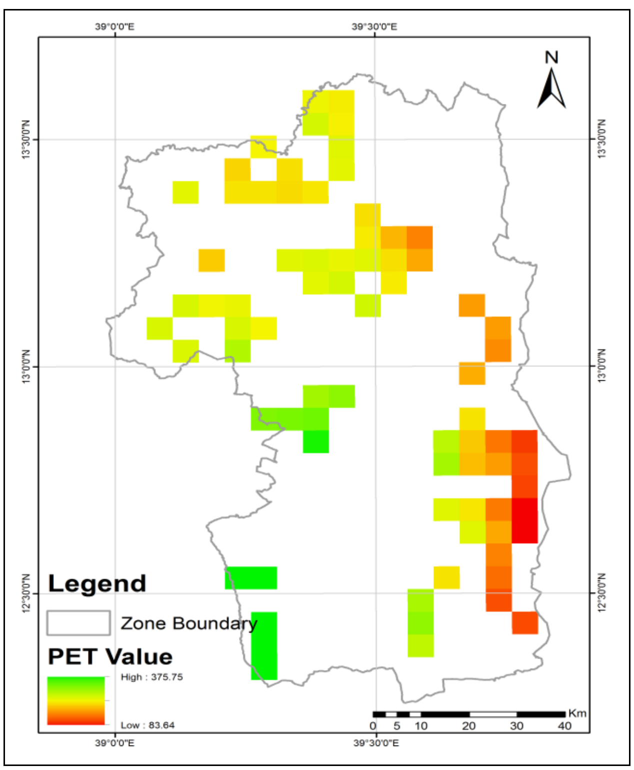


Fig 3.22 NDVI value for the month of July, 2003.

Fig 3.23 Mean ETa for the month of May 2003.



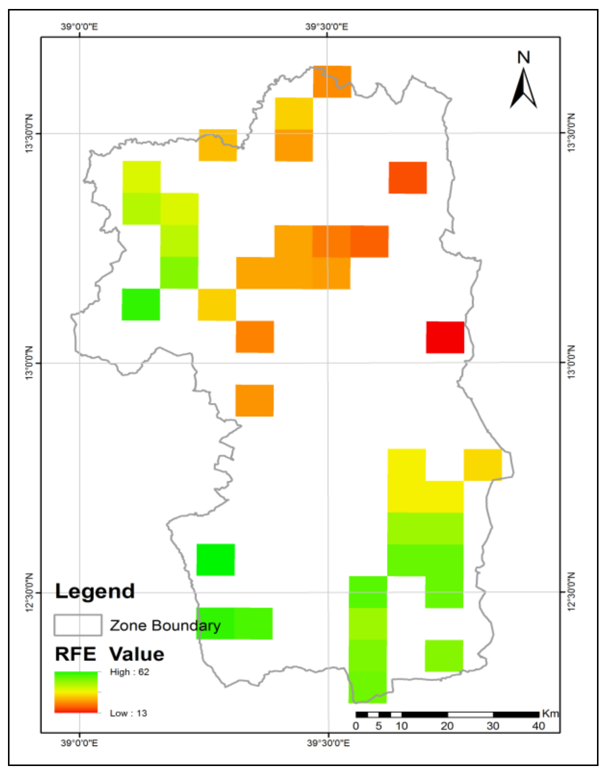


Figure 3.24 PET for the month of May, 2003.

Figure 3.25 RFE for the month of May, 2003.

3.3.5 Multiple linear regression analysis

Spectro-agrometerological yield forecasting using a multiple linear regression starts with a table of data containing yields as dependent and a series of agrometeorological and other variables which are thought to determine the yields (Gommes,2001).

Before correlating the indices with maize yield, data quality control was carried out. This is a checking mechanism for the evaluation of collected data before it is used for model development. The only statistical way is the identification of "outliers" within collected data. Accordingly by seeing the scatter plot diagram 2005 year values which are far from the fit line is considered as outlier and removed from the correlation and hence from the model development (JMP manual, 2009). Table 3.4 indicates the values of yield and dependent variables excluding the outliers.

Table 3.4 Table showing observed yield and independent variables.

No.	Year (Meher season)	Yield in Qt/ hector	May	June	July	August	Sept	NDVIc	ETa	ETa Total	WRSI	RFE2.0
1	2004	10.3	0.25	0.2	0.3	0.48	0.49	1.23	100	351.6	42.2	15.912
2	2006	17.29	0.29	0.24	0.25	0.11	0.04	0.89	139.9	539.1	69.2	33.03333
3	2007	17.93	0.22	0.18	0.39	0.54	0.53	1.33	148.6	574	51.4	31.12667
4	2008	14.66	0.2	0.21	0.25	0.42	0.47	1.08	113.1	462.6	70.5	18.09
5	2009	15.68	0.22	0.18	0.28	0.32	0.04	1	107.2	402.4	38	18.06667
6	2010	21.64	0.25	0.2	0.31	0.46	0.21	1.22	150.6	588.3	67.4	40.75
7	2011	15.38	0.22	0.2	0.14	0.47	0.53	1.03	156.2	568.8	43.5	21.91
8	2012	12.27	0.3	0.23	0.32	0.5	0.53	1.35	157.7	581.3	56.9	23.95333

The objective of multiple linear regression analysis is to predict the single dependent variable by a set of independent variables. There are some assumptions in using this statistics – (a) the criterion variable is assumed to be a random variable (b) there would be statistical relationship (estimating the average value) rather than functional relationship (calculating an exact value) (c) there should be linear relationship among the predictors and between the predictors and criterion variable. Multiple regression analysis provides a predictive equation:

$$Y= a+b_1x_1+ b_2x_2+\ldots\ldots+b_nx_n$$

Where, a = constant

$b1, b2, \ldots b_n$ = beta coefficient or standardized partial regression coefficients (reflecting the relative impact on the criterion variable)

$x1, x2, \ldots x_n$ = scores on different predictors

The b's are the regression coefficients, representing the amount the dependent variable y changes when the corresponding independent changes 1 unit. The *a* is the constant, where the regression line intercepts the y axis, representing the amount the dependent y will be when all the independent variables are 0. The standardized version of the b coefficients is the beta weights, and the ratio of the beta coefficients is the ratio of the relative predictive power of the independent variables (JMP manual, 2009). Lastly the developed model predicts the average value of one variable (Y) from the value of another variable (X). The X variable is also called a predictor. Generally, this model is called a regression model.

CHAPTER FOUR

4 RESULTS

4.1 Correlation analysis of different indices with maize yield

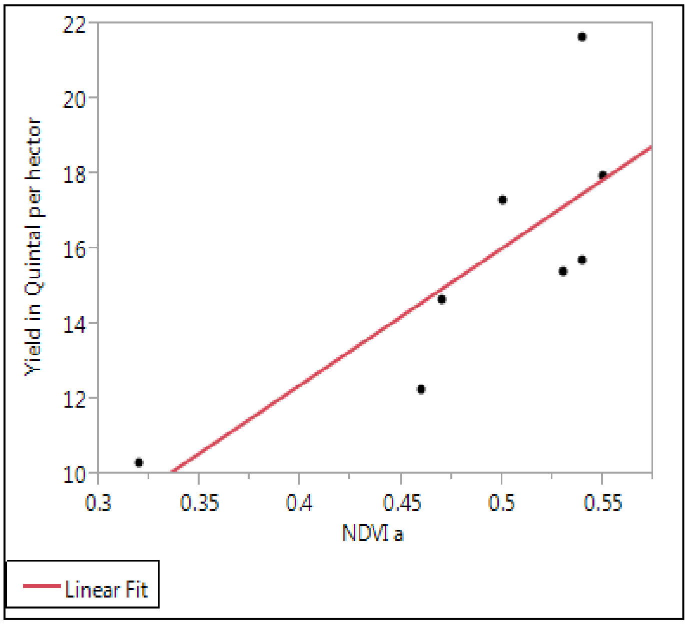
The first step to develop a model is to correlate the independent variables with the dependent variable and by observing the correlation result (Coefficient of correlation, R square, R square adjusted, P value, RMSE), the predictive capability of the independent variable is determined in addition the assumptions were checked and if it is acceptable then will be considered for model development. All statistical analyses were undertaken in JMP statistical discovery software from SAS.

4.1.1 Correlation of NDVI with maize yield

The relationship between NDVI and biomass enables the early estimation of crop yield, a first evaluation of the available NDVI data for area comprised in the maize crop mask was made by computing the monthly NDVI averages of each year for the study area and correlating them with the annual cereal yield values. Accordingly, three variables were created when aggregating the NDVI values on a temporal scale: Figure 4.1 shows monthly maximum value composite (MVC) averages of NDVI (NDVIa), Figure 4.2 shows cumulated NDVI values starting from planting date up to the end of the length of the crop cycle (NDVIc) and Figure 4.3 shows maximum NDVI during the crop cycle (NDVIx). Table 4.1 indicates the correlation between maize yield and different NDVI variables during the time series period.

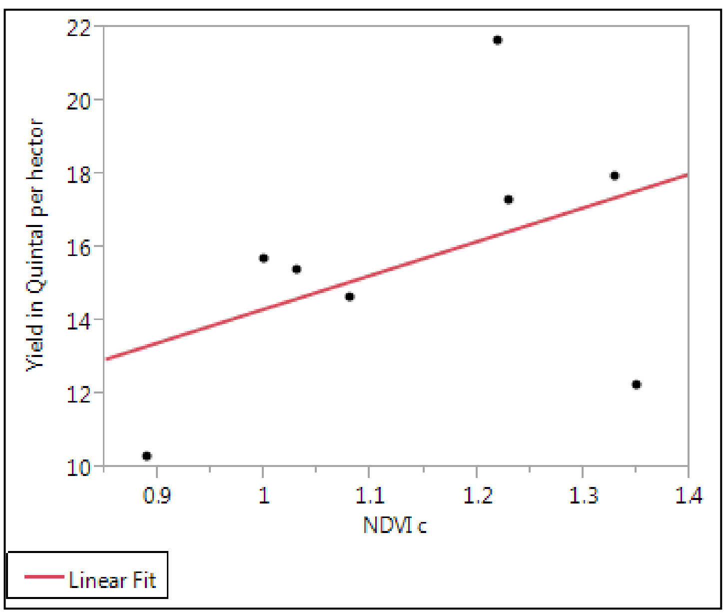
Table 4.1 correlation result of different NDVI values

	Yield in Quintal per hectare	**NDVI a**	**NDVI c**	**NDVI x**
Yield in Quintal/ha	1.0000	**0.7952**	0.4386	-0.0293
NDVI a	**0.7952**	1.0000	0.4793	-0.1177
NDVI c	0.4386	0.4793	1.0000	0.2961
NDVI x	-0.0293	-0.1177	0.2961	1.0000



R square 0.63, R square adjusted 0.57, RMSE 2.28, P value 0.02

Figure 4.1 Graph showing yield and NDVIa.



R square 0.19, R square adjusted 0.06, RMSE 3.38, P value 0.28

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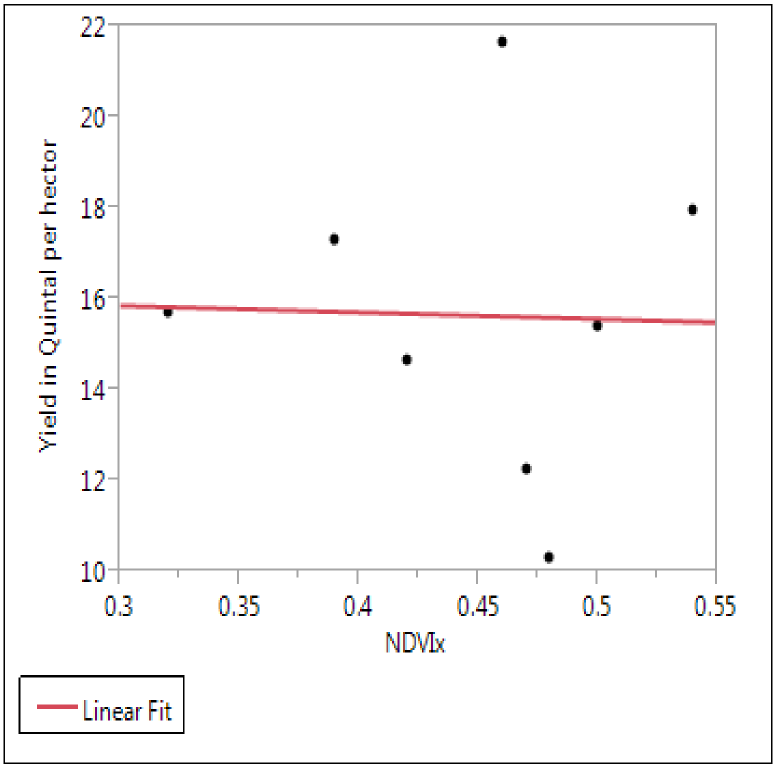
Figure 4.2 Graph showing yield and NDVIc



R square 0.00, R square adjusted -0.17, RMSE 3.76, P value 0.9452

Figure 4.3 Graph showing yield and NDVIx.

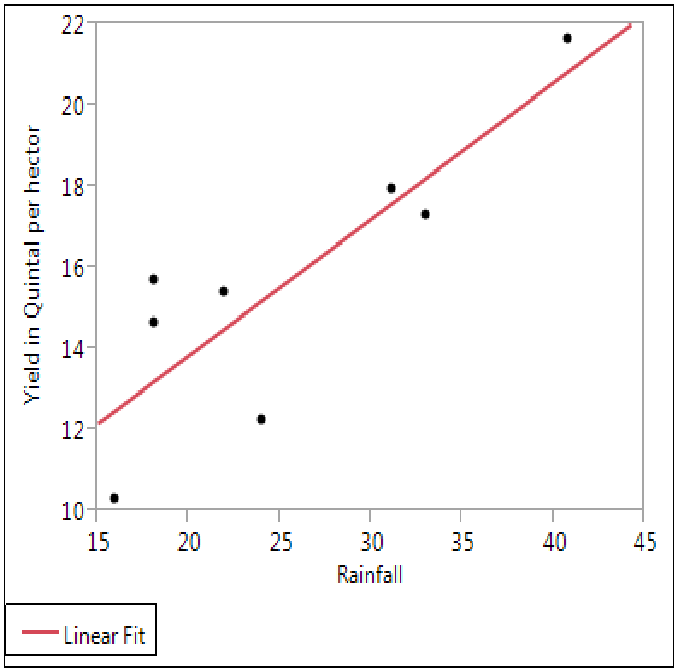
The NDVIa shows the highest value of correlation coefficients among NDVI variables (r = 0.79) with significant P value (0.0183) followed by NDVIc (r =0.44) while NDVIx shows r = -0.023 stating their relationship could not be linear, this fact violates one of the assumptions for the multiple linear regression model and rejected from the model development. When we compare NDVIa and NDVIc correlation strength with maize yield which satisfies the assumptions for the multiple linear regression, their correlation coefficient suggests that the NDVI average is a good indicator of crop yield forecast than NDVIc and was selected for model development from the NDVI categories.

4.1.2. Correlation of rainfall with maize yield

As it was observed in many findings, the spatiotemporal rainfall distribution needs to be incorporated into crop yield models, in addition to vegetation indices deduced from remote sensing data, to predict crop yield of different cereal crops grown in rainfed condition. Accordingly rainfall derived from RFE 2.0 was computed for correlation with yield (Fig 4.4). Table 4.2 shows the correlation between rainfall and maize yield.

Table 4.2 correlation result of rainfall

	Yield in Quintal per hectare	Rainfall
Yield in Quintal per hectare	1.0000	**0.8475**
Rainfall	**0.8475**	1.0000



R square 0.71, R square adjusted 0.67, RMSE 2.0, P value 0.01

Figure 4.4 Graph showing Yield and Rainfall.

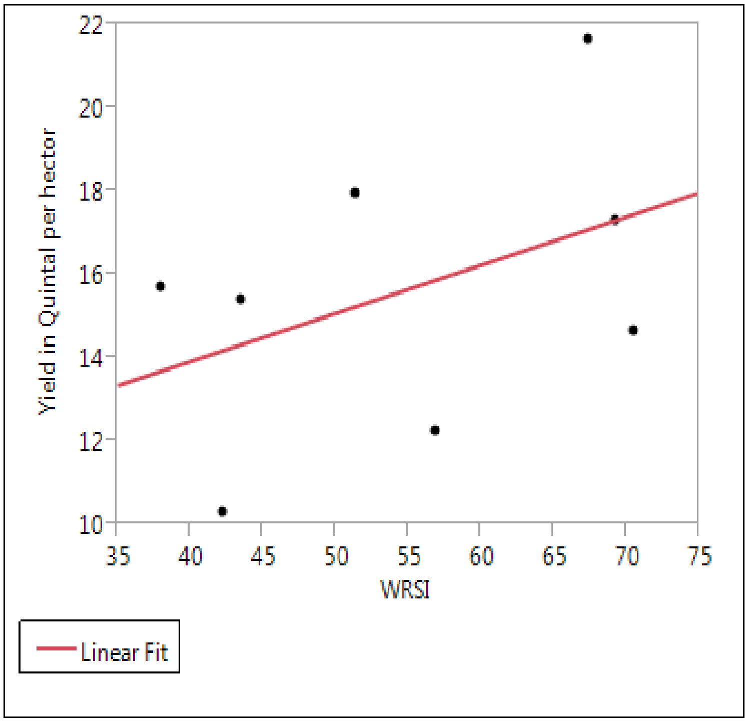
The result shows high value of correlation (85%) with a significant P value of 0.0079 and it also satisfies the assumptions for multiple linear regression analysis. From this, it can be observed that rainfall is a determinant factor for crop production for areas like south Tigray where rainfed agriculture is practiced and this variable is taken for model development in line with the previously identified NDVIa.

4.1.3. Correlation of WRSI with maize yield

Studies proof that there is strong relation between WRSI and maize yield. Accordingly WRSI which was computed for the study area were bring to the correlation analysis with yield. Table 4.3 and Figure 4.5 show the correlation result of WRSI values with maize yield.

Table 4.3 correlation result of WRSI values

	Yield in Quintal per hectare	WRSI
Yield in Quintal per hectare	1.0000	**0.4350**
WRSI	**0.4350**	1.0000



Rsquare0.19, Rsquare adjusted 0.05, RMSE 3.4, P value 0.28

Figure 4.5 Graph showing Yield and WRSI

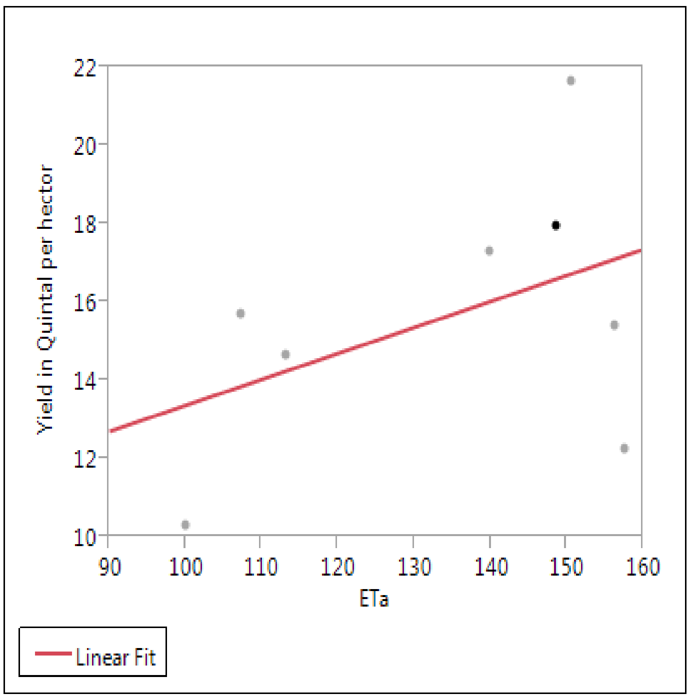
From the result, there is no significant correlation between WRSI and yield in the study area besides the P value is not significant and thus this variable couldn't be considered for model development even though it satisfies the assumptions for multiple linear regression model. This is may be related with the fact that the WRSI model was particularly successful in capturing the response of the crop during a relatively dry year. In areas that never experienced water deficit during the study period, it was possible to infer the magnitude of yield variability that was caused by factors other than water supply.

4.1.4 Correlation of ETa with maize yield

In a related study carried out in Kenya, the coefficient accumulated during the whole cycle of ETa shows high correlation with maize yield. Likewise, evaluation of ETa variables was made by computing the cumulated and average ETa for the whole cycle. Table 4.4, Figure 4.6 and 4.7 indicates the correlation of different ETa variables with maize yield.

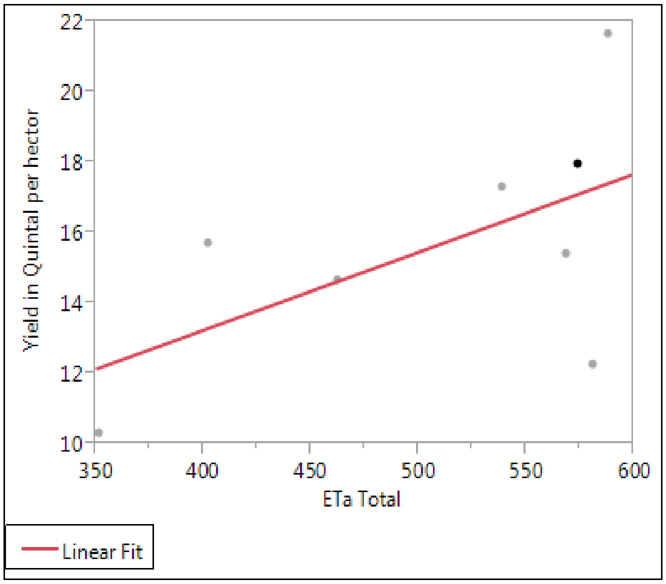
Table 4.4 correlation result of different ETa values.

	Yield in Quintal per hectare	ETa	ETa Total
Yield in Quintal per hectare	1.0000	0.4493	**0.5820**
ETa	0.4493	1.0000	0.9720
ETa Total	**0.5820**	0.9720	1.0000



Rsquare 0.20, Rsquare adjusted 0.07, RMSE 3.4, P value 0.26

Figure 4.6 Graph showing Yield and ETa.



Rsquare0.33, Rsquare adjusted 0.23, RMSE 3.1, P value 0.13

Figure 4.7 Graph showing Yield and ETa total.

From the correlation result we observed that, there is no significant correlation between both average and cumulated ETa and maize yield in the study area even though their correlation satisfies the assumptions for multiple linear regression model. Therefore, this variable couldn't be considered for model development.

4.2 Multiple linear regression model for yield forecasting

The results of the above correlation tables present the correlation matrix of maize yield and the independent variables. Among the seven independent variables: variables derived from remote sensing and climatic variables, variables which satisfies the assumptions for multiple linear regression model with significant P value at 95 % confidence level were derived for the model development. Accordingly, rainfall shows the highest value of correlation coefficients (r 0.85) with significant P value (0.0079) at 95 % confidence level. NDVIa which is a result of monthly maximum value composite (MVC) averages of NDVI from the planting date to the end of the crop cycle gives a correlation coefficient of 0.80 with significant P value of 0.0183 at 95 % confidence level. While others like ETa (total) which have a correlation value of 0.58 and WRSI (r =0.44) with a P value of greater than 0.05 which is beyond the acceptable range at 95 % of confidence level were rejected from the model development.

The researcher selected the two most correlated variables, rainfall and NDVIa, to create a multiple linear regression model since many studies reported that linear regression modeling is the most common method to produce yield predictions by using remote sensing derived indicators together with bio climatic information.

Spectro-agrometeorological yield forecasting using a multiple regression always starts with a table of data containing yields and a series of agrometeorological and remote sensing variables which have high correlation with maize yield.

For this study, maize yield data and data derived from the different indices were prepared for multiple linear regression analysis. The excel sheet which is imported to the JMP statistical software was used to build a multiple linear regression model using the two most correlated variables.

Scatterplots which were indicated in the previous part of this chapter can help to visualize relationships between variables. Once the relationship is visualized, the next step is to analyze those relationships so that they can be describing numerically which is called model.

As a result of all the above processes, highly correlated variables (NDVIa and RFE) were used to develop a model. This model was validated based on its Coefficient of determination (R^2), root mean square error (RMSE) and coefficient of variation (CV) as shows in (Fig 4.8).

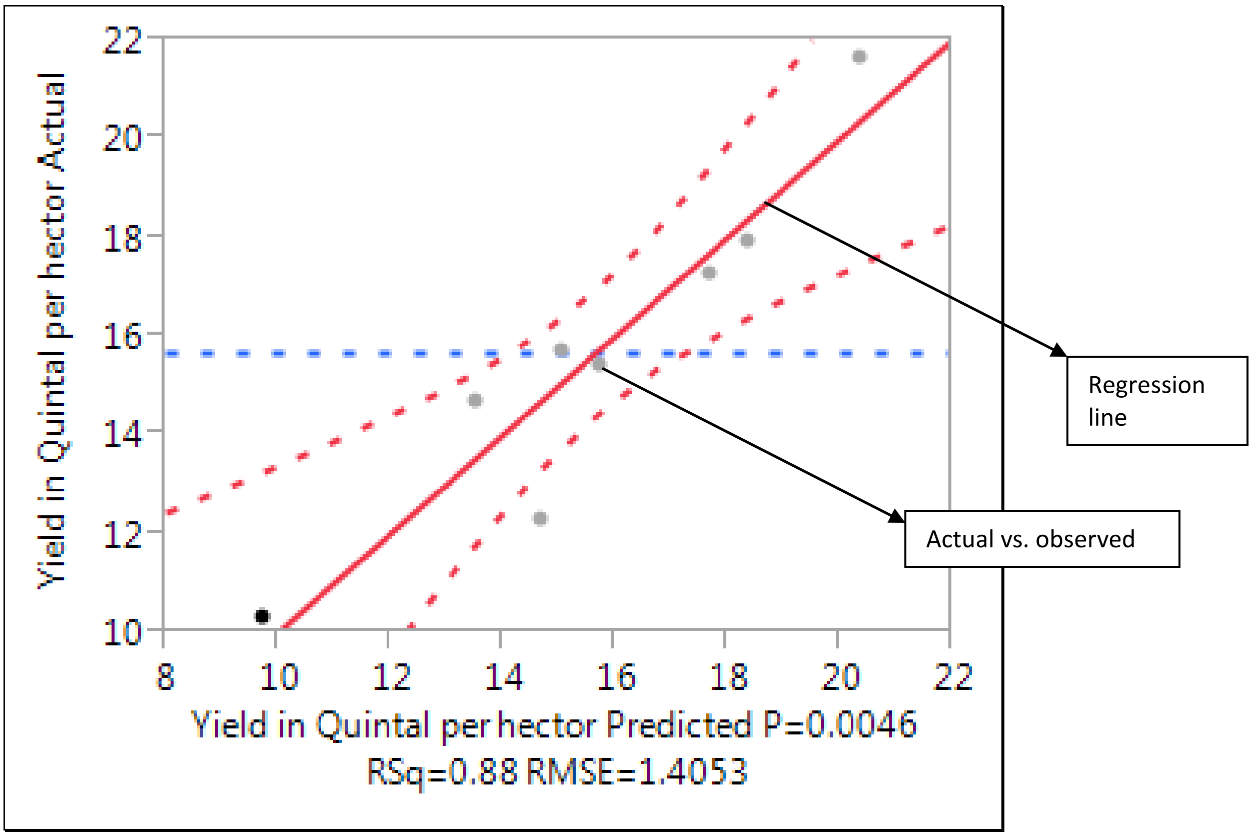


Figure 4.8. Comparison between the maize yield estimated by the spectro agrometeorological model and the observed yields for the study area.

When we see the overall fit of the model by examining the plot of the actual yield per hectare against the predicted yield per hectare, it reveals that, most points lie fairly close to the 45° line (exact prediction line). The R square value of the model is 0.88, R square adjusted is 0.84 with root mean square error of 1.405277 quintal per hectare. The P value of the model is very small(0.0046) at 95 % confidence level and it is a good evidence that at least one independent variable appears to predict maize yield in quintal in a significant value. By observing this P value, it is unclear which independent variable are very good predictor and which is poor.

But the following table 4.5 which shows parameter estimates of the model which reveals that rainfall have significant Probability value and hence high predictive capability than NDVIa.

Table 4.5 Parameter estimates for the maize forecast model

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	-1.063621	3.465188	-0.31	0.7713
NDVI a	21.987048	8.247937	2.67	0.0446*
Rainfall	0.2351072	0.071539	3.29	0.0218*

The analysis of variance as shown in table 4.6 state that maize yield forecast model has an observed significance probability (Prob>F) of 0.0046, which is significant at 0.05 level.

Table 4.6 Maize yield forecast model variance analysis

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	74.994575	37.4973	18.9879
Error	5	9.874012	1.9748	**Prob > F**
C. Total	7	84.868588		0.0046*

Therefore the following equation of the spectro-agrometeorological model was found with 21 % coefficient of variation and acceptable range of validation value :

$$\textbf{Maize yield(qt/ha)= -1.06+21.99*NDVI}_{\textbf{average}}\textbf{+0.24*Rainfall}_{\textbf{average}}$$

4.3 Comparison of conventional crop yield forecast with the developed model

As is the case in many countries, CSA estimate crop production by calling a meeting of knowledgeable people and stake holders. Central Statistical Agency (CSA) had increased the number of stakeholders data on condition factor collected from one to five, that used to be only one prior to the year 2005/06 (1998 E.C.), with the objective to keep up and improve the data quality in terms of reliability and accuracy. Since then, the Annual Crop Production Forecast Survey conducted included stakeholders (sampled households, development agents, chairperson of the rural kebele, community leaders and observations from highly qualified professionals from CSA and FAO) as ultimate statistical unit on collecting “condition factors”(CSA, 2013).

Under such circumstances, any system which will avoid bias and ensure at least a reasonable degree of consistency from year to year and from place to place should be preferred (Gommes, 2001).

Having this recommendation in to consideration, the comparison between the conventional yield forecast and remote sensing supported model result envisages that the developed model shows better quality of the data in that in the conventional approach, the collection of condition factor to assess the condition of the crops in the field is very subjective while the remote sensing supported model uses remote sensing data only which significantly minimizes subjectivity.

The forecast data which is a result of conventional approach reveals a coefficient of variation of 22%, according to CSA report, besides its dependence on subjective nature while the remote sensing supported model shows 21 % with acceptable degree of confidence (95%) and significant probability value (Fig 4.8). More over the forecast result of the remote sensing supported approach can be provided at the end of September considering September as a flowering stage of the maize crop while the conventional method data release calendar is mostly December but includes all cereal crops. Therefore the timeliness issue can be addressed by using the remote sensing supported approach in a better way than the existing approach even if we consider all cereals which CSA has covered.

The other point of difference is the remote sensing supported approach can provide location information in that after the forecast is made, you can verify the result by taking GPS reading and navigate to the areas. Therefore this approach creates an opportunity to exactly indicate which areas have high yield and viceversal in a tangible manner which the conventional approaches lucks badly.

Therefore, it is clear that maize yield forecast using remote sensing and GIS improves both quality and timeliness of the data more over it minimizes subjectivity considerably. Remote sensing supported approach has also a capacity to demonstrate areas (lower administrative areas) where there is relatively high, medium and low production and this makes intervention very easy for the decision makers.

The following figure 4.9 illustrates the comparison between the conventional yield estimate with the remote sensing supported approach result.

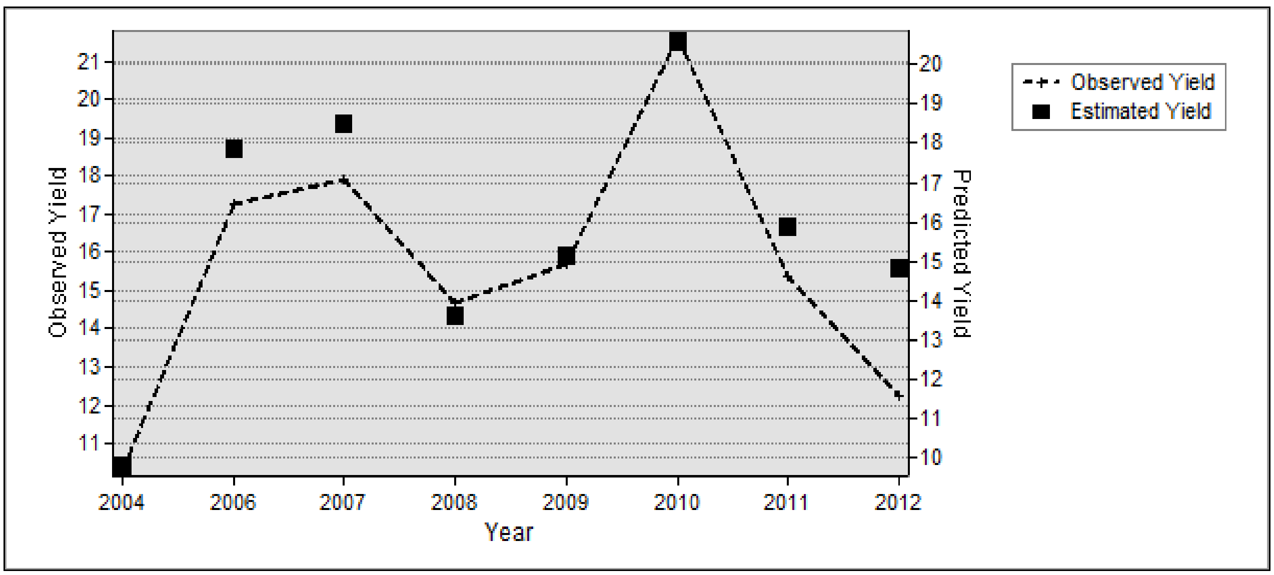


Figure 4.9. Comparison between maize yield (quintal/hectare)estimated by the model and the observed yield.

4.4 A Maize crop forecast for the year 2013

Using the developed model, the 2013 maize crop forecast was made. Accordingly an average of 16.2 quintal per hectare is expected with 20.63 quintal per hectare as the highest and 11.84 quintal per hectare as the lowest. Table 4.7 shows the productivity level of maize crop for the year 2013 in the study area.

Table 4.7 Maize production level of the year 2013 for south Tigray zone

Level of production	Quintal per hectare	Area coverage Percentage
I	19 - 21	9.6%
II	17 - 18	26.3%
III	12 - 16	64.1%

The above table indicates that more than 64.1% of the area covered with maize indicates 12 – 16 quintal/ha production while 9.6% of the area falls in 19 – 21 quintal/ha production. The rest 26.3% of the area is within the range of 17 – 18 quintal/ha production.

As the above table illustrates the productivity of maize crop in south Tigray zone in three categories, the following figure 4.10 demonstrates the spatial situation of the production level.

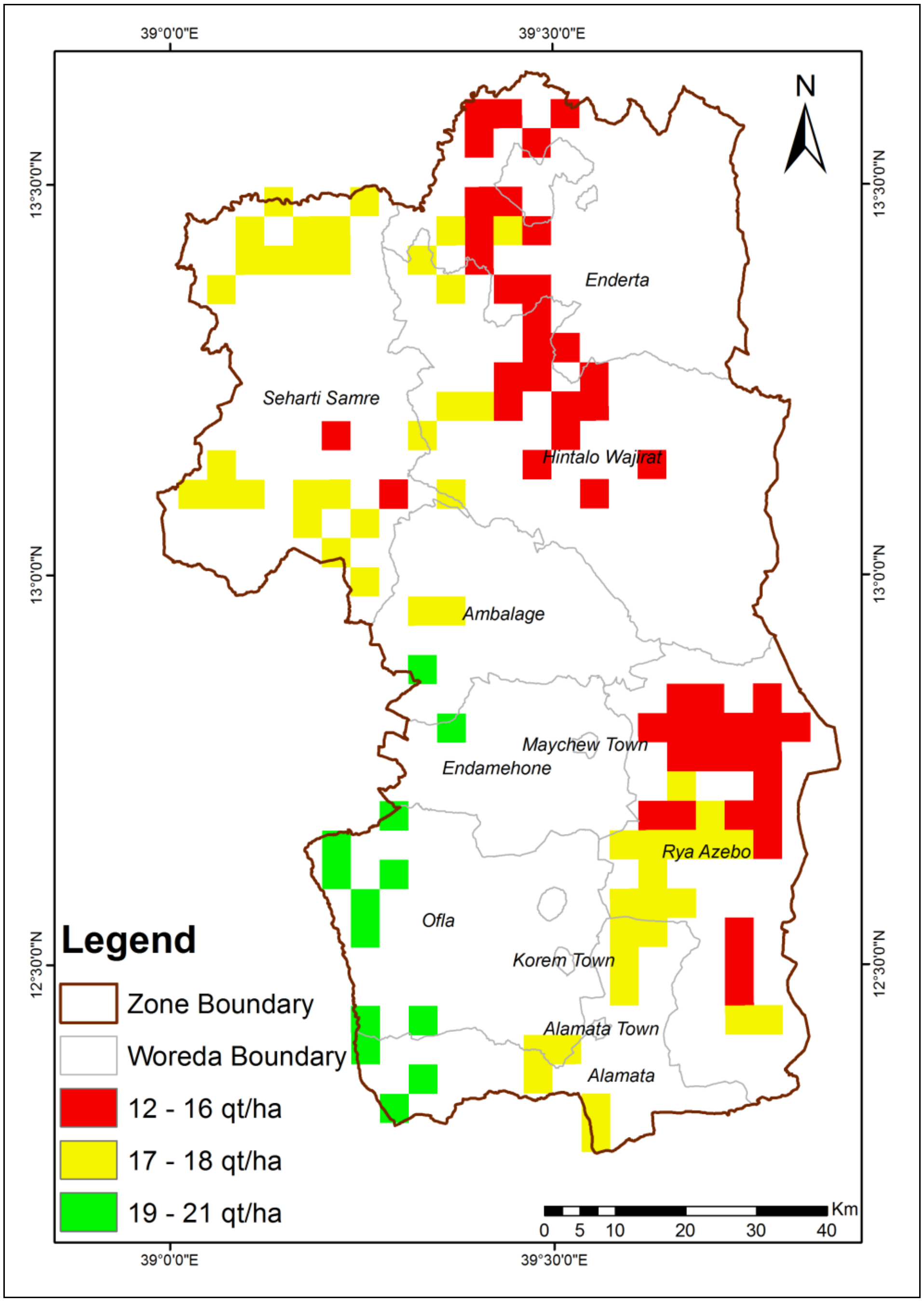


Figure 4.10 Maize yield forecast map of 2013.

The result of the analysis for the year 2013 forecast of maize crop was also compared with zone agricultural office data in a personal communication with Mr. Nebeyiu legesse and it revealed that south western part of the study area (Ofla Woreda) which falls in the most productive area according to the forecast result of the analysis was proofed as the most productive Woreda by the agriculture office too.

CHAPTER FIVE

5 DISCUSSION

The regression-based model developed in this study has utilized official crop statistics from CSA to derive a relationship between different variables derived from remotely sensed parameters and reported maize yield statistics. A correlation analysis was carried out for the identified seven variables and variables with high correlation coefficient (rainfall and NDVI average) were selected with a correlation coefficient of 85% and 80% respectively and they have significant Probability value. These variables were processed for model building using multiple linear regression model.

The results of the model developed showed promising results in that it has high prediction capability (R^2 0.88 and RMSE 1.4 qt/ha). When this result is compared with other findings, there are researches whose results align with the finding and viceversal.

In addition to vegetation indices deduced from remote sensing data, rainfall distribution needs to be incorporated in to crop yield models according to the observation of Potdar *et al*. (1999) as cited in Greatrex (2012). This observation agrees with the result of this research in that there is high correlation between rainfall and maize yield in the analysis of identification of factors determinant for the maize crop forecast.

In a related research conducted on application of remote sensing and agrometeorological derived variables like actual evapotranspiration (ETa) calculated by the FAO CSWB model and NDVI as independent variables in a regression analysis in order to estimate maize yield in Kenya, got the two most correlated variables ETa total and CNDVI with 73% and 87 % correlation coefficient combined in the model to explain 83% of the maize crop yield variance with a RMSE of 0.333 t/ha with 21 % coefficient of variation as it is indicated in Rojas (2006). As compared with the result for south Tigray zone, even though Rojas developed model used ETa instead of rainfall which is not the most correlated variable in this case but the result showed that spectro-agrometerological model is possible in fragmented agricultural land which strengthens the acceptability of the developed spectro agrometeorological model of maize for south Tigray zone since the model was devised for fragmented land.

Rijks *et al* (2007) demonstrates that GEOWRSI is a tool that can be used for reliable and early estimation of maize production estimation in Kenya. According to their findings, WRSI can help improve yield and production estimates but the findings of this research in South Tigray does not agree with this findings because due to its small correlation coefficient and insignificant P value of WRSI with maize yield.

The correlation coefficient for the observed and predicted values of the yield was computed for the study area and it revealed a correlation coefficient of 0.94. This result agrees with Prasad *et al*. (2007) findings in that they also observed a high correlation coefficient of 0.9 between the predicted and observed values in a research conducted on wheat and rice yield forecast in India.

Mantasa *et al*. (2011) in their research entitled Maize Yield Forecasting for Zimbabwe Farming Sectors using Satellite Rainfall Estimates clearly shows that when WRSI values were regressed with historical yield data, the results showed that relatively high skill yield forecasts can be made even when the crops are at their early stage. But this finding is different from south Tigray research in that WRSI is not highly correlated and also have insignificant P value.

The findings of this research demonstrates a clear potential of spectro-agrometeorological factors for maize yield forecasting which aligns with many findings carried out by different researchers for example Rojas 2005 stated that meteorological information of the CSWB model, CPSZ and real time satellite data were used for the crop yield forecast which shows a potential of the spectro-agrometerological factors for crop yield forecast.

CHAPTER SIX

6 CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

Policy makers need accurate and timely information on crop production and areas as soon as possible at the lower administrative level. Such information should be available before the harvest so that preparation can be made which is the very cause of forecasting crop yield using different approaches.

The major objective of this study was to develop a model for maize crop using remote sensing and GIS. Accordingly crop statistical data as a dependent variable and different predictor variables derived from remotely sensed imageries were computed and those variables with higher correlation and significant P value are selected for model development. The analysis result confirmed that rainfall and NDVIa of study area have good correlation (r=0.85 and r=0.8) with significant P value respectively.

Based on these correlation results, spectro-agrometerological yield forecasting using a multiple linear regression was made using a table of data containing yields as a dependent and a series of agrometeorological and remote sensing variables which have high correlation with the yield. The developed spectro-agrometerological model has a predictive capability of 0.88 with RMSE 1.4053 quintal per hectare and it is a very encouraging result. It can be stated that with the demonstrated yield forecasting methods an adequately accurate forecast can be given using remotely sensed data in an area like south Tigray zone where there is fragmented plots of land.

Using the regression model developed for the study area, yield forecast is possible roughly well before the date of the harvest. Maize yield forecast map of the year 2013 was also prepared using the developed model and an average result of 16.2 quintal per hectare was forecasted showing the south western part of the zone having high productivity per hectare and can be used by the decision makers to identify relative productive areas prior to harvest at the lower administration level.

Generally it is possible to conduct maize yield forecast using NDVI derived from SPOT VEGETATION and Rainfall from the RFE 2.0 for areas similar to south Tigray zone.

6.2. Recommendations

Based on the encouraging results of this research output, the developed model can be checked in areas other than south Tigray after a procedures stated in the methodology of the paper is followed meanwhile more research and broader testing is necessary. As an initial effort, this application of the agro meteorological yield model appears promising. Some further effort is necessary to operationalize the results of this research which includes:

- A relatively longer period of time series data should be analyzed in order to reach to operational application.
- A crop mask data should be improved in order to get a more refined crop mask data.
- Expertise from different disciplines(biologists, Agronomists etc.) should be involved to end up with a more sounding result.
- Further investigation should be done to identify more factors that contribute to yield variability and application of remote sensing and GIS in an advanced way.

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Appendix 1: Sample GPS readings for accuracy assessment

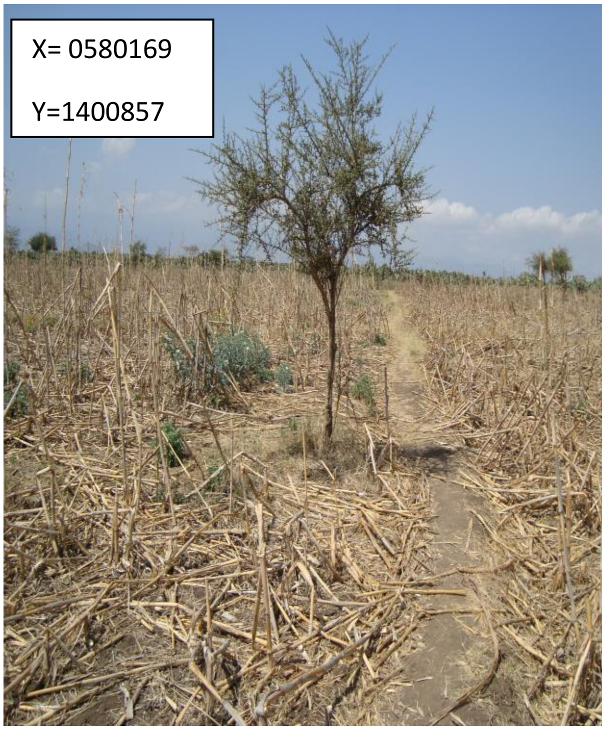
Agriculture class

CID	POINT_X	POINT_Y	MAP CLASS	Ground Truth
1	572364	1407353	Agriculture	
2	540030	1458297	Agriculture	
3	556241	1398341	Agriculture	
4	577254	1373260	Agriculture	
5	560309	1478257	Agriculture	
6	524197	1480418	Agriculture	
7	548230	1472973	Agriculture	
8	543006	1476323	Agriculture	
9	584690	1400727	Agriculture	
10	546073	1497742	Agriculture	
11	565592	1438329	Agriculture	
12	542128	1480989	Agriculture	
13	538367	1414586	Agriculture	
14	583470	1418315	Agriculture	
15	561089	1449430	Agriculture	
16	570908	1376916	Agriculture	
17	535134	1426832	Agriculture	

Non Agriculture Class

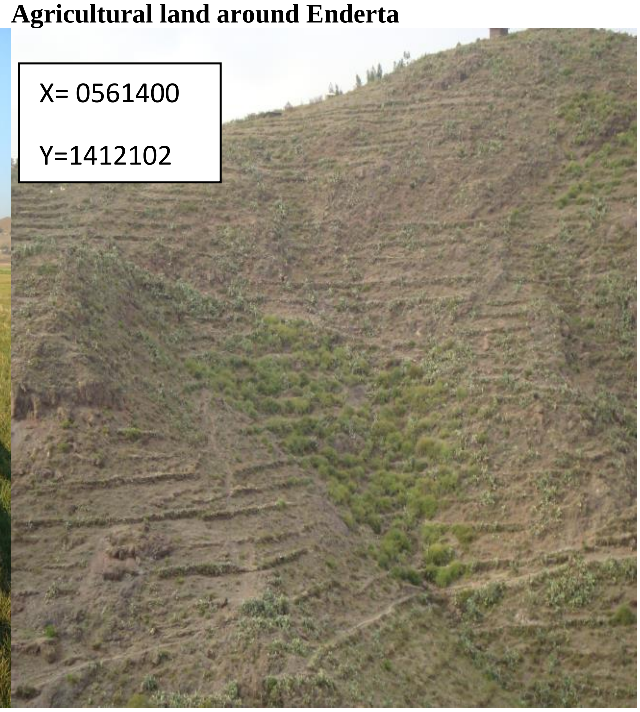
CID	POINT_X	POINT_Y	MAP CLASS	Ground Truth
1	579054	1401026	Non Agriculture	
2	578772	1402925	Non Agriculture	
3	566414	1357933	Non Agriculture	
4	569264	1401047	Non Agriculture	
5	523735	1476518	Non Agriculture	
6	543060	1438304	Non Agriculture	
7	571952	1487850	Non Agriculture	
8	506006	1450361	Non Agriculture	
9	552709	1444101	Non Agriculture	

Appendix 2: Sample pictures from field



Agricultural land in Mehone area

Agricultural land around Enderta



Non Agricultural land around Maychew

Terrace for conservation in Maychew

APPENDIX 3: Accuracy assessment matrix result

REPORT

```
          ----------------------------------------
Image File : c:/abiy/south_unsup.img
User Name  : user
Date       : Thu Apr 10 11:47:01 2014



ERROR MATRIX
-------------

                      Reference Data
                      --------------
Classified Data  Unclassifi    Class 1    Class 2  Row Total
---------------  ---------- ---------- ---------- ----------
   Unclassified           0          0          0          0
        Class 1           0        130         14        144
        Class 2           0         23        121        144

Column Total              0        153        135        288


           ----- End of Error Matrix -----


ACCURACY TOTALS
----------------

          Class  Reference Classified Number     Producers  Users
           Name     Totals     Totals Correct     Accuracy
     Accuracy
     ---------- ---------- ---------- -------    ---------  -----
   Unclassified          0          0       0          ---    ---
        Class 1        153        144     130        84.97%
90.28%
        Class 2        135        144     121        89.63%
84.03%

         Totals        288        288     251

Overall Classification Accuracy =     87.15%

           ----- End of Accuracy Totals -----
```

KAPPA (K^) STATISTICS

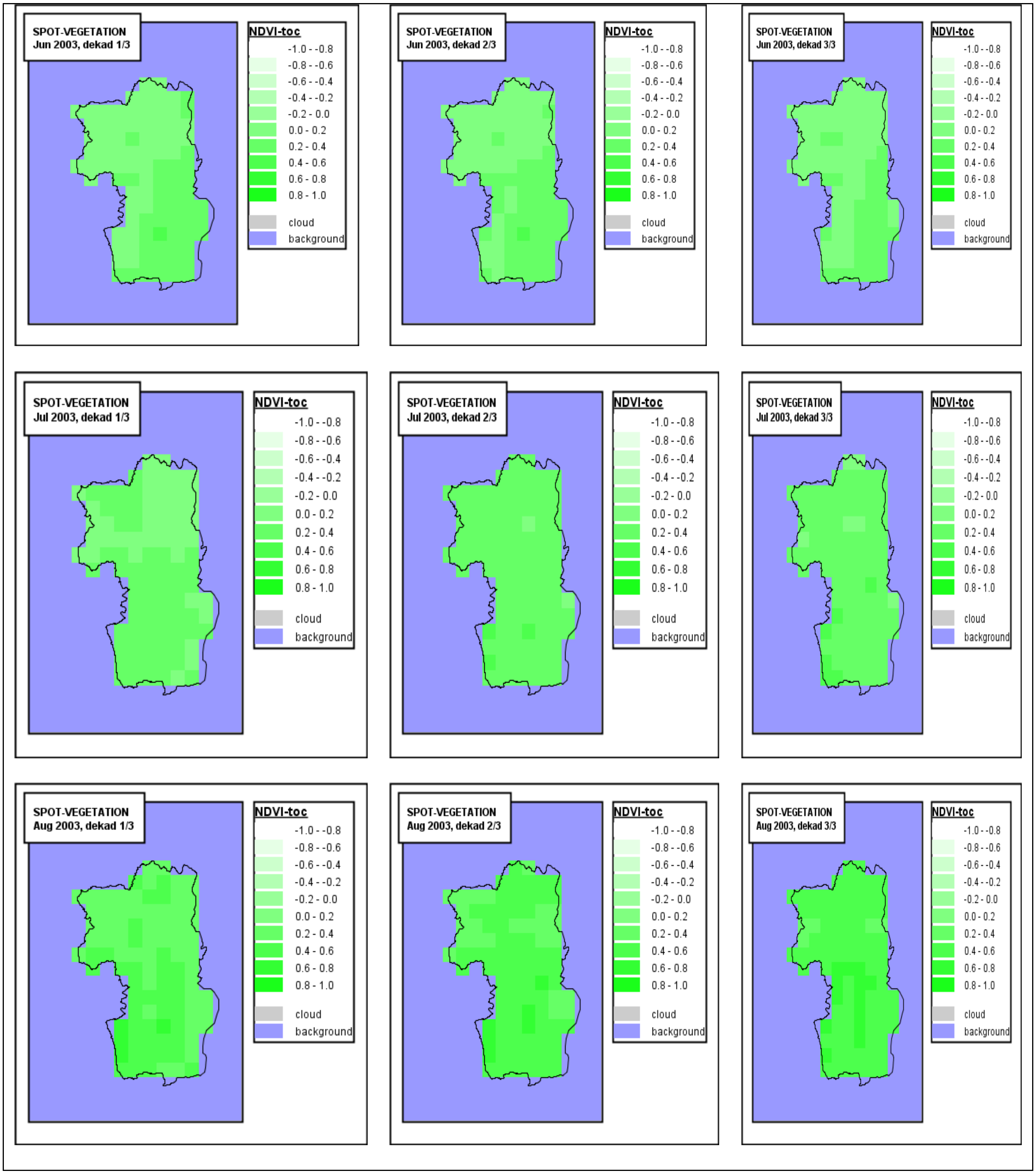
Overall Kappa Statistics = 0.7431

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Class 1	0.7926
Class 2	0.6993

----- End of Kappa Statistics -----

Appendix 4 : Sample Dekedal SPOT VEG image output of SPIRIT software



D E C L A R A T I O N

I hereby declare that the thesis entitled. *SPECTRO AGROMETEREOLOGICAL MAIZE YIELD FORECAST MODEL USING REMOTE SENSING AND GIS IN SOUTH TIGRAY ZONE, ETHIOPIA*. has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2014 as a part of Master of Science program in Remote Sensing and GIS. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

ABIY WOGDERES ZINNA

Signature: ________________________

Addis Ababa University

Addis Ababa

Date: June, 2014

C E R T I F I C A T E

This is certified that the thesis entitled. *SPECTRO AGROMETEREOLOGICAL MAIZE YIELD FORECAST MODEL USING REMOTE SENSING AND GIS IN SOUTH TIGRAY ZONE, ETHIOPIA*. is a bona fed work carried out by Abiy Wogderes Zinna under my guidance and supervision. This is the actual work done by Abiy Wogderes Zinna for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and GIS from Addis Ababa University, Addis Ababa, Ethiopia.

Dr. K. V. Suryabhagavan
Assistant Professor

Signature: ________________________

Department of Earth Science

Addis Ababa University