APPLICATION OF REMOTE SENSING FOR DELINEATION OF DROUGHT VULNERABLE AREAS IN AMHARA REGION

Dissertation Submitted for Partial Fulfillment of the Requirements for the
Award of the Degree of

MASTER OF SCIENCE

In

Remote Sensing and Geographical Information Systems (GIS) of Addis Ababa University, Addis Ababa, Ethiopia.

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JULY 2007

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ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

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D E C L A R A T I O N

I here by declare that the dissertation entitled "**APPLICATION OF REMOTE SENSING FOR DELINEATION OF DROUGHT VULNERABLE AREAS IN AMHARA REGION"** has been carried out by me under the supervision of Dr. K.S.R. MURTHY, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2007-2008 as a part of Master of Science programme 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.

Place: Addis Ababa
Date: July 16, 2007

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C E R T I F I C A T E

This is certified that the dissertation entitled "**APPLICATION OF REMOTE SENSING FOR DELINEATION OF DROUGHT VULNERABLE AREAS IN AMHARA REGION**" is a bonafied work carried out by under my guidance and supervision. This is the actual work done by Amare Degefaw 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.

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Dedicated to my beloved Mama

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Acronyms

ARTEMIS	Africa Real Time Environmental Monitoring Information System
AVHRR	Advanced Very High Resolution Radiometer
BT	Brightness Temperature
CMI	Crop Moisture Index
DEVNDVI	Deviation of NDVI
DMCN	Drought Monitoring Centre- Nairobi
DSI	Drought Severity Index
EMS	Electromagnetic Spectrum
EMSA	Ethiopian Meteorological Service Agency
EOS	Earth Observation System
EROS	Earth Resources Observation System
ESA	European Satellite Agency
ET	Evapotranspiration
FAO	Food and Agricultural Organization for United Nation
FEWS	Famine Early Warning Systems
GAC	Global Area Coverage
GDAL	Geospatial Data Abstraction Library
GIMMS	Global Inventory Monitoring and Modelling Studies
GIEWS	Global Information Early Warning System
GIS	Geographic Information Systems
GSFC	Goddard Space Flight Center
GVI	Global Vegetation Index
HRV	High Resolution Visible
IFRCARCS	International Federation of Red Cross and Red Crescent Societies
IWMI	International Water Management Institute
LAI	Leaf Area Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MVC	Maximum Value Composite
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference of Vegetation Index
NIR	Near Infra Red
NOAA	North Oceanic and Atmospheric Administration
NPOESS	National Polar Operational Environmental Satellite System
NPP NPOESS	Preparatory Project
PDSI	Palmer Drought Severity Index
SPI	Standard Precipitation Index
TCI	Temperature Condition Index
VCI	Vegetation Condition Index
VGT-S10 products	10-day synthesis Vegetation products
VNIR	Visible and Near-Infrared
WFP	World Food Programme
WMO	World Meteorological Organization
WSVI	Water Supply Vegetation Index

Abstract

Drought is the most complex but least understood of all natural hazards. It is broadly defined as “severe water shortage”. Low rainfall and fall in agricultural production has mainly caused droughts. A droughts impact constitutes losses of life, human suffering and damage to economy and environment. Droughts have been a recurring feature of the Ethiopian climate therefore study of historical droughts may help in the delineation of major areas facing drought risk and thereby management plans can be formulated by the government authorities to cope with the disastrous effects of this hazard. The Amhara region is prone to extreme climate events such as drought. Successive years of low and erratic rainfall have left large areas of the region in severe drought that resulted in crop failure, water shortage and has raised serious food security concerns for the region. Drought assessment and monitoring based on available weather data are tedious and time consuming. Beside that the data are not available in time to enable relatively accurate and timely large scale drought detection and monitoring. But, the satellite sensor data are consistently available, cost effective and can be used to detect the onset of drought, its duration and magnitude. In the present work an effort has been made to derive drought vulnerable areas facing agricultural drought by use of temporal images from NOAA-AVHRR (8km) and MODIS (500m) based Normalized Difference Vegetation Index (NDVI) (1981- 2007) and (2000 to 2003) respectively. A deviation of the current NDVI with the long-term mean NDVI, and the Vegetation Condition Index (VCI) derived from the AVHRR and MODIS used in this study for drought detection, monitoring and real time prediction. The results clearly indicate that the temporal and spatial characteristics of drought in Amhara region detected and mapped by the DEV_{NDVI}, and VCI indices. These results were validated by ground truth data such as precipitation and agricultural crop yield. The validation result shows that there is a strong correlation between the satellite derived indices and the ground truth data, both precipitation and agricultural production yield for most of the Zones Amhara region. Correlation and regression analysis was performed between NDVI, drought indices, precipitation and agricultural yield. The NDVI and rainfall was found to be highly correlated in water limiting areas. Apart from this, the highest NDVI-rainfall correlation associated with three -month time lag shows rainfall event induced vegetation growth in subsequent periods. The NDVI-rainfall correlation was found to be highly influenced by mean rainfall condition and vegetation types. It is therefore concluded that temporal variations of NDVI are closely linked with precipitation. The inter sensor relationships were also developed based on data from specific months and the monthly models explain up to 95 percent of variability in the data of two sensors.

1. INTRODUCTION

1.1 BACKGROUND

Drought is an inevitable part of the Earth's climate. It occurs regularly with no clear warning and without recognizing borders. In addition, drought has been defined as a creeping hazard and its impact is said to be cumulative and not immediately observable by ground data (Kogan, 2000). Drought is a normal part of climate for virtually all regions of the world; it results in serious economic, social, and environmental impacts. Drought onset and end are often difficult to determine, as is its severity.

Drought is considered by many to be the most complex but least understood of all natural hazards, affecting more people than any other hazard (Hagman, 1984). However, there remains much confusion within the scientific and policy communities about its characteristics. It is precisely this confusion that explains, to some extent, the lack of progress in drought preparedness in most parts of the world. The impacts of drought are largely non-structural and spread over a larger geographical area than are damages from other natural hazards. The non-structural characteristic of drought impacts has certainly hindered the development of accurate, reliable, and timely estimates of severity and, ultimately, the formulation of drought preparedness plans by most governments.

Drought risk is a product of a region's exposure to the natural hazard and its vulnerability to extended periods of water shortage (Wilhite, 2000). If nations and regions are to make progress in reducing the serious consequences of drought, they must improve their understanding of the hazard and the factors that influence vulnerability. All drought-prone nations should develop national drought policies and preparedness plans that place emphasis on risk management rather than following the traditional approach of crisis management, where the emphasis is on reactive, emergency response measures. Crisis management decreases self-reliance and increases dependence on government and donors

1.2. DROUGHT: DEFINITIONS

Droughts have no universal definition. As drought definitions are region specific, reflecting differences in climatic characteristics as well as incorporating different physical, biological and socioeconomic variables, it is usually difficult to transfer definitions derived for one region to another.

However some of the common definitions of drought can be noted as under:

· The Director of Common Wealth Bureau of Meteorology in 1965 suggested a broad definition of drought as “severe water shortage”.

· Definition given by Palmer states that “Drought is an interval of time, generally of the order of months of years in duration, during which the actual moisture supply at a given place rather consistently falls short of the climatically expected or climatically appropriate moisture supply (Palmer, 1965)

· According to Mc Mohan and Diaz Arena (as cited in Chopra 2006), “Drought is a period of abnormally dry weather sufficiently for the lack of precipitation to cause a serious hydrological imbalance and carries connotations of a moisture deficiency with respect to man’s usage of water.

· Another definition given by Flag is worth mentioning “Drought is a period of rainfall deficiency, extending over months or year of such a nature that crops and pasturage for stock are seriously affected, if not completely burnt up and destroyed, water supplies are seriously depleted or dried up and sheep and cattle perish”.

· According to Hangman (1984), “Drought is considered by many to be the most complex but least understood of all natural hazards affecting more people than any other hazard.” (Wilhite, 2000)

A drought is a complex phenomenon that can be defined from several perspectives (Wilhite 2000). Wilhite (2000) categorize drought definitions into conceptual (definitions formulated in general terms) and operational. Conceptual definitions formulated in general terms; help people understand the concept of drought but these normally do not provide quantitative answers. Operational definitions on the other hand help identify the drought beginning, end and degree of severity. By studying the above definitions it ca be understood that drought is mainly concerned with the shortage of water which in turn affects availability of food and fodder thereby leading to displacement and loss to economies as a whole.

1.3. TYPES OF DROUGHT

Drought has been categorized as meteorological, hydrological, agricultural and socioeconomic drought. The meteorological and hydrological drought deals with physical phenomena while, agricultural and socioeconomic drought deals with supply and demand (Mokhtari, 2005).

· **Meteorological drought**: it simply implies rainfall deficiency where the precipitation is reduced by more than 25%from normal in any given area. These are region specific, since deficiency of precipitation is highly variable from region to region.

· **Hydrological drought:** these are associated with the deficiency of water on surface or subsurface due to shortfall in precipitation. Although all droughts have their origination from deficiency in precipitation, hydrological drought is mainly concerned about how this deficiency affects components of the hydrological system such as soil moisture, stream flow, ground water and reservoir levels etc.

· **Agricultural drought:** this links various characteristics of meteorological or hydrological drought to agricultural impacts, focusing on precipitation shortages, differences between actual potential evapotranspiration, soil, soil water deficits, and reduced ground water or reservoir levels. Plant water demand depends on prevailing weather conditions, biological characteristics of the specific plant, and its stage of growth and the physical and biological properties of the soil.

· **Socio-economic drought:** it is associated with the demand and supply aspect of economic goods together with elements of meteorological, hydrological and agricultural drought. This type of drought mainly occurs when there the demand for an economic good exceeds its supply due to weather related shortfall in water supply

1.4. DROUGHT SITUATION IN ETHIOPIA AND AMHARA REGION

In Ethiopia, it is common to hear horrific stories of poverty and destitution and heart-wrenching tales of massive asset losses during droughts, even the selling of materials from one's house to buy food (Little et al., 2004). Socioeconomic conditions clearly are minimal in this part of the world, even when compared to other low-income areas of rural Africa. Ethiopia is a nation that ranks among the poorest in the world (171 of 174) with an annual per capita income on only $102 (World Bank 2002). Most studies indicate incidences of rural poverty above 40 percent and as high as 78 percent when food aid transfers are discounted (Little, et al., 2004). In one recent study the prevalence of destitution (extreme poverty) in North and South Wollo was said to be 14.6 percent, a situation that is said to have worsened over time through frequent droughts (Sharp et al. 2003).

Drought is a common occurrence in Ethiopia. Four consecutive years of 1996, 97, 98 and 1999, poor rainfall in Ethiopia had a major impact on rural populations across the country during 2000, leading to drought conditions and minimal harvests. This had a cumulative impact on households in both pastoral and agricultural communities, undermining coping strategies and leading to greater vulnerability to drought. Many households were forced to sell their livestock and other assets and some migrated from their land in search of income and food.

“Amhara” region in particular has suffered from a number of severe droughts and associated famines. Of the 105 woredas in the region, forty-eight are drought prone and chronically food-insecure. There has been no single year since 1950 where there was no drought in the eastern part of the region (Team 2000). Famines have been recorded as far back as biblical times. On the other hand, much of the western part of the region has good soils and adequate rainfall and typically produces agricultural surpluses.

Below-averaged belg, secondary rains (march-may) coupled with delayed and sporadic meher, or the main rains (June- September) have led to widespread food insecurity in the region. The lack of sufficient precipitation during the belg season failed to replenish water sources. In addition, given the poor performance of the meher rains, food insecurity continues to spread to agro pastoral and agricultural areas, particularly the lowlands and midlands of the region. USAID’s Famine Early Warning systems Network (FEWS-NET) estimates that overall crop production will be 8-10% below average.

The northern highlands of Ethiopia are facing their fourth successive year in which the belg (Spring) rains have failed. One of the worst hit zones is South Wollo which is an area that was badly affected by the famines in both the years 1974 and 1984 and that has repeatedly required food assistance over the years (IFRCARCS, 2000). Erratic rainfall patterns have characterized the last three years 1997, 1998 and 1999. This year the belg rains have also failed to produce much precipitation although some rain fell at the end of March. The belg rains which normally begin in February and peak in mid April are important as about 2 million people in the northern highlands are dependent on them for the production of short cycle crops. They are also significant in terms of the coming meher season. The high yield, long maturing meher crops of sorghum and corn are normally planted in late April and are dependent on the residual moisture of the belg rains.

The cumulative effect of the failure of successive belg rains in South Wollo has reduced traditional cropping strategies to a point where malnutrition levels are rising. Many households have sold their oxen and other assets and are not in a position to take advantage of the rains even if they do arrive. Prices of livestock have fallen as oxen have been sold by the belg farmers and there are indications that grain prices have risen. There is some movement by people off the land in search of other sources of income and food.

1.5 STATEMENT OF THE PROBLEM

The Amhara region is characterized by erratic rainfall, and often hit by recurring droughts. Major food production is almost completely dependent on rain-fed agriculture. Frequent and severe drought has become a major climate disaster throughout the region. In the past years there were major food security disasters in 1983-1984, 1991-1992, 1999-2000, and, again, in 2002, and minor ones in almost one out of three years. In the 1999- 2000 drought about 75 percent of the population in weredas of Legambo, Desie Zurie, and Jamma of South Wollo and Bati of Oromiya Zone received food aid (Little, et al., 2004). A much smaller proportion received food assistance during the 2002 disaster, an event that received considerable international attention although our data show its impact was minimal in most of the area. The drought of the late 1990s was a prolonged event with uneven consequences, but its onset was gradual. Indeed, the first signs of disaster can be traced to the poor short rains (January-April) (called the *Belg* season) of

1998 where it is estimated that harvests were only 60 percent of normal yields in the main *Belg* growing areas (as cited in IFRCARCS, 2000). In the study area approximately one-half of our households reside mainly in *Belg* growing areas and the others in predominantly *Meher* zones where there is a June to September growing season. Most farmers in Belg- growing areas also depend to some extent on a *Meher* season harvest. Because the *Meher* rains of 1998 were uneventful for some locations, drought and relief agencies in Ethiopia failed to see the looming disaster until the *Belg* season of 1999 emerged as a massive failure (approximately 90 percent loss of crops) (Castro et al. 1999). National and regional estimates for food relief in 1999 were drastically altered after the disaster of the year's *Belg* season (IFRCARCS, 2000). Recurrent drought events cause serious economic, social and environmental problems and are devastating particularly the agricultural economy. Drought assessment and monitoring based on available weather data are tedious and time consuming. Beside that the data are not available in time to enable relatively accurate and timely large scale drought detection and monitoring. But, the satellite sensor data are consistently available, cost effective and can be used to detect the onset of drought, its duration and magnitude (Thiruvengadachari and Gopalkrishna 1993). The Normalized Difference Vegetation Index (NDVI) which derived from remote sensing data has been recognized as a common and powerful practice in delineating drought vulnerable areas (Anyamba and Tucker 2005). Keeping the above drought phenomenon in the country in general and Amhara region in particular in this present project an attempt has been made to identify the drought vulnerable areas in All Zones but in different years. As timely information on the extent and severity of drought can limit impacts of drought related losses, the nearly real time assessment through effective monitoring using satellite image.

1.6 OBJECTIVES

General objective

- Delineating drought vulnerable areas.
- Spatio-temporal drought monitoring.

Specific objectives

- To investigate the effectiveness of satellite derived indices as an indicator for drought assessment
- Assessment of the cases of drought emergence, sporadic, moderate and severe drought

1.7 RESEARCH HYPOTHESIS

The research hypothesis formulated to achieve the research objectives is that drought occurrence can be better evaluated by combining satellite, meteorological data and agricultural production.

2. LITERATURE REVIEW

2.1. THE CONCEPT OF DROUGHT

Drought is a normal, recurrent feature of climate, although it is erroneously considered as a rare and random event. It differs from aridity, which is restricted to low rainfall regions and is a permanent feature of climate. Drought should be considered relative to some long-term average conditions of the balance between precipitation and evapo-transpiration in a particular area. It is also related to the timing and the effectiveness of the rains (Li et al., 2002).

Drought has many facets in any single region and it always starts with the lack of precipitation, but may affect soil moisture, streams, groundwater and human beings. This leads to the identification of different drought, which reflects the perspectives of different sector on water shortages. The deficiency of rainfall starts a drought. The longer and the more spatially extensive this deficiency, the more likely the occurrence of droughts (Mazzanti, 1996).

Because drought is a recurring phenomenon and typical for the majority of world zones, the most productive lands of all continents can lose millions of tons production annually. Social, physical, and economic impacts of drought can be overwhelming, especially in the developing countries. The immediate consequences of drought include water supply shortages, destruction of ecological sources, and losses of agricultural production, resulting in famine, human suffering, death, and desertion of whole geographic regions.

The severity of drought can be measured climatically, socially and economically. A fundamental problem is determining the severity of a drought. To make measurements of drought more meaningful indices have been used which examine the state and development of relevant meteorological and hydrological conditions (Song et al., 2004).

2.2. THE ROLE OF REMOTE SENSING IN DROUGHT MONITORING

The mitigation of the effects of disasters requires relevant information regarding the disaster in real time. Also the possible prediction and monitoring of the disaster requires rapid and continuous data and information generation or gathering. Since disasters that cause huge social and economic disruptions normally affect large areas or territories and are linked to global change, it is not possible to effectively collect continuous data on them using conventional methods (Townshend and Justice, 1986).

Remote sensing techniques can be used to monitor the current situation- before, during or after occurrence of a disaster. They can be used to provide baseline data against which future changes can be compared while the GIS techniques provide a suitable framework for integrating and analyzing the many types of data sources required for disaster monitoring (Song et al. 2004).

In recent years, the ever-increasing population and overstress on natural resources, soil degradation, decrease in water resources, and future projected climate change scenarios have become important areas of concern. The main goal of global agriculture is to feed 6 billion people, a number likely to double by (Kogan 2000). The first requirement of living creature is food, and a setback in agricultural and fodder production leads to socio-economic unrest especially in developing countries. Therefore, management of natural resources in developing as well as developed countries requires information on the state and changes in a range of biophysical variables. Droughts have been viewed as such a disaster where in a shortfall in precipitation has led to substantial reduction in production levels thereby leading to conditions which causes large scale migration and threaten to human life and animals. Therefore there is a need for proper quantification of drought impacts and monitoring and reporting of drought development in economically and environmentally sensitive areas (Johnson et al., 1993).

The impact of drought on society and agriculture is a real issue but it is not easily quantified. Reliable indices to detect the spatial and temporal dimensions of drought occurrences and its intensity are necessary to assess the impact and also for decision-making and crop research priorities for alleviation (Seiler and Kogan et al. 1998). The development and advancements in space technology, to address issues like drought detection, monitoring and assessment have been dealt with very successfully and helped in formulation of plans to deal with this slow onset disaster. With the help of environmental satellite, drought can be detected 4-6weeks earlier than before and delineated more accurately, and its impact on agriculture can be diagnosed far in advance of harvest, which is the most vital for global food security and trade (Kogan, 1990).

Remote sensing is the acquisition of digital data in the reflective, thermal or microwave portion of the electromagnetic spectrum (EMS). Measurements of the EMS are be made either from satellite, aircraft or ground-based systems, but characteristically at a distance from the target. Remotely sensed images are recorded digitally by sensors on board of the satellites. The satellites with appropriate swath width to monitor large areas vary in height above the earth's surface from approximately 700km, which orbit the earth, to some 36,000km, which are geostationary above the equator. The images can be manipulated by computers to highlight features of soils, vegetation and clouds. Each pixel contributing to the images is a measurement of a particular wavelength of electromagnetic radiation at a particular spatial scale for a particular location at a specific time (Mazzanti, 1996).

Remote sensing techniques make possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites. A satellite, which orbits the earth, is able to explore the whole surface in a few days and repeat the survey of the same area at regular intervals. Rapid developments in computer technology and the Geographic Information Systems (GIS) help to process remote sensing observation from satellites in spatial format of maps. The integration of information derived from remote sensing techniques with other datasets provides tremendous potential for identification, monitoring and assessment of droughts.

Recent advances in operational space technology have improved our ability to address many issues of early warning and efficient monitoring. Weather satellites were first designed to help weather forecasts, but were found to be useful for addressing vegetation issues. Since the late 1980's they have also been used for drought detection, monitoring and impact assessment in agriculture (Kogan 1990).

Use of environmental satellites enables us to detect drought 4-6 weeks earlier than before and delineated more accurately, and its impacts on agriculture can be diagnosed far in advance of harvest, which is the most vital need for global food security (Kogan 2000). Spectral radiances have been combined into indices and used as proxies for estimation of the entire spectrum of vegetation health (condition) from excellent to stressed (Kogan 1997).

Since drought covers large areas, it is difficult to monitor those using conventional systems. The space technology or remote sensing tools offer excellent possibilities of collecting this vital data. This is because the technology has capability of collecting data at global and regional scales rapidly and repetitively and the data is collected in digital form. The technology further provides excellent communication medium. Timely information about the onset of drought, its extent, intensity, duration, and impacts can limit drought-related losses of life, minimize human suffering, and reduce damage to the economy and environment (Kogan 1997). Weather data is a fairly good source of information that can be used for drought assessment. However, the scarcity of weather stations in some areas make drought monitoring a daunting task. Lack of information about a drought becomes especially acute in areas where the weather station networks is limited (e.g. sub-Saharan Africa). Furthermore, the data is often incomplete for the few available weather stations and/or not available early enough to enable timely drought detection and impact assessment (Johnson et al., 1993). Use of satellite data avoids most of these problems. Moreover, observations from space provide permanent data archive and extra visual information. Also it is cost effective and enables one to have a regular and repetitive view of nearly the earth's entire surface (Kogan 1990).

The ability to use satellite data in drought detection and mapping is based upon the fact that moisture-stressed vegetation has a higher reflectance than green, healthy, and photosynthethically active vegetation in the visible spectral band and a lower reflectance in the near-infrared band (Unganai and Kogan 1998). Surfaces such as water, snow, and clouds tend to have higher reflectance in the visible region compared to near-IR and consequently NDVI assumes negative values for these features. Bare soil and rocks exhibit similar reflectance in both the visible and near-infrared regions, thus the NDVI values tend to zero. Once calibrated with the ground truth, satellite data can be used to monitor the onset of drought, the vegetation's response to drought, and its recovery from the resulting stress (Unganai and Kogan 1998).

The main limitation of remote sensing data for drought monitoring is that the most common satellite-derived drought indicators like NDVI are difficult for interpretation. As NDVI provides only a very rough measure of crop growing conditions or vegetation vigor, high NDVI values do not necessarily reflect the condition of food crops. Also since the vegetation indices represent the condition of the overall vegetation cover and do not allow for the differentiation of cereal and other food crops, a sudden increase in the vegetation at the beginning of the rainy season does not always indicate the presence of that particular crop. Furthermore, the NDVI images cannot be used to determine which crops have reached maturity or harvested. Hence, to properly interpret NDVI it is essential to know the actual crop calendar.

2.3. PREVIOUS WORKS ON DROUGHT MONITORING AND ANALYSIS

Several studies have been devoted towards drought with the aid of satellite-derived information. Reflectance in the visible, near-infrared and thermal bands were combined into Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Normalized Difference Vegetation Index (NDVI), which considerably improved early drought detection, watch and monitoring of drought's impacts on agriculture. Using NOAA Advanced Very High Resolution Radiometer (AVHRR) data, researchers have successfully extended satellite data analysis to large-area vegetation monitoring (Kogan, 1999) and biomass productivity estimates (Townshend and Justice, 1986). Since vegetation indices derived from the AVHRR sensor are directly related to plant vigor, density, and growth conditions, they may also be used to detect unfavorable environmental variables. The relationship between NDVI and rainfall is known to vary spatially, notably due to the effects of variation in properties such as vegetation type and soil background (Li et al., 2002; Nicholson & Farrar, 1994), with the sensitivity of NDVI values to fluctuations in rainfall, therefore, varying regionally. Vegetation amount and condition are a function of environmental variables such as rainfall. Consequently, a strong relationship, involving a brief time–lag in the vegetation response to rainfall, would be expected between vegetation indices, such as the NDVI (Li et al., 2002). Many studies have focused on the relationship between the NDVI and rainfall

A study regarding the modelling of drought risk areas by using remotely sensed was carried out by Mongkolsa Wat et al. (2000) in Northeast Thailand, where drought has the most profound effect on the lives and regional economy. In this paper the severity of drought was considered to be a function of rainfall, hydrology and physical aspect of landscape. Three different types of droughts i.e. meteorological, hydrological and physical drought were analyzed after which an overlay matrix operation was performed that yielded the areas which faced drought risk wherein drought risk was classified into four classes. The result obtained was satisfactory confirming that the model developed in this study could help in the mapping of drought risk area in the Northeast Thailand.

Since launching of the Africa Real Time Environmental Monitoring Information System (ARTEMIS) by FAO in 1988 (Mazzanti 1996), it is possible to obtain a routinely every 10-days vegetation Index (NDVI) imagery covering Africa based on the data obtained from the Meteosat and NOAA series of satellites. A temporal profile can be constructed for each pixel and an image of a certain month or decades are compared with the average of that period. Hence, the FAO ARTEMIS database provides a good view of the behavior of the vegetation index over a season.

The Global Information and Early Warning System (GIEWS) has been utilizing low resolution satellite remote sensing data to monitor vegetation and rainfall development over large areas in real time. Satellites images are often the only information available in near real-time for many parts of the world. Also, they provide a “snapshot” of the vegetation and meteorological conditions through the growing season. Furthermore, satellite images from the current growing season can be compared with the historical archive containing images dating back as early 1980s for Africa. Since the late 1980s, the images have been provided by the Advanced Real Time Environmental Monitoring Information System (ARTEMIS) of the FAO in aim to provide policy analysts and decision makers with the most up-to-date and accurate information available on all aspects of food supply and demand. The main reasons for the selection of these low spatial but high temporal resolution satellites are area coverage, observation frequency and cost. High resolution satellite systems would provide a more detailed view of agricultural or affected areas concerned, but do not permit weekly or decadal monitoring, which is necessary for timely early warning and interventions.

Increased demand for information and prediction services prompted the establishment of a specialized institution, Drought Monitoring Centre-Nairobi (DMCN) for the east African countries. Its main objective is to timely provide climate information and prediction services for enhanced application of such products to reduce climate and weather-related risks to food security for sustainable development of the horn of Africa. The DMCN produces and disseminates two types of products on routinely basis, decadal (10-days) and monthly products.

Several studies have been conducted in sub-Saharan African countries. Most of them use vegetation indices for monitoring of drought in the region. Among them, one is a method developed by Kogan (Kogan 1997) which is based on the relationship of the Vegetation Condition Index and Temperature Condition Index (VCI-TCI) indices for drought detection and monitoring. The method follows the consideration that the absolute maximum and minimum of NDVI and Brightness Temperature (BT) calculated from several years of data that contain the extreme weather events (drought and non-drought years) can be used as criteria for quantifying the extreme conditions (Kogan 1995). Accordingly the maximum and minimum

NDVI and brightness temperature (BT) values were calculated from the long term records of remote sensing data for each of the weeks in the year and for each pixel. The result presented in this method shows the high potential VCI-TCI indices have for maintaining a global drought watch.

The method has been validated in many parts of the region using agricultural production yield anomaly with encouraging results. For example, the tool was tested in two African countries, Zimbabwe in Southern Africa and Ethiopia in Eastern Africa. The agriculture of these countries is very important for food self-sufficiency, and food production is highly dependant on drought. To test the indices as a tool for drought monitoring, the method used averaging the weekly VCI-TCI values over each districts of the selected administrative provinces of a country to correlate with 9-yr corn anomalies (departure from the mean). Weather conditions in these years were varied from favorable to extremely unfavorable. Correlation obtained between corn yield and weekly indices, when the weather is critical for crop growth, was very strong. However, the correlation degrades in regions where corn area is small and/or environmental resources are very limited for successful farming. Thus, the method suggests that when crop yield is used as a validation tool in marginal areas, VCI spatial aggregation should be done only for the areas of intensive farming.

The validation results clearly indicate the utility of VCI as a sole source of information about vegetation stress and consequently drought as a major cause of the stress. Moreover, this study concludes as they were also useful for real-time assessments and diagnosis of vegetation condition and weather impact on vegetation. However, the TCI derived from the thermal channel need to be treated with caution since the information content of composited TIR measurements is uncertain, as TIR emissions from the earth change rapidly with time of day and atmospheric conditions. Moreover, existing algorithms have limitations in accounting and correcting for factors such as emmissivity variations in space, time, different wavelengths and view angle.

The other method makes use of the relationship between NDVI and rainfall for drought monitoring in the Sudan (Li et al., 2002). This study explores the use of NDVI, since it has been widely used in drought monitoring, and is one of the most reliable and widely available of indices. In this study, regression techniques were used to verify whether there is a correlation between NDVI and rainfall data in Sudan, between 1982-1993.Then after establishing a positive correlation, the NDVI values over a twelve-year period were used to classify ecological areas in Sudan and produce a drought risk classification map. The result showed that there is a strong positive relationship of NDVI to rainfall in Sudan within each year, regression coefficients obtained for each year ranges between 0.74 to 0.8. Also, in order to see the trend over 10 years, the annual rainfall was plotted against the cumulative annual NDVI values and it appeared that the NDVI values corresponded to the rainfall, but with a time lag of one year. This study comes up with a hypothesis that there is a time lag between the rainfall and the NDVI response. The results obtained in this method were compared with two other methods, the relationship between NDVI and rainfall during the plant-growing season and with the method using the relationship of NDVI with rainfall and surface temperatures. The former characterizes the dynamics of the vegetation development via its growing season's parameters on consistent spatial scale and the second method is based on the relationship of the Global Vegetation Index (GVI) and the Temperature Condition Index (TCI) with rainfall.

Another study related to early detection of drought in East Asia was done by Song et al. (2004) NDVI from NOAA/AVHRR had been used wherein standard NDVI and up-to-date NDVI were calculated to derive difference NDVI image, to detect the intensity and agricultural area damaged by drought. The difference images were used to create drought risk maps. The study was successful in detecting and monitoring drought effects on agriculture.

There have also been studies dealing with the estimation of grain production that is very vital for global food security and trade (Kogan, 1990). A study made by Kogan for drought early warning applied a new numerical method, introduced in late 1980's based on a three spectral channel combination visible, near infrared and infrared. The new method is built on three basic environmental laws: law of minimum (LOM), law of tolerance (LOT) and principal of carrying capacity (CC). This method was applied to the NOAA Global Vegetation Index (GVI). With the introduction of this method drought can be detected 4-6 weeks earlier and delineated more accurately and its impact on grain production can be diagnosed long before harvest.

Wilhelmi and Wilhite (2002) presented a method for spatial, Geographic Information Systems- based assessment of agricultural drought vulnerability in Nebraska. It was hypothesized that the key biophysical and social factors that define agricultural drought vulnerability were climate, soils, landuse and access to irrigation. The framework for derivation of an agricultural drought vulnerability map was created through development of a numerical weighting scheme to evaluate the drought potential of the classes within each factor. Results indicated that the most vulnerable areas to agricultural drought were non-irrigated cropland and rangeland located in areas with a very high probability of seasonal crop moisture deficiency.

A research done by Herrmann et.al (2000) investigates temporal and spatial patterns of vegetation greenness and explores relationships between rainfall and vegetation dynamics in the Sahel, based on analyses of NDVI time series and gridded precipitation estimates at different spatial resolutions. Overall positive trends in NDVI and rainfall over the period 1982 to 2003 were confirmed. Linear correlations between the two variables were found to be highly significant throughout the entire Sahel. Herrmann et.al thus considered that rainfall is the most important constraint to vegetation growth in this semi-arid zone, which justifies the attempt to predict vegetation greenness from rainfall estimates through linear regression.

Similarly a case study relating to drought risk evaluation was carried out by K.Prathumchai et al. (2001), the objective of the study being to evaluate criteria for identifying drought risk areas. In this study physical and meteorological factors were analyzed and drought risk areas were identified. Drought risk areas were calculated as a weighted linear combination of a set of input factors such as topography, soil drainage, ground water resource, irrigation area, annual evaporation, average annual rainfall and frequency of rainfall days. The relationship between NDVI change and drought risk level was calculated from the average NDVI change collected by masking each drought risk area. The study concluded that NDVI could be used as a main indicator to evaluate drought. However the limitation of the study was that it was unable to consider change in species, type, age and characteristic of the vegetation.

Anyamba and Tucker (2005) analysed seasonal and interannual vegetation dynamics in Sahel using NOAA-AVHRR NDVI. The study concentrated only on NDVI patterns in growing season, which was defined by examining the long-term patterns of both rainfall and NDVI. Year to year variability in NDVI patterns was examined by calculating yearly growing season anomalies. The correlation between NDVI and rainfall anomaly time series was found to be positive and significant, indicating the close coupling between rainfall and land surface response patterns over the region.

A study by Wang et al. (2001) concentrated on temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. In this study it was found that average growing season NDVI values were highly correlated with precipitation received during the growing season and seven preceding months. Relations between temperature and rainfall with NDVI were examined within growing season, across growing seasons and across years. It was concluded that precipitation has the primary influence on NDVI and by inference, on productivity.

Another approach utilizes the relationship between NDVI and crop yield production to analyze the crop yield reduction in the state of Kansas, located in the heart of the central Great Plains region of the North America. The method examined correlations between NDVI and annual corn and wheat production based on masks that delineate landscape patterns where these crops are produced in Kansas. The relationship were analyzed using NDVI integrated over all combination of continuous time intervals (based on starting date and duration). The crop mask was created based on the characteristic that the crop produces high NDVI in the maturing time of the cropping season and low NDVI in the time after harvest. The result showed that annual corn production was more strongly correlated with NDVI integrated over the maturing period of the growing season. Thus, the method suggests that the NDVI can serve as a reliable predictor of crop yield (Wang, M.Rich et al. 2005). Moreover, it has been shown that there exists a good correlation between NDVI anomaly and food grain anomaly in drought risk assessment study for Gujarat, India (Chopra 2006).

In another study (M.Rich et al. 2005), the possibility of using NDVI data for crop and natural vegetation monitoring has been analyzed by measuring the cross-correlation between time series of NDVI and vegetation indicators such as rainfall for areas where rainfall is a limiting factor. The result showed there is a fairly good correlation between NDVI and rainfall with coefficients of correlation between 0.7 and 0.9, and NDVI is found to lag behind rainfall by between one and three months. The study concludes if it is assumed that the rainfall data can be used as indicator for vegetation development over the season, there are limitations with the capability of NDVI for monitoring temporal variations in vegetation

2.4. DROUGHT INDICES

Drought indices can be used to quantify the moisture condition of a region and thereby detect the onset and measure the severity of drought events; and to quantify the spatial extent of a drought event thereby allowing a comparison of moisture supply condition between regions (Quiring and Papakryiakou 2003). They are normally continuous functions of rainfall and/or temperature, river discharge or other measurable variable. Rainfall data are widely used to calculate drought indices; because of the long-term rainfall records are often available. Moreover, drought indices integrate various hydrological and meteorological parameters like rainfall, evapotranspiration (ET), runoff and other water supply indicators into a single number and gives a comprehensive picture for decision making (Narasimhan and Srinivasan 2005). There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms. Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses.

2.5. METEOROLOGICAL DROUGHT INDICES AND DROUGHT DETECTION

A drought index assimilates thousands of data on rainfall, snow pack, stream flow and other water-supply indicators into a comprehensible picture. There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms. Some of the widely used drought indices include Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI) and Standardized Precipitation Index (SPI).

2.5.1. PALMER DROUGHT SEVERITY INDEX (PDSI)

Palmer (1965) developed a soil moisture algorithm which uses precipitation, temperature data and local Available Water Content (AWC) of the soil. AWC is effectively a "model parameter", which has to be set at the start of calculations. Calculations result in an index (PDSI), which indicates standardized moisture conditions and allows comparison to be made between locations and between months. PDSI varies roughly between -6.0 and +6.0. More wet conditions are indicated by positive values of PDSI, and more dry by negative values. The thresholds for the classification of different wetness are arbitrary. PDSI values between -2 and +2 would normally indicate normal conditions, although the sub-range of -1 to -2 could also be treated as a mild drought. PDSI values are normally calculated on monthly basis. Further interpretation of monthly PDSI allows drought duration to be taken into account as well. PDSI values may lag behind emerging droughts by several months. This limits its application in areas of frequent climatic extremes.

PDSI has been used in west –Hungary as soil moisture indicator and has been widely used in United States for drought monitoring. It has been utilized as a tool to trigger actions associated with drought contingency plans. Several researchers have given limitations of PDSI. The Palmer Drought Severity Index (PDSI, Palmer, 1965) has a time scale of about 9 months (Guttman, 1998), which does not allow identification of droughts at shorter time scales. Also PDSI is applied within the United States and has less acceptance elsewhere (Kogan, 1990). To solve these problems, McKee et al. developed the Standardized Precipitation Index (SPI), which can be calculated at different time scales to monitor droughts in the different usable water resources. Moreover, the SPI is comparable in time and space (Svoboda et al. 1999).

2.5.2. CROP MOISTURE INDEX (CMI)

Three years after the introduction of his drought index, Palmer (1968) introduced a new drought index based on weekly mean temperature and precipitation known as Crop Moisture Index (CMI). It was specifically designed as an agricultural drought index. It depends on the drought severity at the beginning of the week and the evapotranspiration, soil deficit or soil moisture recharge during the week (Heim 2000). It measures both evapotranspiration deficits (drought) and excessive wetness (more than enough precipitation to meet evapotranspiration demand and recharge the soil). CMI is designed to monitor short-term moisture conditions affecting a developing crop; therefore CMI is not a good long-term drought-monitoring tool. The CMI's rapid response to changing short-term conditions may provide misleading information about long-term conditions. Svoboda et al. (1999) used CMI for estimating surface moisture status, because CMI depicts changes in soil moisture situation more rapidly than PDSI. It was found that CMI indicates more favourable moisture conditions over a particularly wet or dry month even in the middle of a serious long-term wet or dry period.

2.5.3. STANDARDIZED PRECIPITATION INDEX (SPI)

Tom Mckee, Nolan Doesken and John Kleist of the Colorado Climate Centre formulated the SPI in 1993. The purpose is to assign a single numeric value to the precipitation that can be compared across regions with markedly different climates. Technically, the SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. Since precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follow a normal distribution.

The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale while groundwater, stream flow, and reservoir storage reflect the longer-term precipitation anomalies.

The SPI calculation for any location is based on the long-term precipitation record that is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edwards and McKee, 1997). A drought event occurs any time the SPI is continuously negative and reaches intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be termed the drought's "magnitude".

SPI Values	
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Table 2.1 SPI Values

Source: http:drought.unl.edu/monitor/spi, January 2007

2.6. DROUGHT INDICES DERIVED FROM REMOTE SENSING DATA

Several indices, which could be used amongst the others for drought monitoring, have been developed over the past few decades using remote sensing data. They are calculated from the reflectance and brightness temperature in different bands and may be obtained for each pixel (the size of the pixel depends upon the resolution of a sensor). These indices have a few advantages over conventional climate data related indices, as they cover large areas and may show how drought is progressing over the area. They have to be calibrated against ground climate data. Most commonly applied indices are discussed below.

2.6.1. NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)

The Normalized Difference Vegetation Index (NDVI) is related to the proportion of photo-synthetically absorbed radiation. Many natural surfaces are about equally as bright in the visible red and near-infrared part of the spectrum with the notable exception of green vegetation. Red light is strongly absorbed by photosynthetic pigments (such as chlorophyll) found in green leaves, while near-infrared light either passes through or is reflected by life leaf tissues, regardless of their color. This means that areas of bare soil having little or no green plant material will appear similar in both the red and near-infrared wavelengths, while areas with much green vegetation will be very bright in the near-infrared and very dark in the red part of the spectrum. In other words, for healthy living vegetation, this ratio will be high due to the inverse relationship between vegetation brightness in the red and infrared regions of the spectrum. The Normalized Difference Vegetation Index (NDVI) provides a measure of the amount and vigor of vegetation at the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation. So, the normalized difference vegetation index (NDVI) provides us with an indication of how much green vegetation exists at a particular place on the ground. The NDVI values range from -1 to +1 with most values ranging from 0 to 0.6. Healthy green vegetation has a high NDVI value because more near-infrared light is reflected than red light. For bare soil on the other hand, both near-infrared and red light are strongly reflected so the NDVI would be near zero. Water and ice reflect a little more red than near-infrared light so those values tend to be slightly negative. Two characteristics of the NDVI that make it ideal for vegetation monitoring are that no other surface exhibits higher NDVI values than vegetated surfaces and that, when vegetation vigor changes due to the nature of vegetation growth and development or environmental induced stress such as drought, the NDVI also changes (Anyamba and Tucker 2005). Therefore, the NDVI does have potential in drought detection and climate impact assessment.

NDVI is calculated from two channels sensor, the near-infrared (NIR) and visible (VIS) wavelengths, using the following algorithm:

$$NDVI = (NIR - VIS) / (NIR + VIS)$$

Where NIR and VIS is the reflectance in the near infra-red and red bands respectively.

NDVI ranges from -1 to +1.NDVI is a nonlinear function that varies between –1 and +1 (undefined when NIR and VIS are zero). Values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating healthy vegetation.

NDVI by itself does not reflect drought or non-drought conditions. But the severity of drought may be defined as NDVI deviation from its long-term mean (DEV_{NDVI}). This deviation is calculated as the difference between the NDVI for the current month and a long term mean for this month (IWMI 2006).

$$DEV_{NDVI} = NDVI_i - NDVI_{mean,\, i}$$

Where $NDVI_i$ is the current NDVI for month I and NDVImean, i is the long term mean NDVI for a calendar month, i. When DEV_{NDVI} is negative, it indicates the below-normal vegetation condition and, therefore, suggests a prevailing drought situation. The greater the negative departure the greater the magnitude of a drought. In general, the departure from the long-term mean can be used effectively as drought indicator as it would reflect the conditions of healthy vegetation in normal and wet years. Its limitations are that the deviation from the mean does not take into account the standard deviation, and can be misinterpreted when the variability in vegetation conditions in a region is fluctuate in any given year(Thenkabail 2004).

2.6.2. WATER SUPPLY VEGETATION INDEX (WSVI)

Water supply vegetation index is based on the fact that, in drought conditions, the Normalized Difference Vegetation Index (NDVI) values derived from satellite data will fall below normal. At the same time, the crop canopy temperature as seen by the same satellite will rise above normal. Both effects are related to available water supply, and by combining both effects in one index, a sensitive measure of drought conditions can be obtained. When crops are suffering from drought, their stomata openings are partly closed in order to reduce the loss of water. It causes an increase of temperature of the leaf surface. For initial and advance stage of a drought, the higher the temperature of the leaf surface is the more stress. At the same time, the growth of crops is affected by drought, resulting in the decrease of leaf area index (LAI). Besides, leaves will also be wither under high air temperature. All of these may result in reduction of NDVI. The smaller WSVI is the more severe drought is.

WSVI is given by:

$$WSVI=NDVI/Tb$$

Where Tb is the brightness temperature. When vegetation suffers from drought, the NDVI decreases and the temperature of the canopy increases. So, WSVI decreases (Jiren and Musul 2002).

2.6.3. VEGETATION CONDITION INDEX (VCI)

Although the NDVI has been extensively used in the past for vegetation monitoring, it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. Vegetation condition index was first suggested by Kogan (1995). It shows, effectively, how close the current month's NDVI is to the minimum NDVI calculated from the long-term record of RS images. VCI enables to separate the short-term signal from the ecological signal.

$$VCI_j = \frac{(NDVI_j - NDVI_{min})*100}{(NDVI_{max} - NDVI_{min})}$$

Where, $NDVI_{max}$ and $NDVI_{min}$ are calculated from the long-term record for that month, and j is the index of the current month. NDVI values are calculated using the formula above. The condition of the ground vegetation presented by the VCI is measured in percent. The VCI values around 50% reflect fair vegetation conditions. The VCI values between 50 and 100% indicate optimal or above normal conditions. At the VCI value of 100%, the NDVI value for selected month (week) is equal to NDVImax, which indicates optimal condition of vegetation. Different degrees of drought severity are indicated by VCI values below 50% Kogan (1995) illustrated that a VCI threshold of 35% may be used to identify extreme drought conditions and suggested that further research is necessary to categorize the VCI by its severity in the range between 0 and 35% (Thenkabail 2004). The VCI value close zero percent reflects an extremely dry month, when the NDVI value is close to its long term minimum. Low VCI values over several consecutive time intervals indicate to drought development.

The VCI captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas. The VCI not only permits the description of land cover and spatial and temporal vegetation change but also allows quantifying the impact of weather on vegetation. Also the VCI makes it possible for one to compare the weather impact in areas with different ecological and economical resources. VCI values indicate easily how much the vegetation has advanced or deteriorated in response to weather and how far vegetation development is from the potential maximum and minimum defined by ecological limits.

2.6.4. TEMPERATURE CONDITION INDEX (TCI)

During the rainy season, it is common for overcast conditions to prevail for long periods of time. If this period lasts more than 3 weeks, the weekly NDVI values tends to be depressed giving the false impression of water stress or drought conditions. To remove the effects of cloud contamination in satellite assessment of vegetation condition, Kogan (1995, 1997) suggested Temperature condition index (TCI) and is calculated similarly to VCI but its formulation was modified to reflect vegetation's response to temperature (the higher the temperature the more extreme the drought). TCI is based on brightness temperature and represents the deviation of the current month's value from the recorded maximum. That makes it necessary to use TCI as tool to verify drought conditions. However, in contrast to the VCI, the TCI includes the deviation of the current month's value from the recorded maximum. In combination with meteorological observations, the relationship between surface temperature and the moisture regime on the ground will detect drought-affected areas before biomass degradation occurs. Hence, TCI can play an important role in drought monitoring.

$$TCI_j = \frac{(BT_{max} - BT_j)*100}{(BT_{max} - BT_{min})}$$

Where BT is the brightness temperature. The maximum and minimum values of BT are calculated from the long term records of Remote Sensing images.

3. MATERIALS AND METHODS

3.1 DESCRIPTION OF STUDY AREA

The Sate of Amhara is located in the north western and north central part of Ethiopia. The region geographically located $8^0 36'\ 0''$ N to $13^0 48'\ 0''$ N latitude and $35^0 12'0''$ E to $40^0 24'0''$ E longitude. The State shares common borders with the state of Tigray in the north, Afar in the east, Oromiya in the south, Benishangul/Gumuz in the south west, and the Republic of Sudan in the west. The state has 10 zones namely Simen Gonder, Debub Gonder, Agew Awi, Mirab Gojjam, Misrak Gojam, Wag Himra, Simen Wollo, Debub Wollo, Simen Shewa and Oromia Zones.

3.1.1 DEMOGRAPHICS

Based on figures from the Central Statistical Agency of Ethiopia (CSA) published in 2005, Amhara Region has an estimated total population of 19,120,005, consisting of 9,555,001 men and 9,565,004 women. 16,925,000 or 88.5% of the population are estimated to be rural inhabitants, while 2,195,000 or 11.5% are urban. With an estimated area of 170,752 square kilometers, this region has an estimated density of 120.12 people per square kilometer. Of the total population of the State, 81.5% were Orthodox Christians, 18.1% Muslims, and 0.1% Protestants. The majority of the population is Amhara, which is estimated to be 91.2%; other groups include the Oromo (3%), Agaw/Awi (2.7%), Qemant (1.2%), and Agaw/Kamyr (1%).

3.1.2 MAJOR ECONOMIC ACTIVITIES

About 85% of the people are engaged in agriculture. The State is one of the major Teff (staple food) producing areas in the country. Barely, wheat, oil seeds, sorghum, maize, wheat, oats, beans and peas are major crops produced in large quantities.

Cash crops such as cotton, sesame, sunflower, and sugarcane grow in the vast and virgin tract of the region's lowlands. The water resources from Lake Tana and all the rivers found in the region provide immense potential for irrigation development.

About 450,000 hectares of arable land is irrigable and suitable, especially for horticultural development.

3.1.3 TOPOGRAPHY AND CLIMATE

The State of Amhara is topographically divided into two main parts, namely the highlands and lowlands. The highlands are above 1500 meters above sea level and comprise the largest part of the northern and eastern parts of the region. The highlands are also characterized by chains of mountains and plateaus. Ras Dejen (4620 m), the highest peak in the country, Guna (4236 m), Choke (4184m) and Abune – Yousef (4190m) are among the mountain peaks that are located in the highland parts of the region.

The lowland part covers mainly the western and eastern parts with an altitude between 500-1500 meters above sea level. Areas beyond 2,300 meters above sea level fall within the "Dega" climatic Zone, and areas between the 1,500-2,300 meter above sea level contour fall within the "Woina Dega" climatic zone; and areas below 1,500 contour fall within the "Kolla" or hot climatic zones. The Dega, Woina Dega and Kolla parts of the region constitute 25%, 44% and 31% of the total area of the region, respectively.

The annual mean temperature for most parts of the region lies between 15^0C-21^0C. The State receives the highest percentage (80%) of the total rainfall in the country. The highest rainfall occurs during the summer season, which starts in mid June and ends in early September.

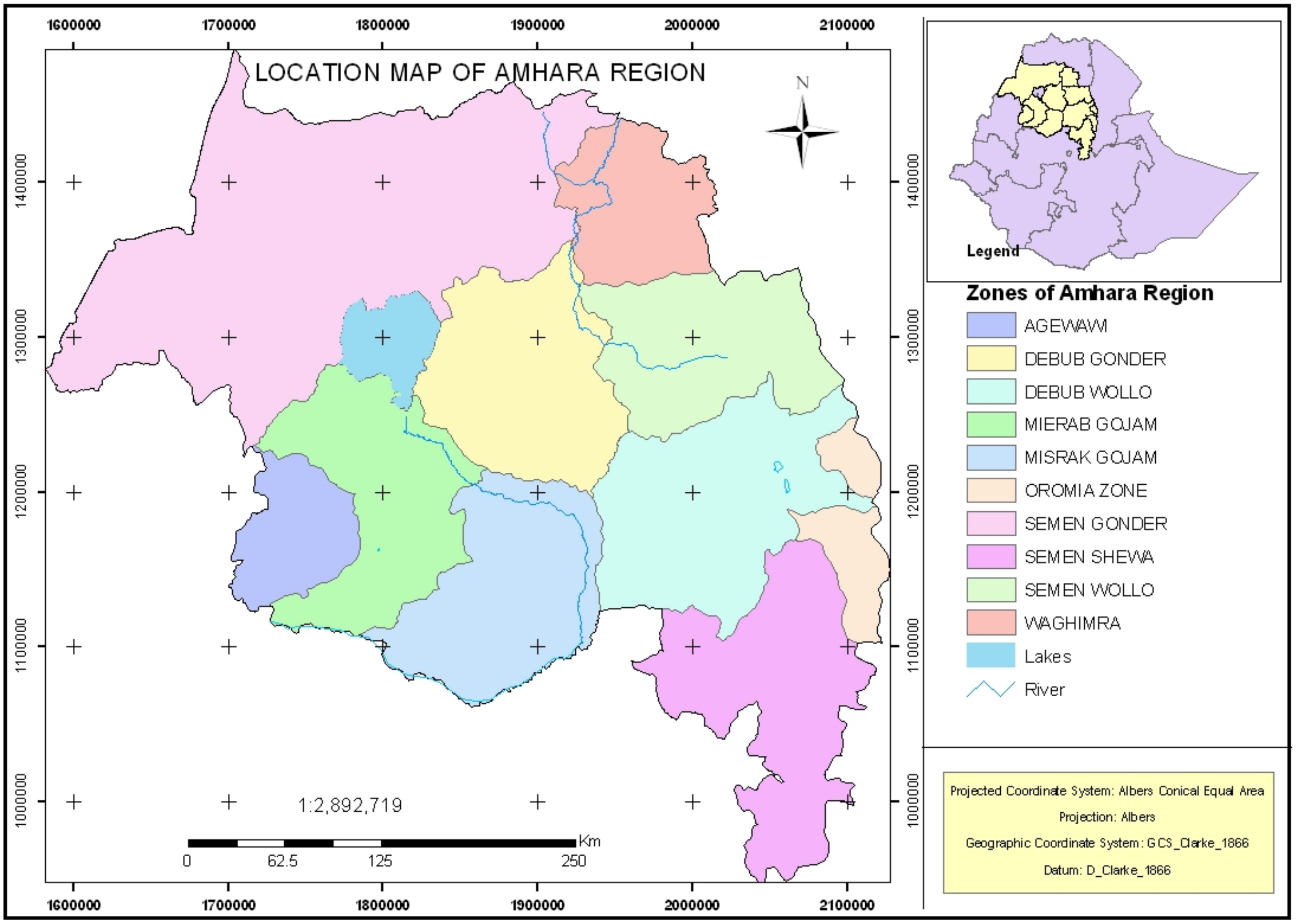


Figure 3.1 Location map of study area

3.1.4 RIVERS AND LAKES

The State of Amhara is divided mainly by three river basins, namely the Abbay, Tekezze and Awash drainage basins. The Blue Nile (Abbay) river is the largest of all covering approximately 172,254 Km^2. Its total length to its junction with the White Nile in Khartoum is 1,450 Km, of which 800 km is within Ethiopia. The drainage-basin of the Tekeze river is about 88,800 km^2. Tana, the largest lake in Ethiopia is located at center of the region. It covers an area of 3,6000 km^2. The rivers and lakes of the region have immense potential for hydroelectric power generation, irrigation and fishery development.

3.1.5 LIVESTOCK

The CSA of Ethiopia estimated in 2005 that farmers in Amhara had a total of 9,694,800 head of cattle (representing 25% of Ethiopia's total cattle), 6,390,800 sheep (36.7%), 4,101,770 goats (31.6%), 257,320 horses (17%), 8,900 mules (6%), 1,400,030 asses (55.9%), 14,270 camels (3.12%), 8,442,240 poultry of all species (27.3%), and 919,450 beehives (21.1%). About 40% of the livestock population of the country is found in this region. The huge livestock potential of this region gives ample opportunity for meat and milk production, food processing as well as leather and wool production.

3.1.6 FAUNA

Walia ibex, Semien fox, Gelada-baboon, Grey Duiker, Klipspringer, Hyenas and Corocodile are among the twenty-one species (three endemic) that are found in the region, especially at the Semien mountain national park. Wild fowls, Francolins, Pelicans, Cranes, Ibises, and Stocks are among the birds that are found in the region.

3.1.7 MINERALS

The Sate of Amhara has mineral resources such as coal, shell, limestone, lignite, gypsum, gemstone, silica, sulfur and bentonite. Hot springs and mineral water are also found in the region.

3.1.8 TOURISM AND HERITAGE

The 12^{th} century Rock-Hewn churches of Lalibela, and the palaces in Gondar the world known heritages of the country. The traditional mural paintings and hand craft, the preserved corpse of the royalty found in the ancient monasteries in Lake Tana, as well as the Semien mountains national park, which shelters the endemic Walia ibex are spectacular tourist attractions, three tourist attractions found in the region are registered in the UNESCO list of world heritages. Besides these known heritages, the Blue Nile Falls, the caves and unique stones in northern Showa, and the Merto Le Mariam church are special tourist attractions.

3.2. DATA AND ACQUISITION METHODS

3.2.1. AGRICULTURAL PRODUCTION YIELD DATA

The characteristics of satellite derived indices must be validated by ground truth data. The ground data intended to be used mainly in this study is agricultural production yield. As agricultural yields are sensitive to weather fluctuations, it will reduce abruptly during severe drought periods. Therefore, “average yield of grain crops for country’s administrative regions can be used for validation of satellite-derived droughts” (Kogan 1997). For this study the ground data was collected for “Amhara” region for validation purpose. The agricultural yield production statistics has been taken for most of the “Amhara region”. These data has been collected from CSA (Central statistic Agency) Hand Book. Agricultural production yield data is obtained for five years starting from 2000 to 2004.

Table 3-1 shows the agricultural statistics data of all the districts for five years (2000-2004). The table summarizes total production yield and cultivated land over the main cropping season.

	Semien wollo		Debub Wollo		Semien Shewa	
year	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)
2000	227098	1281015	478877	3780348	531239	4993977
2001	229499	1809300	470363	3223848	548506	5608172
2002	204917	2442211	356139	3836259	353597	3938673
2003	193420	138857	331122	2461770	375073	2512286
2004	217294	2735107	382490	4733845	374207	4655269

year	Agew Awi		Wag Hemra		Oromia	
	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)
2000	302547	390735	106498	395628	84161	595630
2001	326881	4373839	117260	322698	83178	705803
2002	184740	2554974	67103	489648	44526	500102
2003	152166	1665913	74260	402505	59330	390031
2004	190986	1972649	79000	572776	55271	553448

year	Mirab Gojjam		Misrak Gojjam		Semien Gonder		Debub Gonder	
	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)	Cultivated land (ha)	Production (Quintal)
2000	578029	9437080	573144	8605175	843297	7935839	586505	6487056
2001	78624	1041232	614257	8856071	716977	7847587	587853	4469455
2002	408340	5929767	431725	5650957	485009	5263940	370912	3857770
2003	392763	44812115	397966	3617575	472208	2704661	403552	3122056
2004	409023	5361453	278735	5065554	523527	4859031	412007	3208232

3.2.2. METEOROLOGICAL DATA

Apart from the agricultural production yield data, rainfall data has been collected from 40 stations on decadal basis to see the relation of NDVI with variability of rainfall. The stations are distributed in four Zones of the region namely Debub Wollo, Simen Wollo, Wag Himra and Simen Shewa. The data source is the Ethiopian Meteorological Service Agency (EMSA).

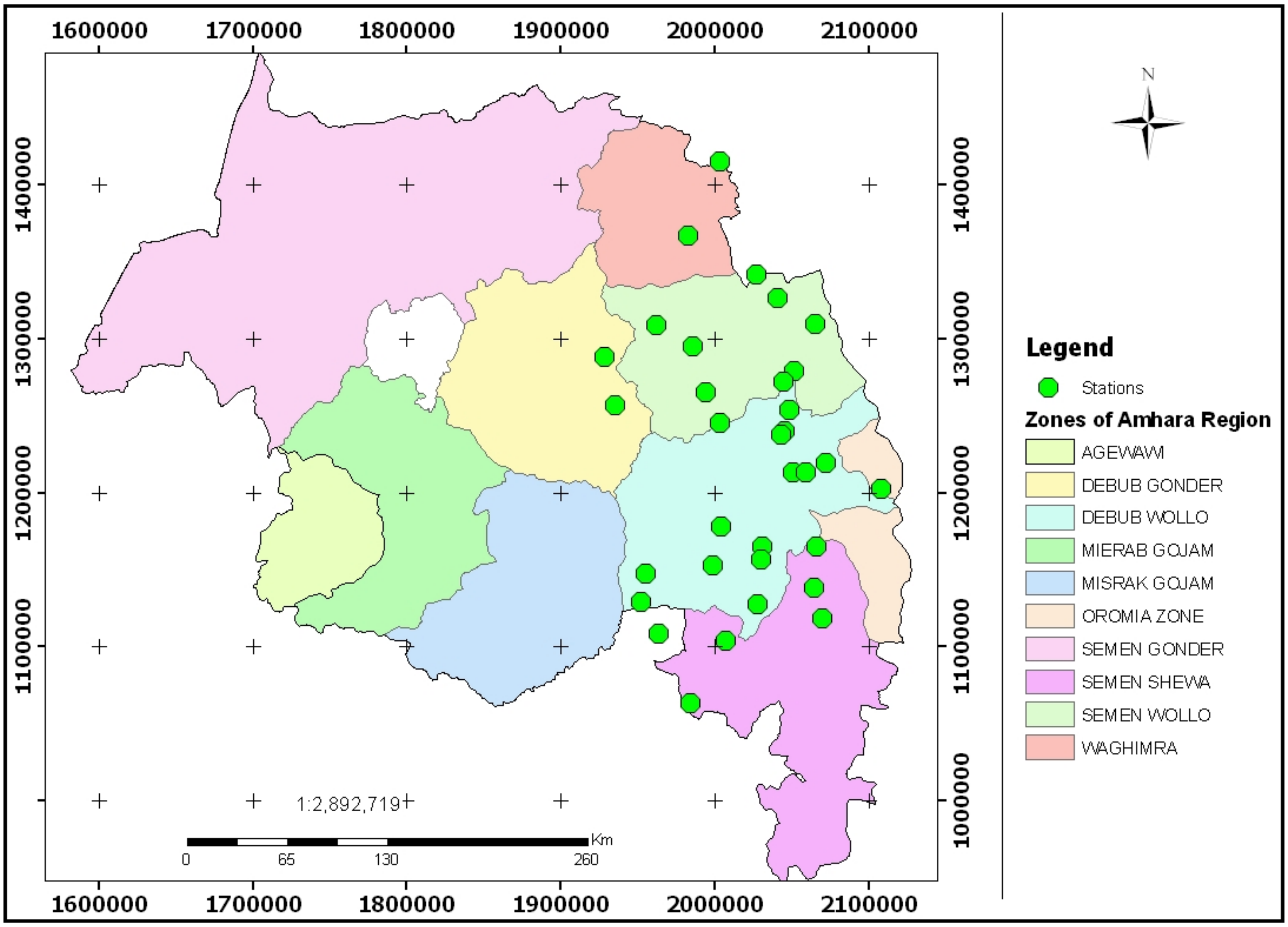


Figure 3.2 Map of Rainfall stations in Four Zones of Amhara Region

Meteorological data has been used to get the response of NDVI with the variability of rainfall in all the districts of the region. Use of inverse distance method was made for distributing the influence of each station over the entire region.

3.3.3. REMOTELY SENSED DATA

3.3.3.1. NOAA-AVHRR DATA ACQUISITION AND PRE-PROCESSING

The MODIS and AVHRR, carried on board of Terra-Aqua and NOAA series satellites respectively, are cost effective sensors, which cover the globe at least once a day. The AVHRR sensor (Kidwell, 1991) collects radiance data in five spectral bands including red visible (0.58–0.6 μm), near-infrared (0.725–1.1 μm), mid-infrared (3.55–3.93 μm) and two thermal infrared bands (10.3–11.3 μm and 11.5–12.5 μm). But only four bands together with the normalized difference vegetation index are useful for this and similar studies (Table 3.2) due the unresolved calibration issues with the mid-infrared band (Smith et al. 1997). The AVHRR radiance data have the spatial resolution of 0.1^o (pixels of approximately 10 X 10 km) and are available with a decadal step resolution for a period from 1981 to 2007. Long-term mean (1981-2004) of decadal composite NOAA pathfinder NDVI values encompassing the continent Africa were downloaded from the Famine Early Warning System (FEWS-NET) archive website: http://earlywarning.cr.usgs.gov/adds/datatheme.php; and Decadal Long-term NDVI values are extracted for the study area only. NDVI is derived from data collected by the National Oceanic and Atmospheric Administration (NOAA) satellites, and processed by the Global Inventory Monitoring and Modeling Studies group (GIMMS) at the National Aeronautical and Space Administration (NASA). The data set was generated from original $1.1km^2$ NOAA-AVHRR data as 10- day maximum value composites (MVC) aggregated to an 8km × 8km pixel resolution. EROS processes and archives a decadal (i.e., ~ 10-days, 36/year) Africa NDVI product from NASA GIMMS group. The data is inter-calibrated with SPOT Vegetation NDVI, and uses NOAA-17 since January 2004. The NOAA-17 NDVI data have also been inter-calibrated with NOAA-16 and previous products.

No correction has been applied to correct for atmospheric effects due to water vapour, Rayleigh scattering or stratospheric ozone. An artefact in NDVI due to satellite drift has been corrected using empirical mode decomposition, which is especially important in tropical regions (Pinzon et al., 2004). NDVI is archived as byte data files, and once imported, is referred to as 'raw data'. In order to recover the -1 to +1 range of NDVI values, the following formula has been used and water pixels are masked (Tucker et al., 2005).

$$NDVI = raw/250$$

The procedure of deriving decadal (i.e., ~ 10-days, 36/year) MVCs includes the examination of daily radiance values for each waveband together with NDVI values – for each decade for each pixel. The highest daily radiance/NDVI value in a decade (i.e., ~ 10-days) is identified and retained. This minimizes problems of cloud impacts typical to single-date remote sensing studies (Goward et al., 1994; Eidenshink and Faundeer, 1994).

The converted AVHRR decadal time-series data for 1981-2004 were used for historical drought analysis, while 2000-2001 data were used for regression analysis between AVHRR and MODIS. There were 932 images for NDVI during 1981-2007. For the purpose of further analyses, the 1982-2007 data were stacked decadal (36 decade), monthly and yearly files. The first file each decade contained 25 to 27 layers ((25- 27) $_{years}$* 36) and the second file 12 layers per month (12* (25-27) $_{years}$) and the third file 1 layer per year ((25- 27) $_{years}$) NDVI data.

Drought index	Band or index used to compute the index		Range	Normal condition	Severe drought	Healthy vegetation
	AVHRR	MODIS				
1. Normalized difference vegetation index (NDVI)	Band 1 (0.58-0.68µm) Band 2 (0.73-1.10µm)	Band 1 (0.62-0.67µm) Band 2 (0.84-0.87µm)	-1 to +1	Depends on the location	-1	+1
2. Drought severity index (DEV_{NDVI})	NDVI NDVI long-term mean	NDVI NDVI long-term mean	-1 to +1	0	-1	+1
3. Vegetation condition index (VCI)	NDVI NDVI long-term minimum NDVI long-term maximum	NDVI NDVI long-term minimum NDVI long-term maximum	0 to 100 %	50 %	0%	100%

Table 3.2 Remote sensing data, indices and thresholds relevant to drought assessment used in the study.

3.3.3.2. MODIS DATA ACQUISITION AND PRE-PROCESSING

The MODIS, is the primary sensor for monitoring the terrestrial ecosystem for the NASA Earth Observing System (EOS) program (Justice et al. 2002) and has several advancements over AVHRR (Table 3.2). The MODIS is more sensitive to changes in vegetation dynamics (Huete et al. 2002) and was found to be a more accurate and versatile instrument to monitor the global vegetation conditions than the AVHRR (Gitelson and Kaufman, 1998; Justice et al., 2002).

The MODIS sensor acquires data in 36 spectral bands, in variable spatial resolution of 250-1000 meters, in narrow bandwidths and in 12-bits. The 36 MODIS bands are a compromise of atmospheric, land and ocean studies of which seven bands are considered optimal for land applications (Justice et al., 2002). MODIS data have a temporal resolution of 32 days and are available since 2000 till present. The 32-day, 7-band data are made available by Global Land Cover Facility (GLCF) (similarly to the pre-processed AVHRR reflectance data by NOAA GIMMS) (NASA (2007), after corrections for molecular scattering, ozone absorption and aerosols. The data are also adjusted to nadir (sensor looking straight down) and standard sun angles with the use of bi-directional reflectance (BRDF) models (Vermote et al. 2002, Justice et al. 2002). The 7 bands have waveband centers 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm respectively.

All MODIS data are directly downloadable for free from Global Land Cover Facility (GLCF) data center (http://glcf.umiacs.umd.edu/data/). MODIS data were composed into 2 mega files for 2000-2003 periods: i) a file of 72 wavebands (12 images per year * 2 bands per image * 3 years), and ii) a file of 24 NDVI layers (12 NDVI layers per year * 3 years).

MODIS data continuity from Terra and Aqua satellites is guaranteed over time with successor satellite and sensor systems already planned and assured for at least till 2018 with National Polar-Orbiting Operational Environmental Satellite System (NPOESS) series of satellites (Justice 2002).

3.3.3.3 POST- PROCESSING OF SATELLITE DATA

After organizing of MODIS image, 32 day NDVI values are computed from the reflectance of the visible and near-infra red bands by using the universally defined formula as follow:

$$NDVI = (NIR-VIS) / (NIR+VIS).$$

Then, 32 day MODIS NDVI's are aggregated into yearly basis. In this way 12 monthly NDVI maps per year are obtained. Finally, each monthly MODIS NDVI map and AVHRR NDVI map were used for computation of drought in "Amhara" region.

In this study use of two different sensor data with different time series was applied: the NOAA-AVHRR data (1981-2007), and MODIS data (2000-2003). Decadal long-term mean value of 23-years (1982-2004) was obtained from AVHRR sensor and used as input in computing the drought monitoring indices. Monthly NDVI values from 2000-2003 were obtained from MODIS Sensor. The current NDVI values (from 2004 to 2007) obtained from the NOAA AVHRR data was used during computation of drought monitoring indices. However, the NDVI's obtained from the MODIS sensor were used for regression analysis between AVHRR and MODIS. Absolute maximum and minimum NDVI values for each decade and month are derived from long-term record of AVHRR data. The available five years agricultural production yield with precipitation data used for validation. After driving of the drought indicating indices based on the sated criteria the Deviation of NDVI and Vegetation condition index were reclassified and overlaid to obtain drought severity map.

3.3 METHODS

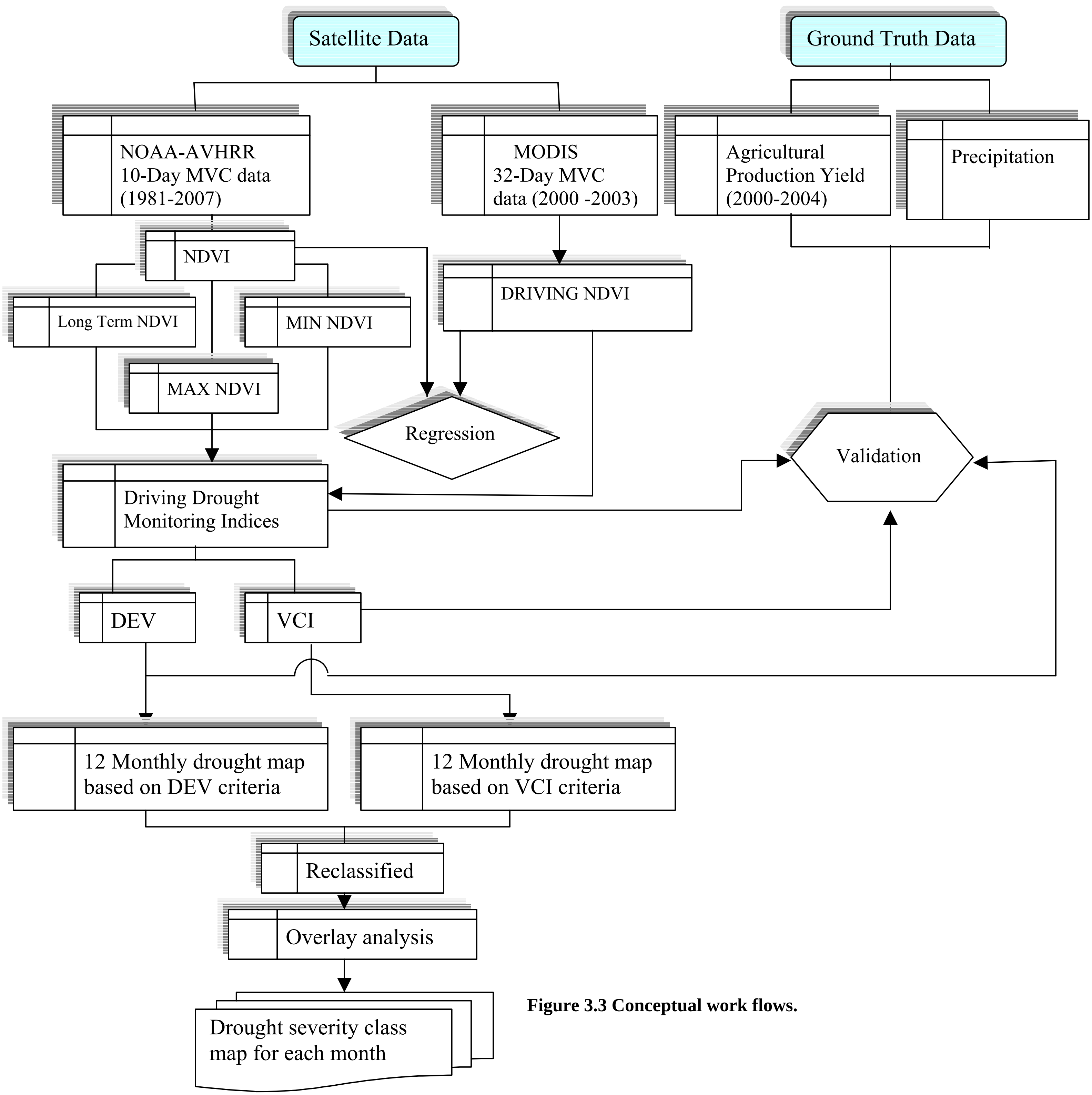


Figure 3.3 Conceptual work flows.

4. DATA ANALYSIS

4.1. PROCESSING OF SATELLITE DATA

4.1.1. DERIVING OF DROUGHT- MONITORING INDICES

The indices, which could be used for drought monitoring, are derived from AVHRR and MODIS data (Table 3.2). Indices are normally radiometric measures of vegetation condition and dynamics, exploiting the unique spectral signatures of canopy elements, particularly in the red and NIR portions of the spectrum (e.g. Huete et al., 1997, 2002) and are sensitive to vegetation type, growth stage, canopy cover and structure (Clevers and Verhoef, 1993; Thenkabail, 2004; Thenkabail et al., 2004). The indices utilize the reflectance data in two spectral bands thus enhancing the vegetation signal and canceling out the effects of topography, sun angle and atmosphere.

4.1.1.1. NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI).

NDVI was first suggested by Tucker (1979) as an index of vegetation health and density.

$$NDVI = \mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS}) / (\mathrm{NIR} + \mathrm{VIS})$$

Where NIR and VIS are the reflectance in the near infrared (NIR) and red bands respectively (Table 3.1). The NDVI was also shown to reflect vegetation vigor (Teillet et al., 1997; Kogan et al. 2000), percent green cover, Leaf Area Index (LAI- Baret and Guyot, 1991), biomass and water stress and yield (Thenkabail et al., 2002; Thenkabail et al., 2004).

The NDVI is the most commonly used index (Jensen, 1996). It varies in a range of -1 to + 1. However, NDVI: (a) uses only two bands and is not very sensitive to influences of soil background reflectance at low vegetation cover, and (b) has a lagged response to drought (Reed, 1993; Rundquist and Harrington, 2000; Wang et al., 2001) due to a lagged vegetation response to developing rainfall deficits. Previous studies have shown that NDVI lags behind antecedent precipitation by up to three months (Justice et al., 1986; Farrar et al., 1994; Wang, 2000; Wang et al., 2001). The lag time is dependent on whether the region is purely rain-fed, fully irrigated, or partially irrigated (Farrar et al., 1994; Wang, 2000). The greater the dependence on rainfall is the shorter the lag time.

4.1.1.2. DEVIATION OF NDVI (DROUGHT SEVERITY INDEX)

NDVI itself does not indicate drought or non-drought conditions. But the severity of a drought (or the extent of wetness – on the other end of the spectrum) may be defined as NDVI deviation from its long-term mean (DEV_{NDVI}). This deviation is calculated as the difference between the NDVI for the current time step (e.g., January 2000) and a long-term mean NDVI for that month (e.g., a 23-year long mean NDVI of all Januaries from 1982 to 2004) for each pixel: Decadal long-term mean NDVI maps of 23-years (1982-2004) have been derived from NOAA- AVHRR results, which are freely accessible

$$DEV_{NDVI} = NDVI_i - NDVI_{mean,m}$$

where $NDVI_i$ is the NDVI value for month i and $NDVI_{mean,m}$ is the long-term mean NDVI for the same month m (e.g. in a data record from 1982 to 2004) there are twenty three monthly NDVI values for the same month (e.g. twenty three Aprils), and twelve long-term NDVI means (one for each calendar month). When DEV_{NDVI} is negative, it indicates the below-normal vegetation condition/health and therefore points to the prevailing drought situation. The greater the negative departure, the greater is the magnitude of a drought. In general, the departure from the long-term mean NDVI is effectively more than just a drought indicator, as it would reflect the conditions of healthy vegetation in normal and wet months/years. This indicator is widely used in drought studies (e.g. Johnson et al., 1993). Its limitations are that the deviation from the mean does not take into account the standard deviation and hence can be misinterpreted when the variability in vegetation conditions in a region is very high in any one given year.

4.1.1.3. VEGETATION CONDITION INDEX (VCI).

The VCI was first suggested by Kogan (1995, 1997). It shows, effectively, how close the NDVI of the current month is to the *minimum* NDVI calculated from the long-term record.

$$VCI_J = \frac{(NDVI_J - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} * 100$$

Where NDVImax and NDVImin are calculated from the long-term record (e.g., 23 years) for that month (or week) and *j* is the index of the current month (week). The condition/health of the ground vegetation presented by VCI is measured in percent. The VCI values around 50% reflect a fair vegetation conditions. The VCI values between 50 to 100 % indicate optimal or above-normal conditions. At the VCI value of 100% the NDVI value for this month (or week) is equal to NDVImax. Different degrees of a drought severity are indicated by VCI values below 50%. The VCI value close to zero percent reflects an extremely dry month, when NDVI value is close to its long-term minimum. Consistently low VCI values over several consecutive time intervals may point to drought development/presence.

Figure 4.1 shows the Decadal long-term mean of NDVI map for the first decade of January and December which is derived from 23 years NDVI map of the study area using a software ERDAS IMAGINE 8.7 Modeler function and used as input to drive the deviation of NDVI from the particular period of NDVI image.

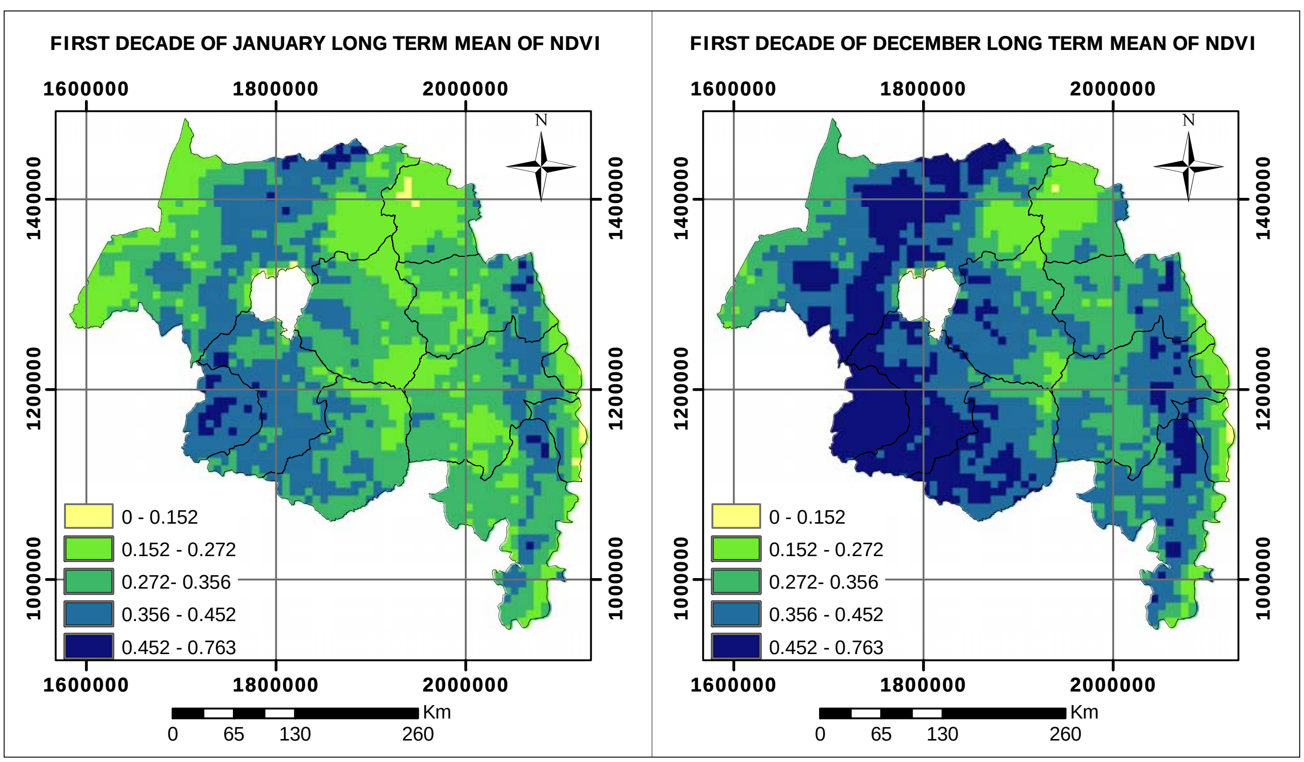
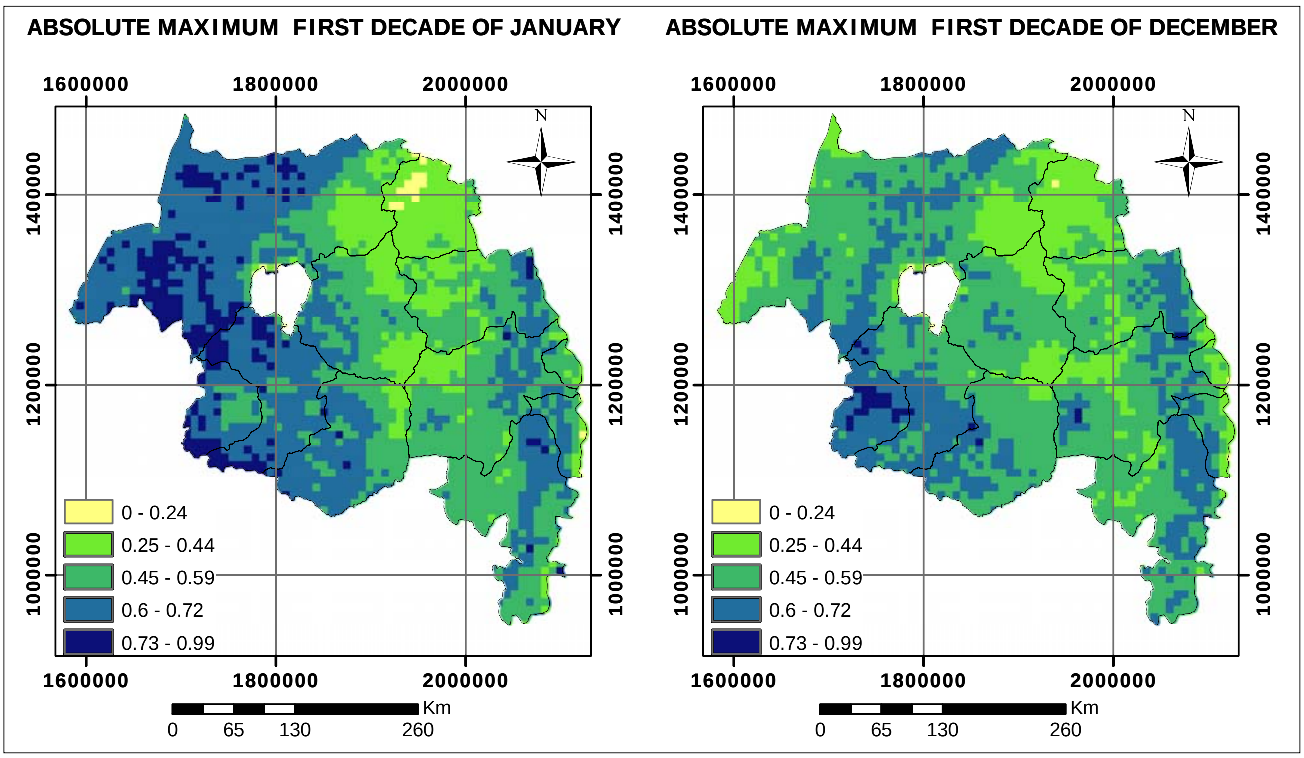


Figure 4.1 Decadal long-term mean of NDVI map for the first decade of January and December.

Figure 4.2 shows the Absolute maximum and minimum of NDVI map for the first decade of January and December which is derived from 23 years NDVI map from stacked decadal images using a soft ware ERDAS IMAGINE 8.7 Modeler function. The Absolute maximum and minimum of NDVI map of the study area used to calculate the VCI map of the study area.



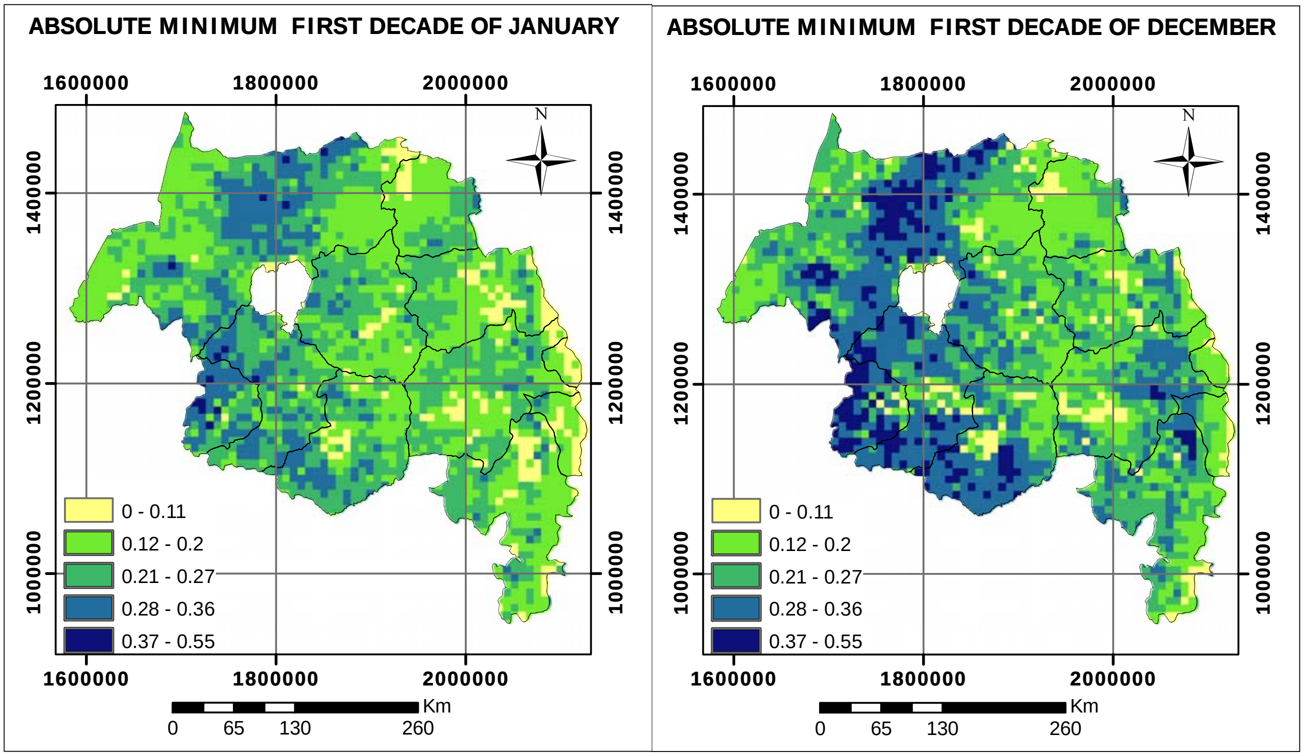


Figure 4.2 Maximum and Minimum NDVI maps derived from long records of remote sensing data for first decade of January and December.

To derive the DEV_{NDVI} and VCI map of the study area, the decadal long term mean images were stacked and monthly base long term mean was calculated. And also the absolute maximum and minimum of NDVI map of the study area derived from the long term image of the study area were used as input. Finally based on the formula given, the software ERDAS IMAGINE 8.7 Modeler used to calculate the DEV_{NDVI} and VCI map of the study area.

Figure 4.4 and 4.5 shows the DEV_{NDVI} and VCI map of January 2006 and 2007 and Figure 4.6 the model that used to drive the map of DEV_{NDVI} and VCI of the study area.

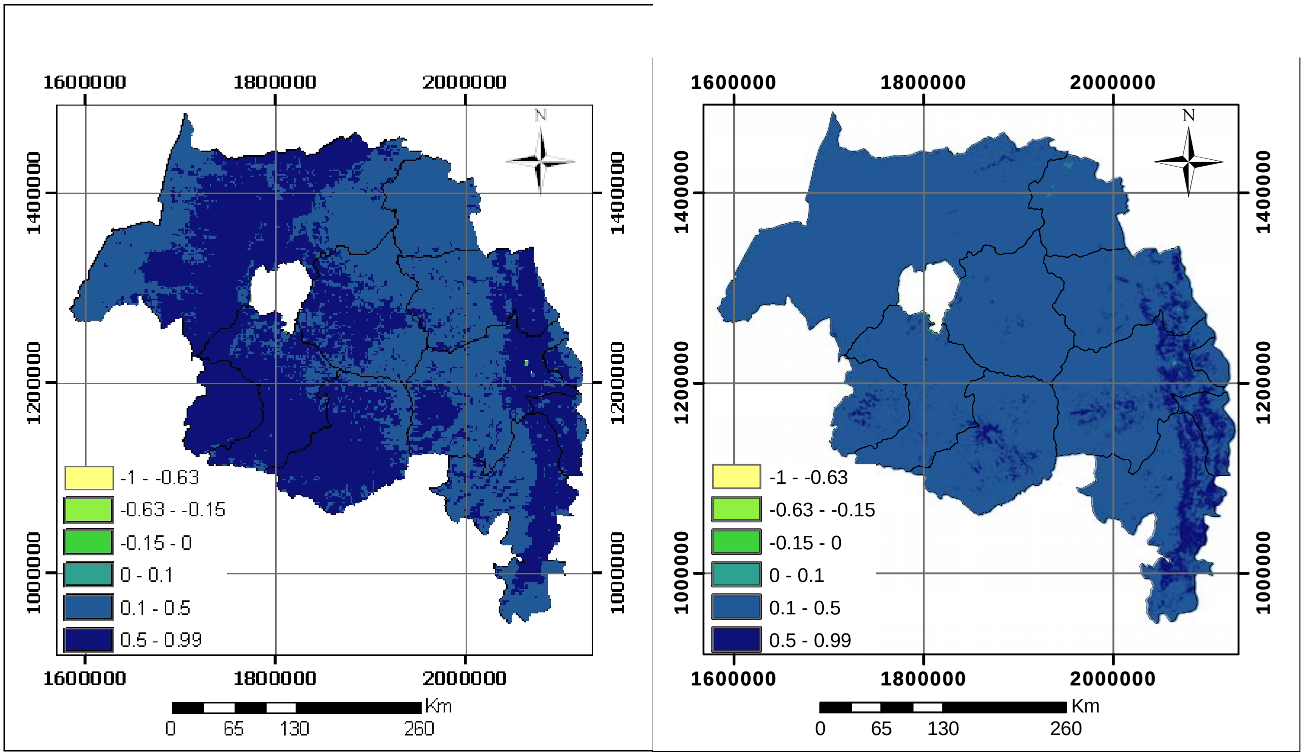


Figure 4.3 December 2000 and February 2001 NDVI maps of MODIS images.

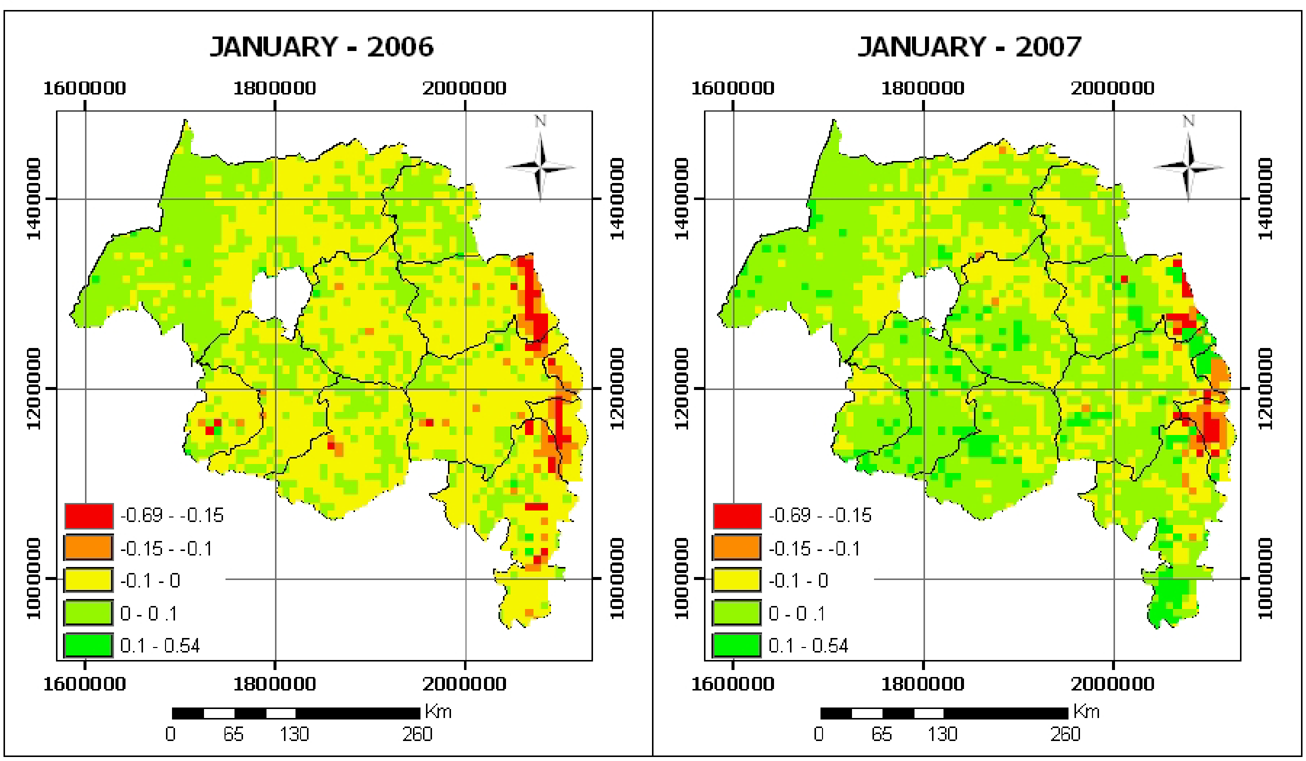


Figure 4.4 Deviation of NDVI (Drought Severity Index) for the month January 2006 and 2007.

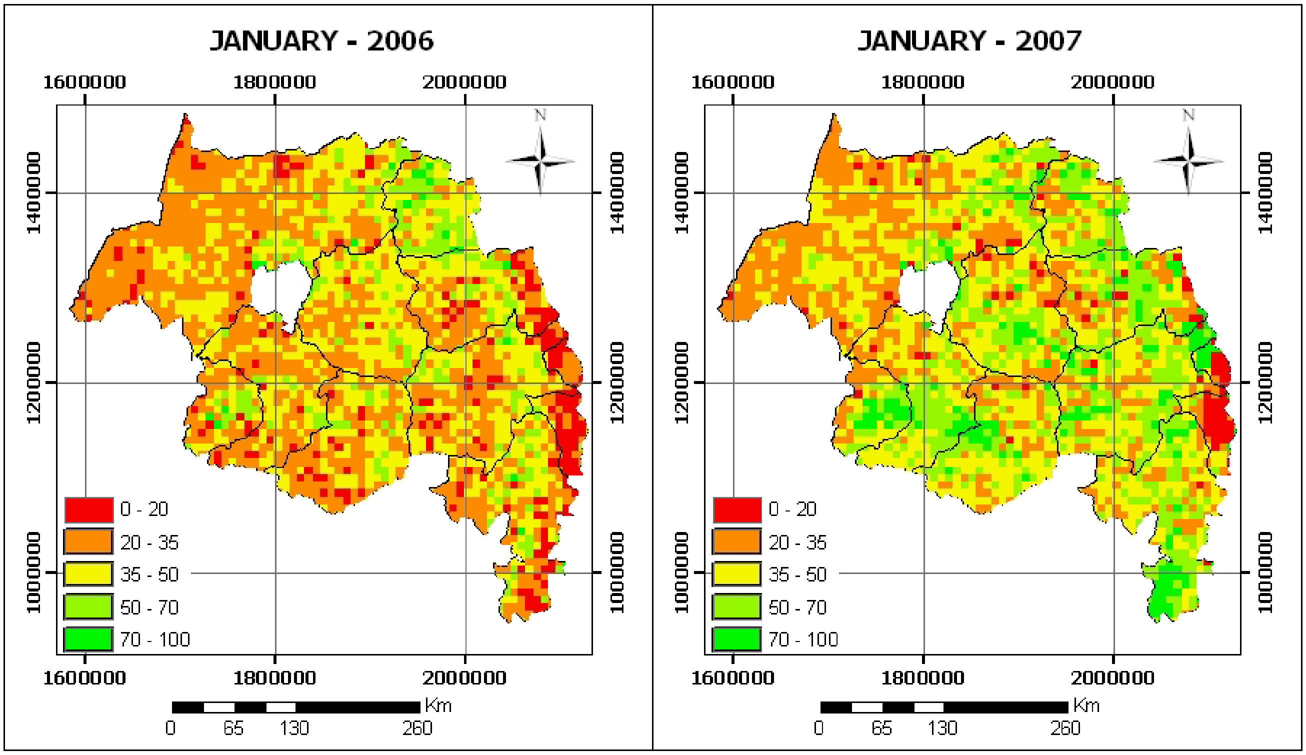


Figure 4.5 Vegetation Condition Index (VCI) for the month January 2006 and 2007.

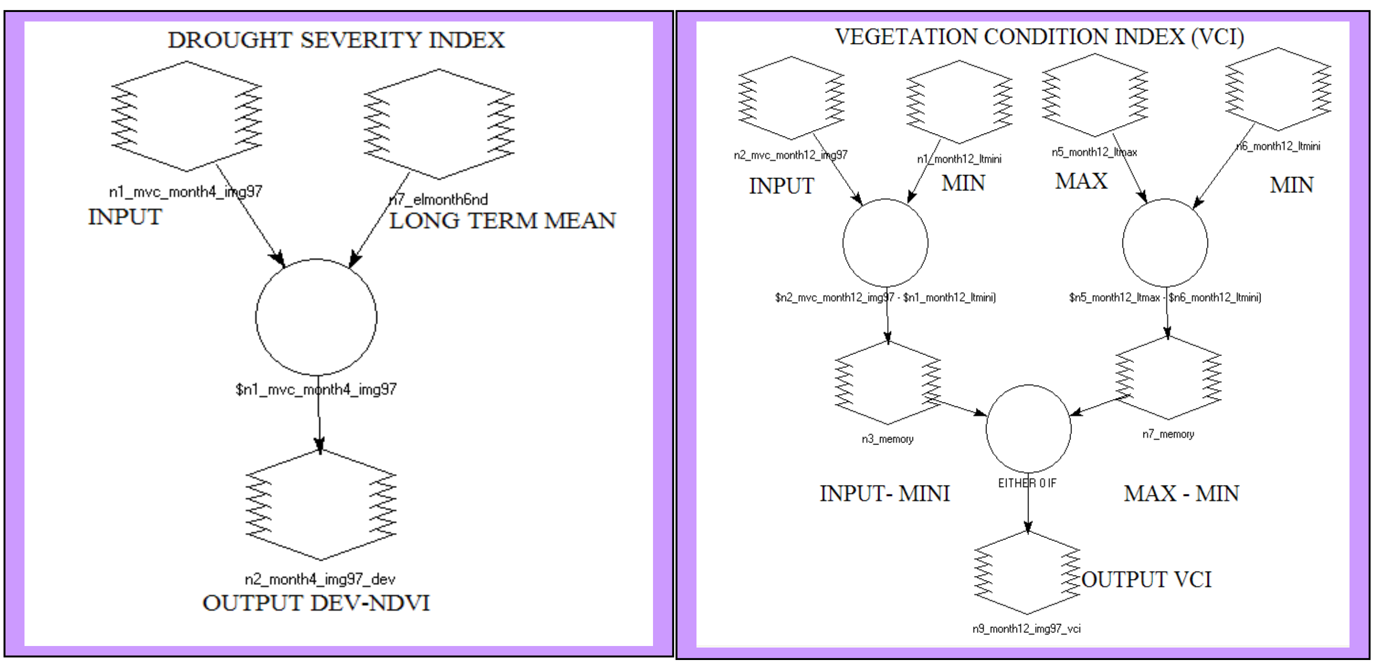


Figure 4.6 The model that used to drive the map of DEV_{NDVI} and VCI of study area.

4.1.2. INTER-SENSOR RELATIONSHIP

4.1.2.1. DERIVING NDVI FROM MODIS DATA

For purposes of data reduction and removal (or minimization) of bad data it is useful to take the best observations over a series of days and produce one output. This process is called compositing and has been done for years with a variety of different satellite data products. For the MODIS instrument the repeat cycle of nadir overpasses is 16 days. This means that every 16 days the instrument will be traveling on nearly the exact same path. For this reason standard composite periods for MODIS are multiples of 8 days, exactly the mid-point of the repeat cycle. MODIS data products are processed by the University of Maryland. From 32 day Maximum value composite (MVC) image of MODIS NDVI was calculated from band 1 and band 2 as described in Table 3.2.

4.1.2.2. LINKING AVHRR AND MODIS DATA

MODIS and AVHRR, both sensors and their related data types have distinctly different features, as was described in relevant sections above (Table 3.2). Apart from this, the two data sets have other differences, including but not limited to pre-processing methods (e.g., atmospheric correction) and spatial resolution (10km for AVHRR versus 0.5km for MODIS). To ensure continuous flow of data for drought assessment, the inter-sensor relationships need to be developed. The two datasets overlap during the last month (December) of 2000 to 2003. This offers the opportunity to explore the relationships between the two data sets (e.g. linking $NDVI_{AVHRR}$ with $NDVI_{MODIS}$).

From December 2000 to January 2004), there are 38 months of concurrent data that are available from both AVHRR and MODIS sensors. The MODIS data are monthly, while AVHRR data have the temporal resolution of 10-days. To make both data sets comparable, the three 10-day AVHRR NDVI images were composed into 30-day NDVI images through maximum value compositing (MVC) procedure. The AVHRR NDVI composites were then re-sampled to 500m pixel resolution to coincide with MODIS pixels.

Then the $NDVI_{AVHRR}$ and $NDVI_{MODIS}$ were generated for every pixel within various administrative units during the 38-months long concurrent period. The $NDVI_{MODIS}$ will not be exactly the same as $NDVI_{AVHRR}$ due to different sensor characteristics. The narrower MODIS spectral bands eliminate the water absorption region in the NIR and also render the red band more sensitive to chlorophyll absorption (e.g. Huete et al., 2002). The atmospherically corrected $NDVI_{MODIS}$ generally have higher dynamic range than the atmospherically corrected $NDVI_{AVHRR.}$ This is attributed to the narrow band width of MODIS (Huete et al., 2002). The narrow bands result in a greater dynamic range of NDVI for the same given biomass. The $NDVI_{AVHRR}$ is therefore likely to "saturate" faster in the study of vegetation biomass than $NDVI_{MODIS}$, saturation being the loss of sensitivity of a sensor after full canopy cover is achieved. The study established regression models for two NDVI types for each month (as well as for the pooled data of all 38 months) for all terrestrial biomes in the study area. The established relationships between NDVI from two sources allow drought occurrences to be examined across sensors and time periods from 1981 to present day and well into the future.

4.2. PROCESSING OF GROUND TRUTH DATA

4.2.1. PRODUCTION YIELD PROCESSING

Agricultural production yield is the main ground truth data used for validation of the satellite derived results. It is important to analyze the correlation between Zone level crop yields and NDVI to quantify the impact of drought on production of the major crops in the districts of the "Amhara" region. Since NDVI takes advantage of the reflective and absorptive characteristics of plants in the red and near-infra red portions of the electromagnetic spectrum, it can be used for assessment of weather impacts on vegetation and evaluation of vegetation health and productivity (Unganai and Kogan 1998).

4.2.2. RAINFALL PROCESSING

Decadal (10-days) records of 40 stations found in four Zones of Amhara region which are spatially distributed over the Zones are arranged into spreadsheets, provided by the Ethiopian Meteorological Service Agency. Rainfall data for the crop-growing season ranging from June to October have been used and decadal (10-day) rainfall summed up to get the total monthly rainfall received during this period in each year (1996-2006). Since the rain gauge data are point measurements, use of inverse-distance moving average interpolation technique has been applied to obtain the contribution of each station over the areas. Inverse distance average technique is used because it better suits for interpolation of rainfall distribution over heterogeneous topographical terrain, as that of the “Amhara” region. Thus seasonal rainfall interpolated maps have been prepared to establish relationship of rainfall variability with NDVI and agricultural yield production.

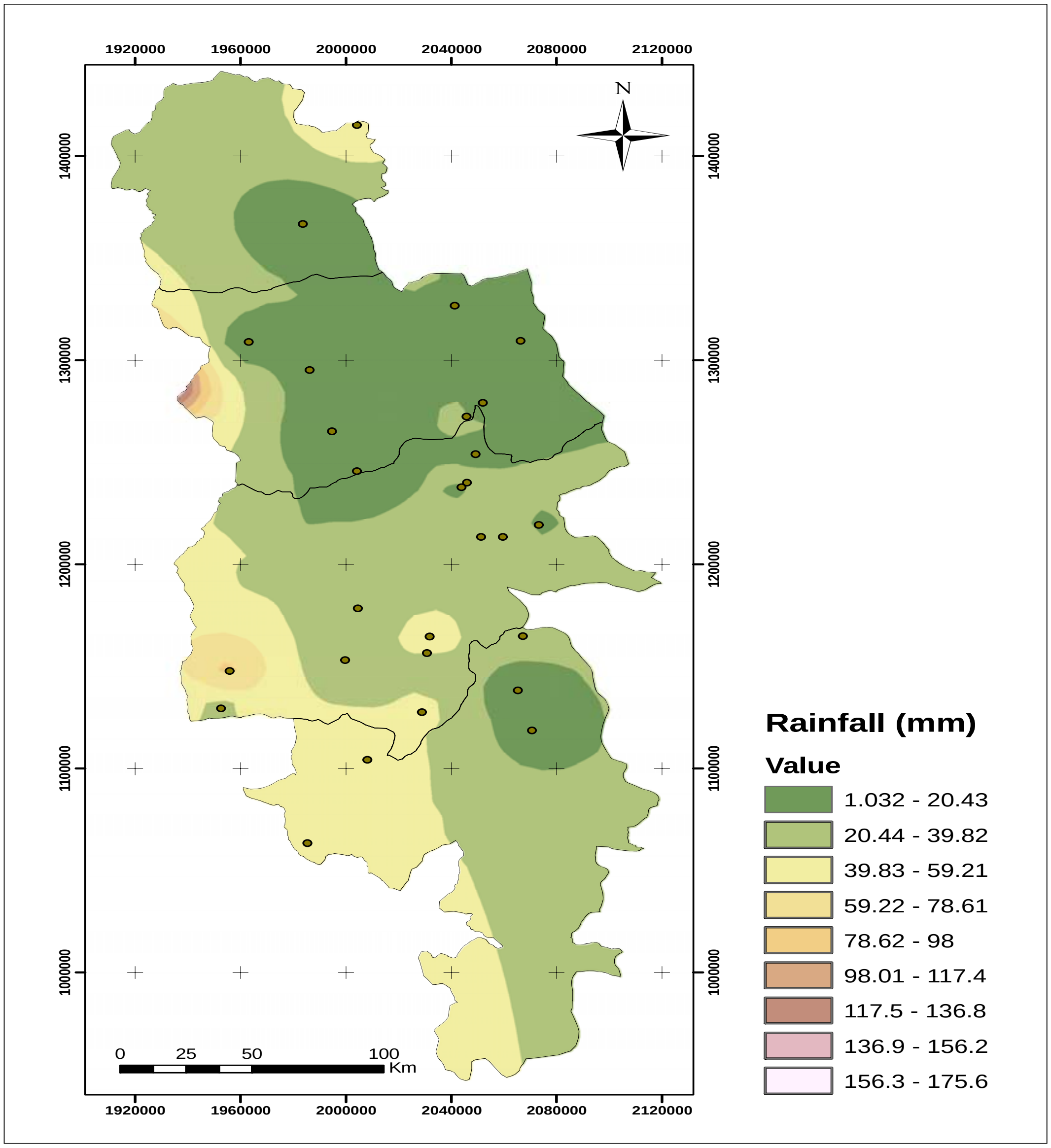


Figure 4.7 Total rain fall distribution of 4 zones of Amhara region for July of 2000

5. RESULTS AND DISCUSSION

5.1 HISTORICAL DROUGHT INTERPRETATION

The extent of negative deviation of NDVI from its long term mean, and the duration of continuous negative deviations are powerful indicators of drought magnitude and persistence. The NDVI monthly means indicate the condition of ground vegetation month-by-month and allow dry and wet months in different parts of the region to be identified. Figure 5.1 shows the long-term NDVI conditions (NDVI mean for each decade) and relative to it, the driest (1983 and 1991) and relatively the wet (2006) years' NDVI values for each month for the entire study area. Averaging of NDVI values over the entire study area was done primarily to illustrate that, the region was dry during the main rainy season (from July to September) in 1983 and 1991 or relatively wet during the same month in 2006 despite the variability of wetness is not to much in the region in both years.

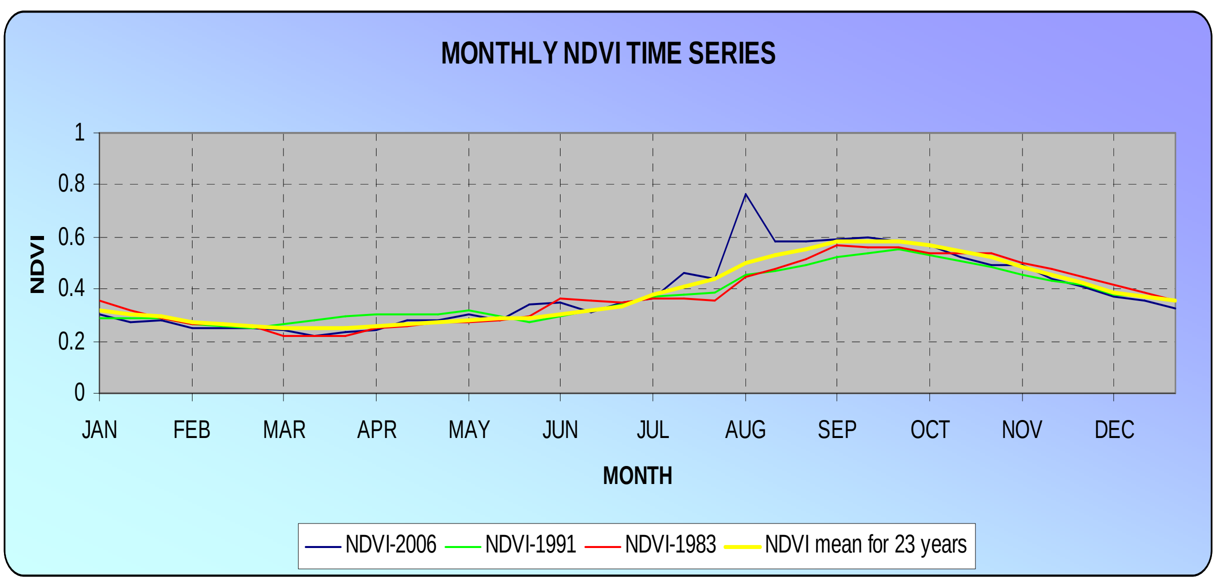
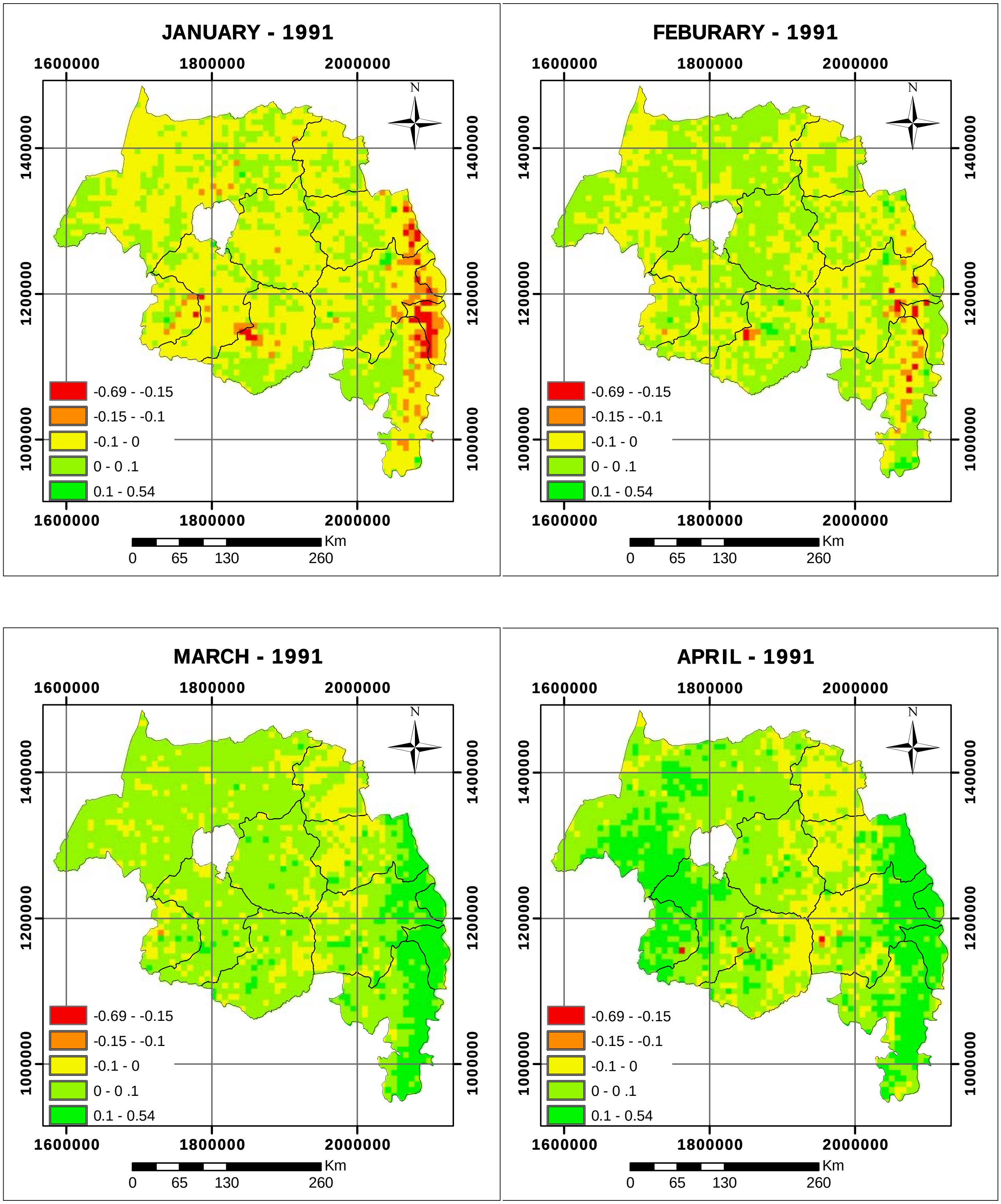
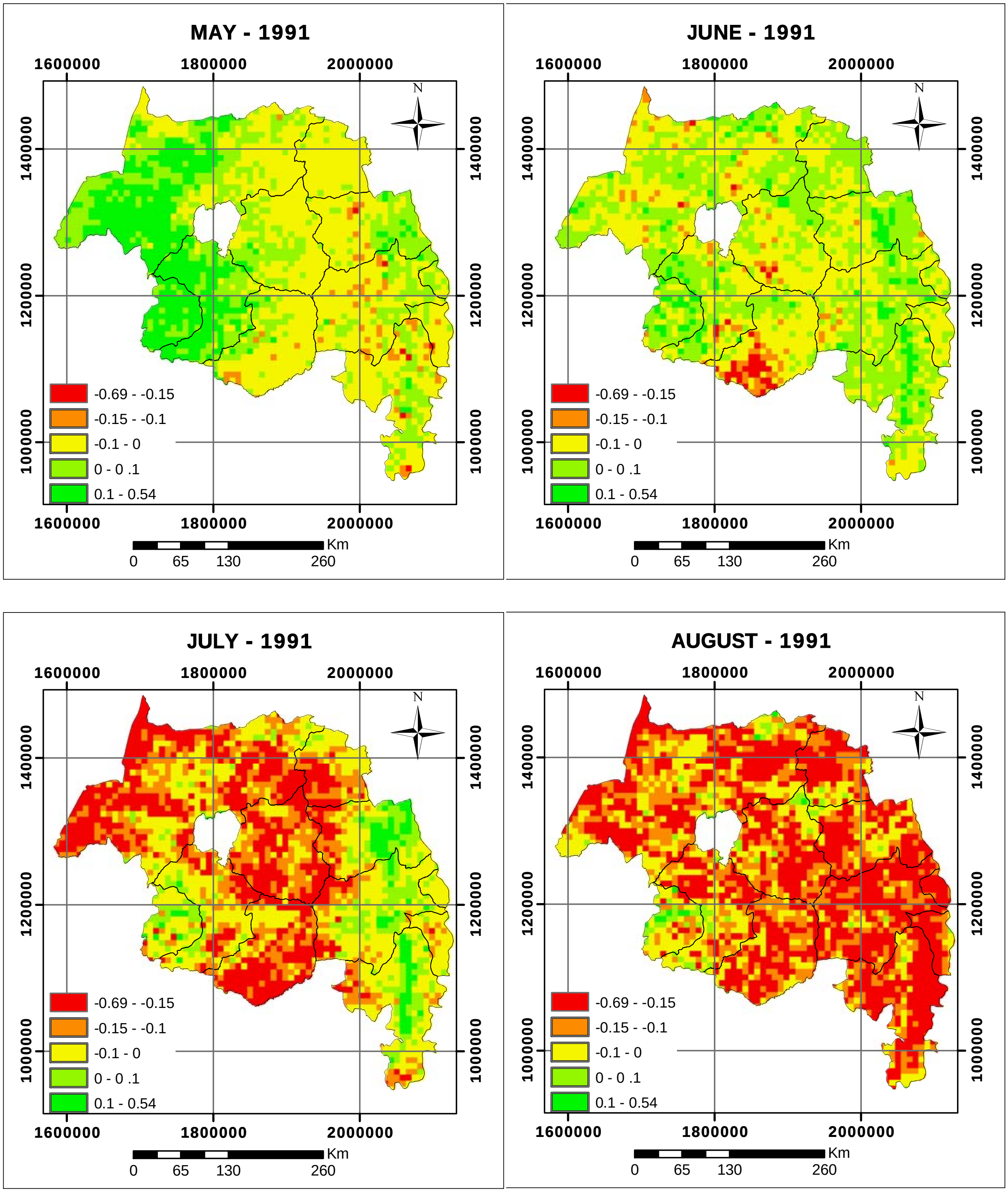


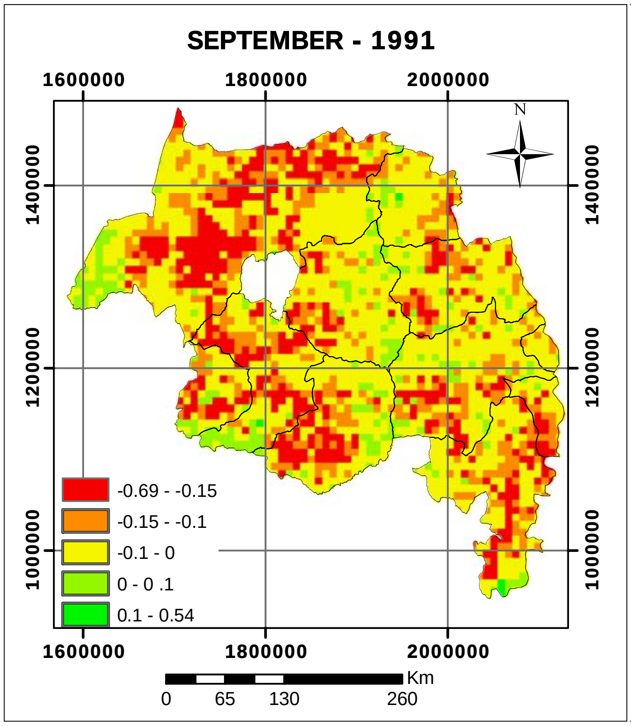
Figure 5.1 A monthly NDVI time series for a drought year (1983 and 1991) and a year1993 compared to the NDVI long term mean (averaged for the study area).

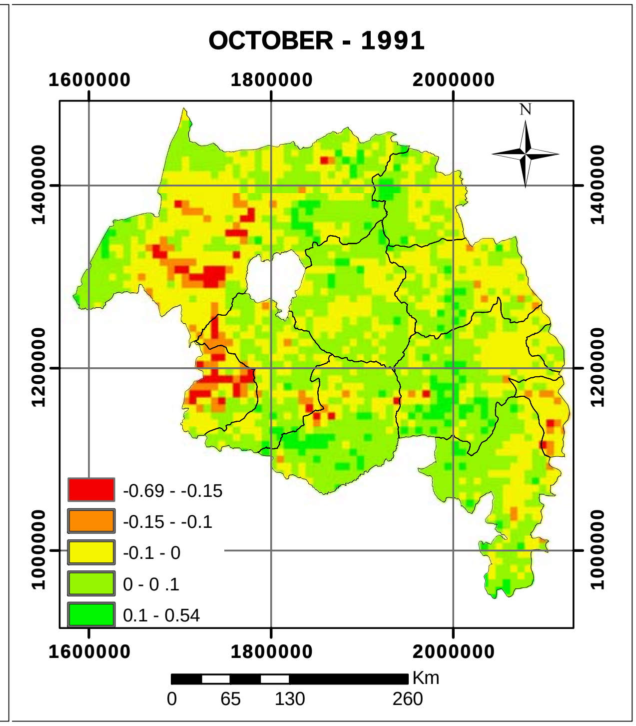
The differences between the long-term NDVI means and the NDVI values in specific months are the deviations of NDVI (DEV_{NDVI}). A month-by-month spatial distribution of DEV_{NDVI} in the study area during the dry year of 1983 is illustrated by Figure 5.2, where areas in different shades of yellow, orange and red are “drought affected” and areas in different shades of light green, and bright green are those with a more dense and healthy vegetation. Most of the pixels in the study area have persistent shades of yellow, indicative of the negative deviation from NDVI mean. It can be seen how a major drought-affected area is developing in June to September primarily over the Amhara region, with a drought in Wag Hemra Zone persisting until December. Semen and Debub Gonder and Mirab Gojjam Zones however remain relatively “drought-free” during the month March, April, and December. Similarly to the entire Amhara region, the drought onset, magnitude and duration/persistence can be monitored at a scale of zone, any administrative unit level (Wereda), or a single pixel level (10 by 10 km with AVHRR data and 0.5 by 0.5 km with MODIS) using the series of consecutive images. The degree of averaging NDVI values obviously decreases with the scale, and more area-specific analysis could emerge.

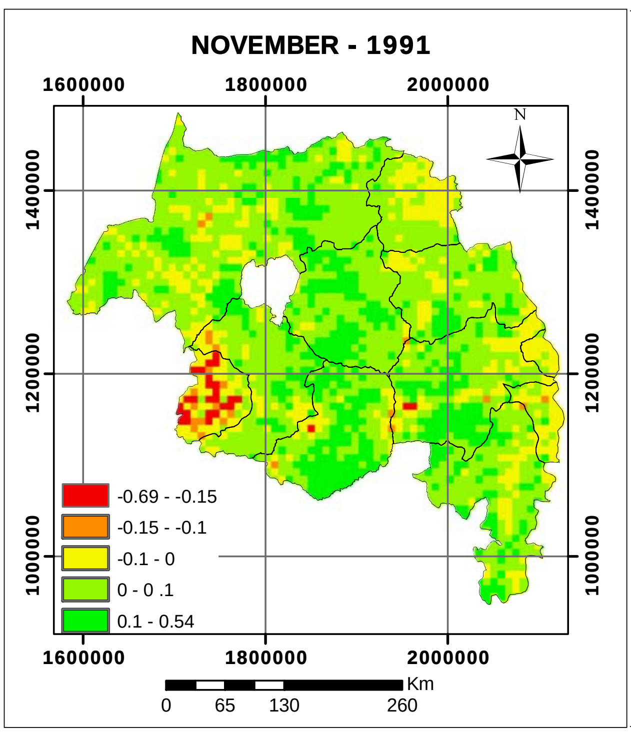
Figure 5.2 Amhara Region monthly images of AVHRR DEVNDVI for the drought year of 1991.

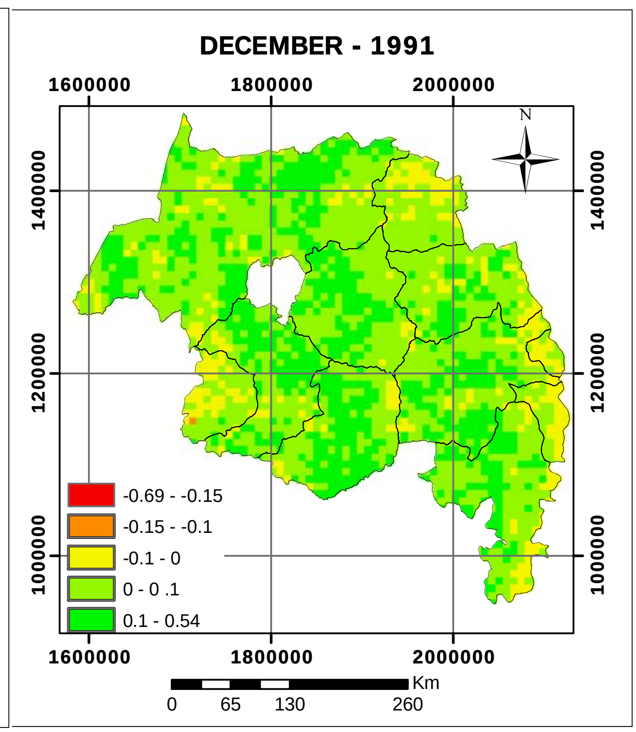



MAY - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260
JUNE - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260
JULY - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260
AUGUST - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260


SEPTEMBER - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260


OCTOBER - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260


NOVEMBER - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260


DECEMBER - 1991
1600000
1800000
2000000
1400000
1200000
1000000
N
-0.69 - -0.15
-0.15 - -0.1
-0.1 - 0
0 - 0 .1
0.1 - 0.54
Km
0
65
130
260

The vegetation levels (measured in terms of NDVI) are normally higher in Semien Gonder and Mirab Gojjam as a whole through most of the months when compared with Debub Wollo and Semien Shewa (Figure 5.3). There is also a clear seasonality fluctuation in NDVI within and across seasons and years for Semien Gonder, Mirab Gojjam, Debub Wollo and Semien Shewa. The pattern of fluctuations is however very different between the four Zones of the Region. The Amhara's Region vegetation is rain-fed and NDVI follows predominantly uni-modal vegetation condition cycle, determined by precipitation.

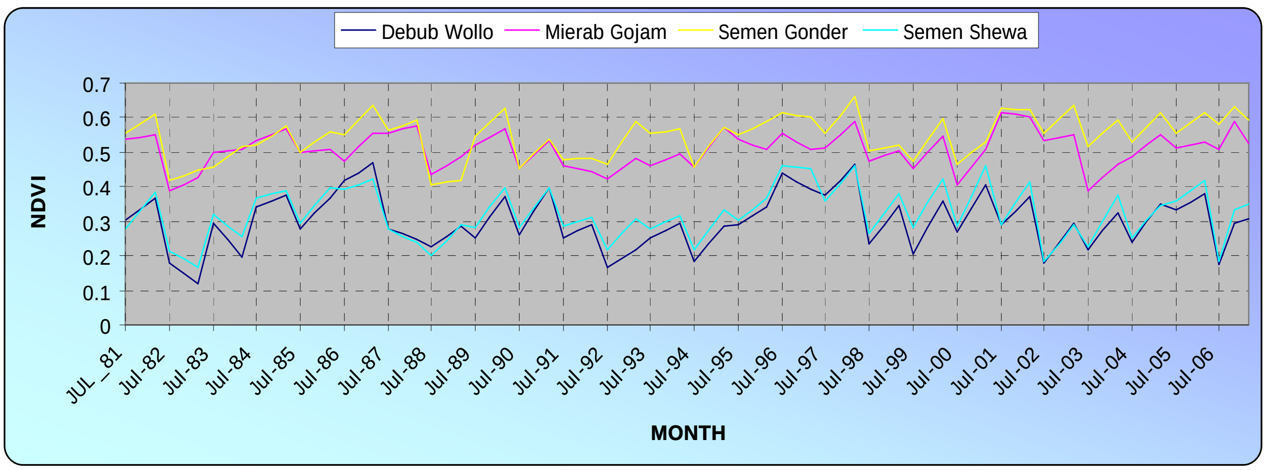


Figure 5.3 The NDVI variability for Amhara region over 26 years

The variability of two drought-related indices (DEV_{NDVI}, and VCI) for the period of 1983-1994 (containing a few successive droughts) is illustrated in Figure 5.4 and 5.5 using Semien Gonder, Mirab Gojjam, Semien Shewa and Debub Wollo as example. The DEV_{NDVI} 0 value indicates the normal condition of the vegetation. When an index deviates below the value 0 for a period of a few successive months, it points to a drought condition. Deviations above the normal for a few during successive months in a year point to a better-than-normal vegetation conditions. The magnitude of a drought is directly proportional to a magnitude of the deviation below normal. The duration of the successive months below normal conditions and the magnitude of the deviation constitute two powerful indicators of drought severity. In this context, the period from July to September 1983, June to October 1991, April to early 1999 and March to June 2000 were predominantly a continuous drought in Debub Wollo and Semien Shewa Zones. From June to October 1999, July to October 2000 in Semien Gonder and Mirab Gojjam, April to August, April to June 1983 in Mirab Gojjam and Semien Gonder and April to June 1999 in Mirab Gojjam also there were a continuous drought (Figure 6a- 6d), which implies unfavorable vegetation condition of the area and hence implies reduction of the production yield during the main growing season from the long-term yield trend. Similar temporal profiles of the drought severity condition can be observed for all of the districts in the "Amhara" region.

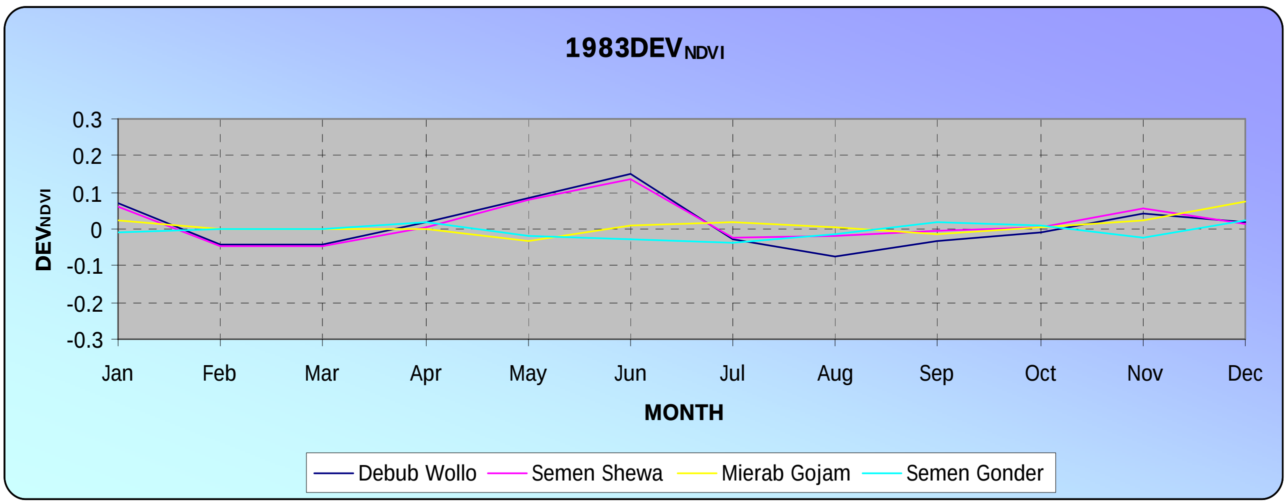


Figure 5.4.A. Temporal profile of Deviation of NDVI during 1983

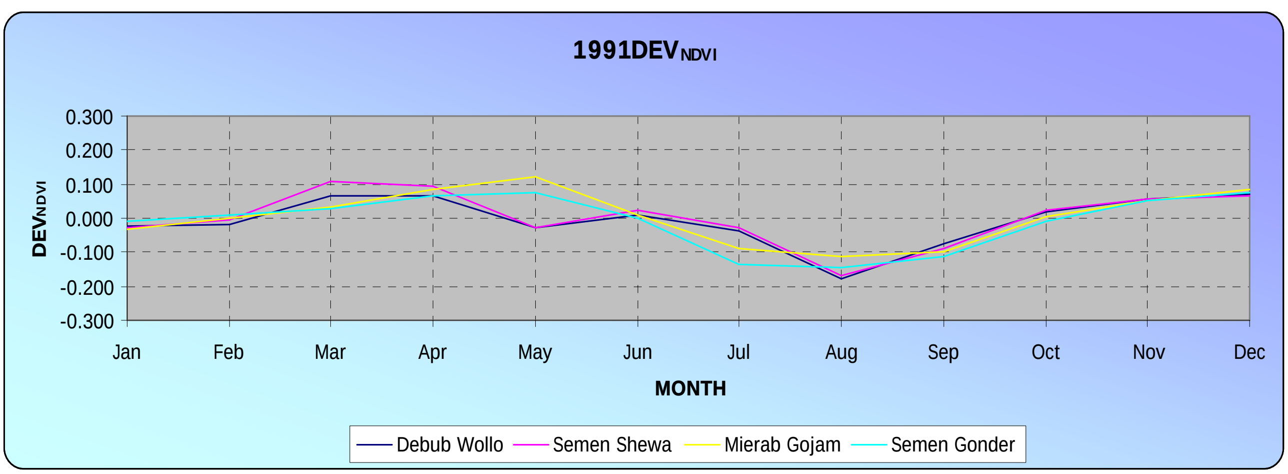


Figure 5.4. B. Temporal profile of Deviation of NDVI during 1991

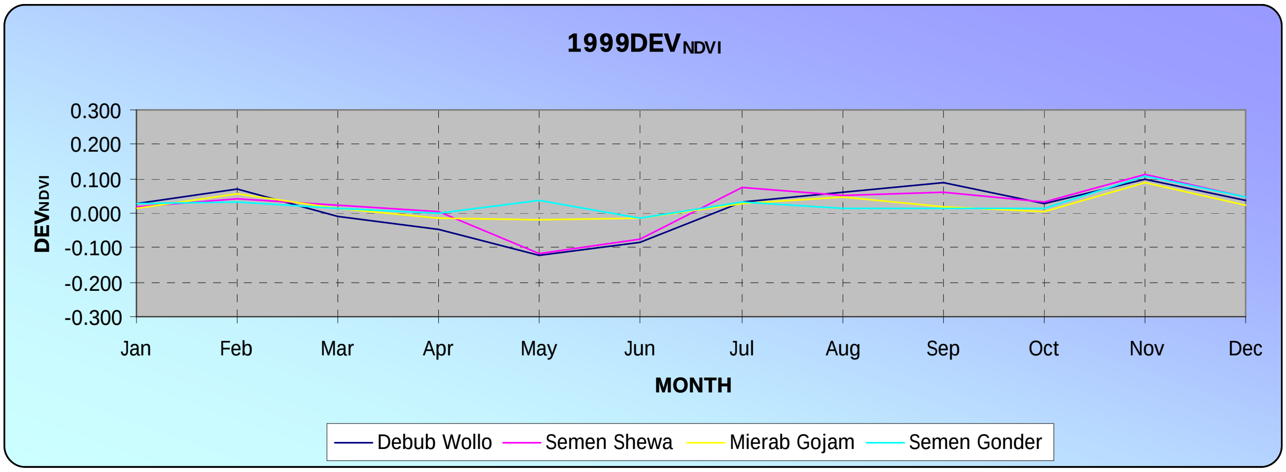


Figure5.4. C. Temporal profile of Deviation of NDVI during 1999

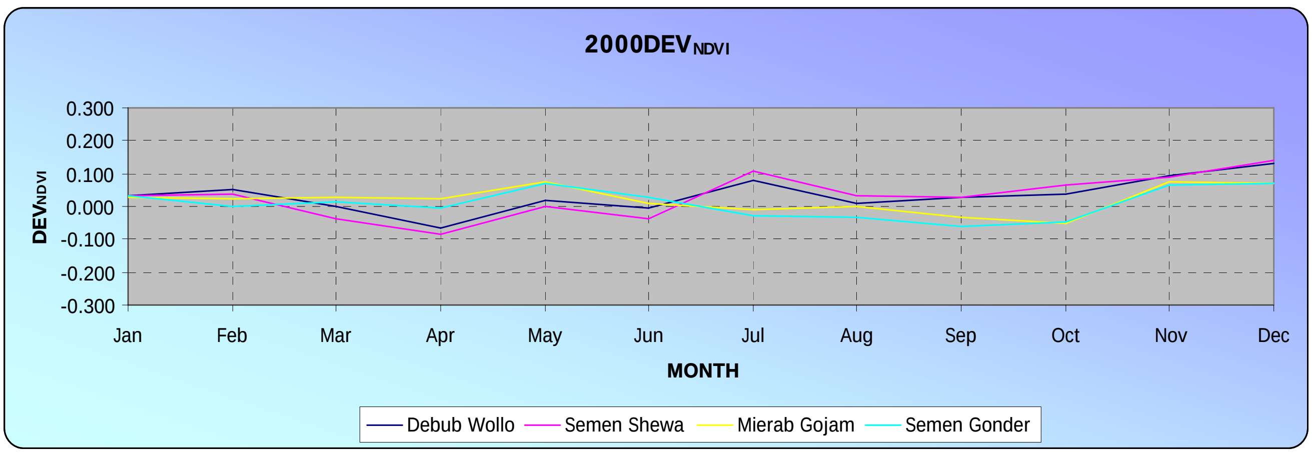


Figure5.4.D. Temporal profile of Deviation of NDVI during 2000

During the year 1991 the deviation was less than 0.10 from the period June to mid July for Debub Wollo and Semien Shewa Zones and from June to early July for Semien Gonder and Mirab Gojjam, so the drought severity condition is categorized as mild drought. And the period between mid July to mid August for Debub Wollo and Semien Shewa Zones and July to September for Semien Gonder the deviation ranges between 0.1 and 0.15, this shows the occurrence of a moderate drought severity condition.

As shown in the Figure 5.4 C the deviation of the NDVI for the year 2000 is less than 0.1 and the drought severity condition is categorized as mild drought from the period mid Februarys to June for Semien Shewa, and March to May for Debub Wollo. Also the mild drought condition happened for Semien Gonder and Mirab Gojjam during the main growing season from the period mid June to mid October.

The satellite-derived DEV $_{NDVI}$ values have been verified by correlating with the ground truth data precipitation, during the main growing Season (May to October). There exists a good relationship between the DEV $_{NDVI}$ values and the rainfall for Debub Wollo as it is shown in Figure 5.5.and similar graphs for the other district is given in appendix-B

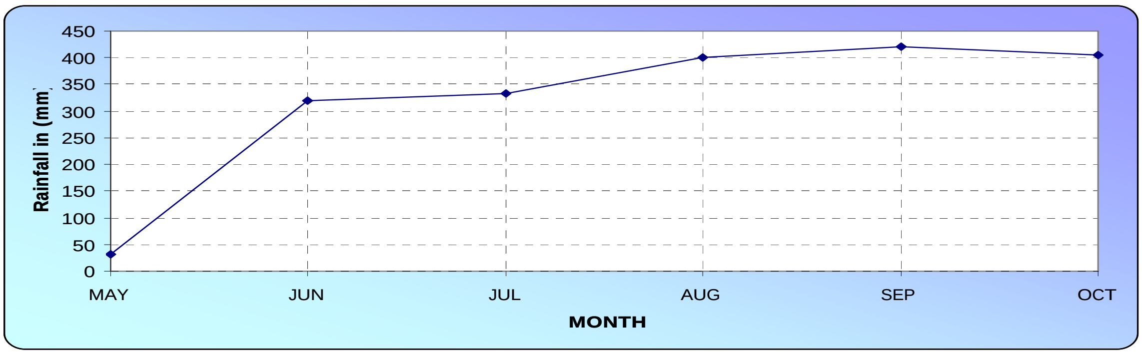


Figure 5.5.A. Rainfall distributions of Debeb Wollo over the growing season during 2000

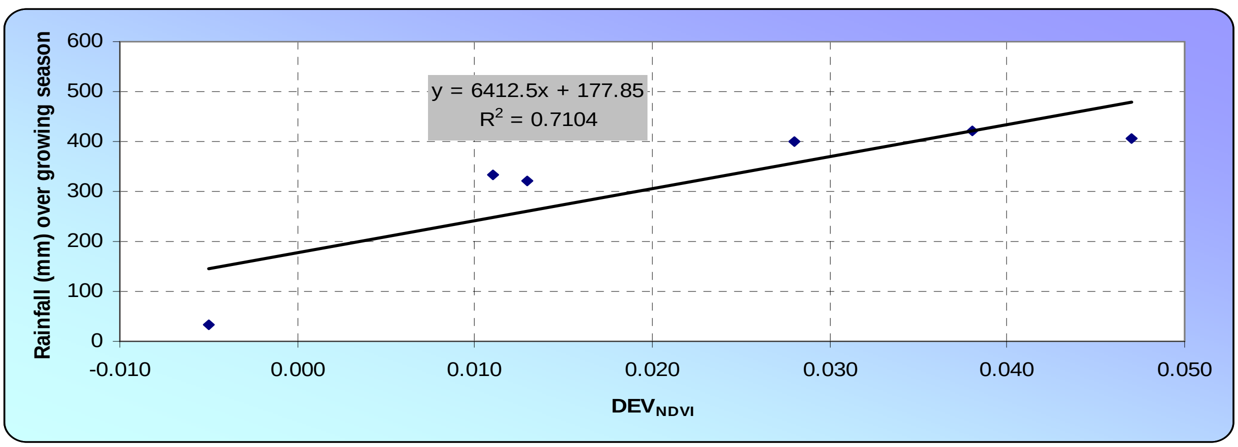


Figure 5.5.BCorrelation between the DEV NDVI and precipitation for Debeb Wollo

The VCI value at 50 % indicates that the vegetation is at normal condition. When an index deviates below the value 50 % for a period of a few successive months, it points to the existence a drought condition in the area.

It can be seen from this Figure 5.6.A- 5.6.D that the Vegetation Condition Index (VCI) values are below 50% for some months during the years for both Zones. In general, this indicates the occurrence of drought situation in this year. However, the VCI values are different from month to month ranging between 20-80 %, which indicates that the drought severity condition is different over all the month. At the start of the growing season, that is July the values goes beyond 40% up to 20% and then grows slowly up to 60% except that of Debub Wollo and Semien Shewa Zones in 1983. There was a continuously decrease in VCI during from June to August and continuous increase in VCI from August to September, indicating an improvement of drought severity condition in the rest of the growing season. But, the VCI values are above 20% in most of the months. In general, the VCI values falls below 35% for most of the decades in the year that reveals an existence of drought severity according to the recommendation suggested by the developer of the Vegetation Condition Index (VCI).

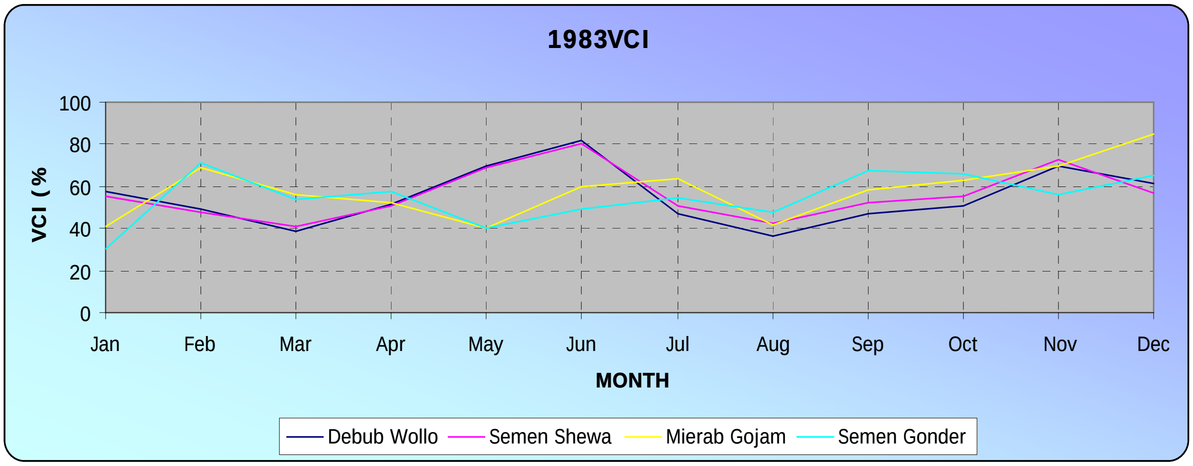


Figure 5.6.A. Temporal profile of VCI during 1983

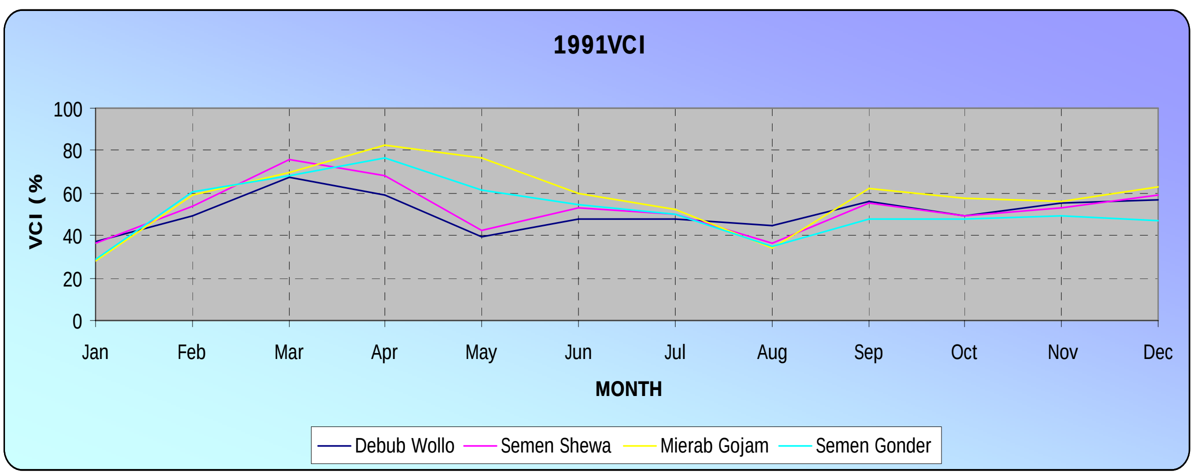


Figure 5.6. B. Temporal profile of VCI during 1991

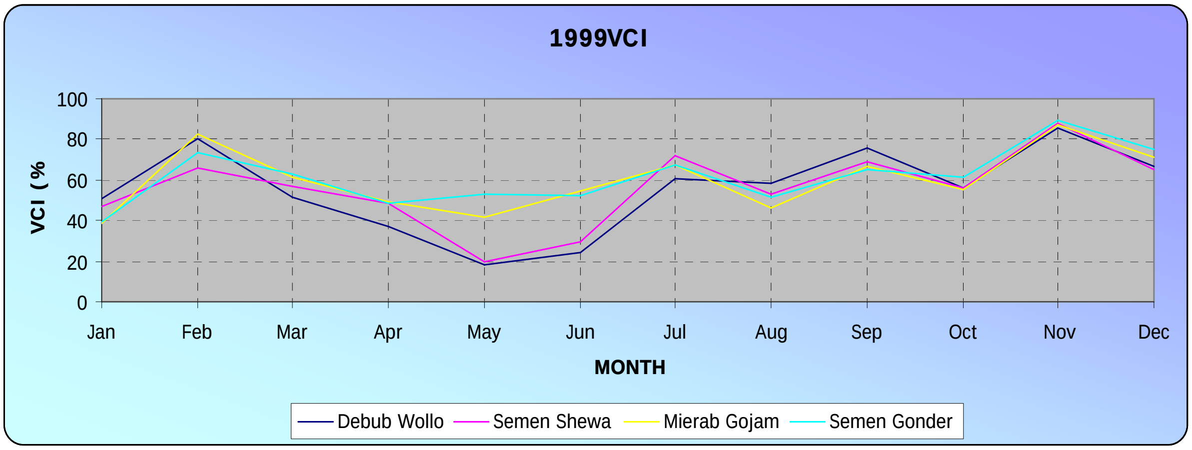


Figure5-6: C. Temporal profile of VCI during 1991

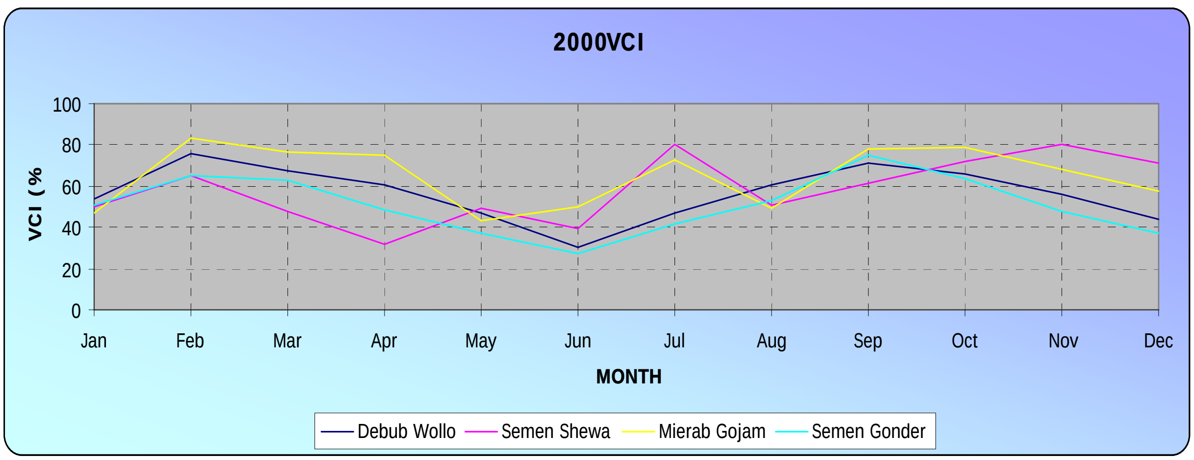


Figure5-6.D. Temporal profile of VCI during 2000

The Vegetation Condition Index (VCI) in 1991 has been improved at the beginning of the growing season and starts to decrease slowly thereafter. In this year also the Vegetation Condition Index is below 50 % for most of the months, indicating existence of drought for all the districts in the region. Here also the results obtained from the Vegetation Condition Index show similarities with the results of the other index, the Drought Severity Index (DSI). These results can be verified by in situ data of precipitation and crop yield collected from the "Amhara" region. The relation of the VCI and precipitation for the growing season of 2000 for one of the Zone is given in Figure 5-7 and similar graphs for the other districts is given in appendix-B. There exists a good relationship between the Vegetation Condition Index (VCI) and precipitation for Debub Wollo.

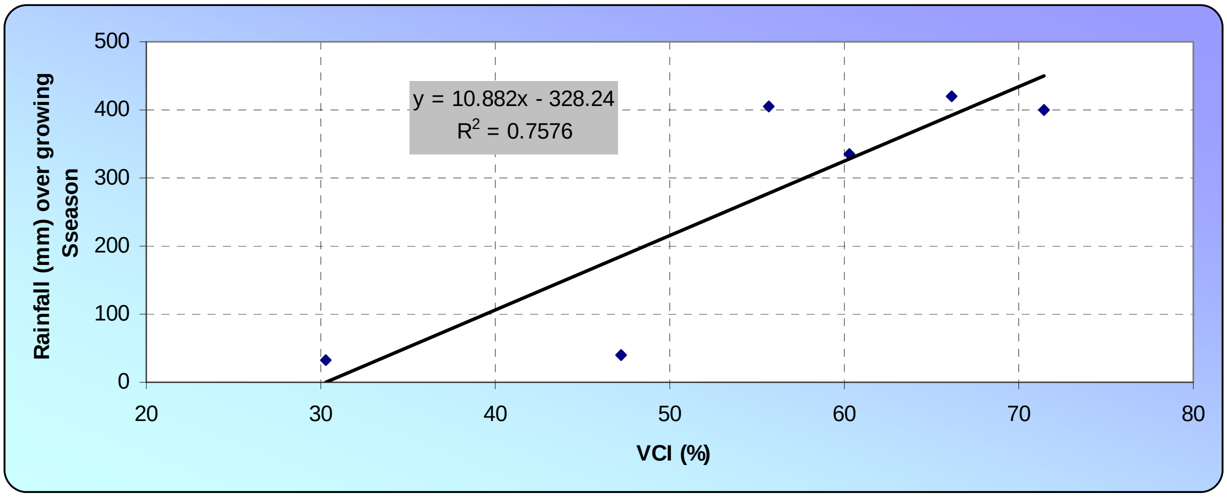


Figure 5-7 Correlation between the VCI and precipitation for Debeb Wollo.

In most cases, the VCI and DEV_{NDVI} complement each other and therefore strong correlations should exist between the two (Figures 5.5 and 5.7). Wherever stress or stunted growth of vegetation and crops due to moisture excess occur, the VCI values are low, the DEV_{NDVI} is below normal. This may apply to wetland and/or flooded agriculture, for example. When NDVI is close to its long-term minimum, the continuously low consecutive values of VCI, and DEV_{NDVI} indicate severe drought (or vegetation stress) conditions.

5.2 VALIDATION OF INTER-SENSOR RELATIONSHIPS

MODIS imagery has finer spatial and temporal resolution and is more attractive for drought monitoring. MODIS data are, however, only available since 2000 and therefore, long-term characteristics used in indices described above needs to be assessed from AVHRR data. This in turn leads to the need to build inter-sensor relationships to allow both MODIS and AVHRR to be integrated for future drought monitoring and analyses. This integration has been done by developing a regression relationship between concurrent NDVI values from AVHRR and MODIS data, as described in the Methodology section.

The established regression relationship between concurrent NDVI values of MODIS and AVHRR at regional scale is given below

$$NDVI_{MODIS} = 0.8531\ NDVI_{AVHRR} + 0.0418$$

This relationship is illustrated in figure 5.8. The relationships were also developed based on data from specific months (Table 5.1). The monthly models explain up to 95 percent of variability in the data of two sensors. The models presented in equation, table 5.1 and figure 5.8 are critical in linking the data from two sensors and facilitating continuous monitoring of vegetation conditions, in a drought context, over time and well into the future.

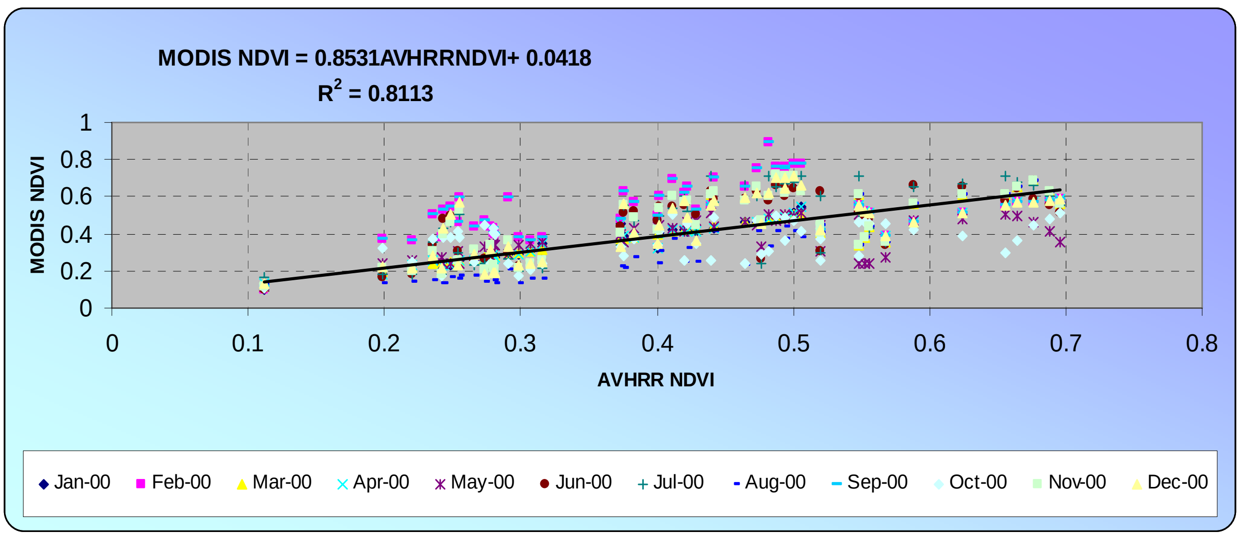


Figure 5.8. Regression relationship between NDVIMODIS and NDVIAVHRR. The regression model is built on the data for 12 months (January 2001 to December 2001) from all administrative units in the study area.

Month	Equation	R^2
January	MODIS NDVI (January) = 0.0662 + 1.2549 AVHRR NDVI (January)	0.9385
February	MODIS NDVI (February) = 0.0108 + 1.014 AVHRR NDVI (February)	0.9279
March	MODIS NDVI (March) = 0.0313 + 1.0348 AVHRR NDVI (March)	0.9522
April	MODIS NDVI (April) = 0.0852 + 0.7614 AVHRR NDVI (April)	0.8805
May	MODIS NDVI (May) = 0.111 + 0.8117 AVHRR NDVI (May)	0.767
June	MODIS NDVI (June) = 0.1132 + 1.0473 AVHRR NDVI (June)	0.7273
July	MODIS NDVI (July) = 0.1193 + 1.0266 AVHRR NDVI (July)	0.7869
August	MODIS NDVI (August) = 0.0998 + 1.1546 AVHRR NDVI (August)	0.9119
September	MODIS NDVI (September) = 0.0789 + 1.0878 AVHRR NDVI (September)	0.9178
October	MODIS NDVI (October) = 0.0596 + 1.0959 AVHRR NDVI (October)	0.8923
November	MODIS NDVI (November) = 0.1272 + 1.2171 AVHRR NDVI (November)	0.7794
December	MODIS NDVI (December) = 0.1674 + 0.833 AVHRR NDVI (December)	0.6364

Table 5.1. Regression models relating 500-m MODIS NDVI data and resampled 500-m AVHRR NDVI values for individual months

5.3. VALIDATION OF REMOTLY SENSED DATA WITH GROUND TRUTH DATA

5.3.1. CORRELATION BETWEEN NDVI AND PRECIPITATION

Rainfall is an important meteorological parameter which influences the type of vegetation in a region. As NDVI is effectively used for monitoring crop yield and drought, use of NDVI is well established in assessing the vigour and productivity (Anyamba and Tucker 2005). Theoretically, NDVI can be considered as a climatic recorder mainly rainfall. According to studies of (Henericksen 1986) cited in (Richard and Poccard 1998), it has been shown that NDVI was highly sensitive to an extended rainfall anomaly, the 1984 Ethiopian drought. Moreover, a study by (Anyamba and Tucker 2005) concluded that there exists strong correlation between NDVI and rainfall. In this study, the monthly NDVI was calculated as the Maximum of consecutive three decades in each month, whilst the sum of the rainfall in the three decades of the same month was assigned as the monthly rainfall.

The correlation between NDVI and rainfall was computed only for 4 zones and maximum correlation is obtained for a lag time of three months. The districts under study have varying proportions of vegetated and non-vegetated areas. The graph below shows the correlation of monthly NDVI and rainfall for Debub Wollo in 2000. Graphs for other Zones are presented in the appendix-C.

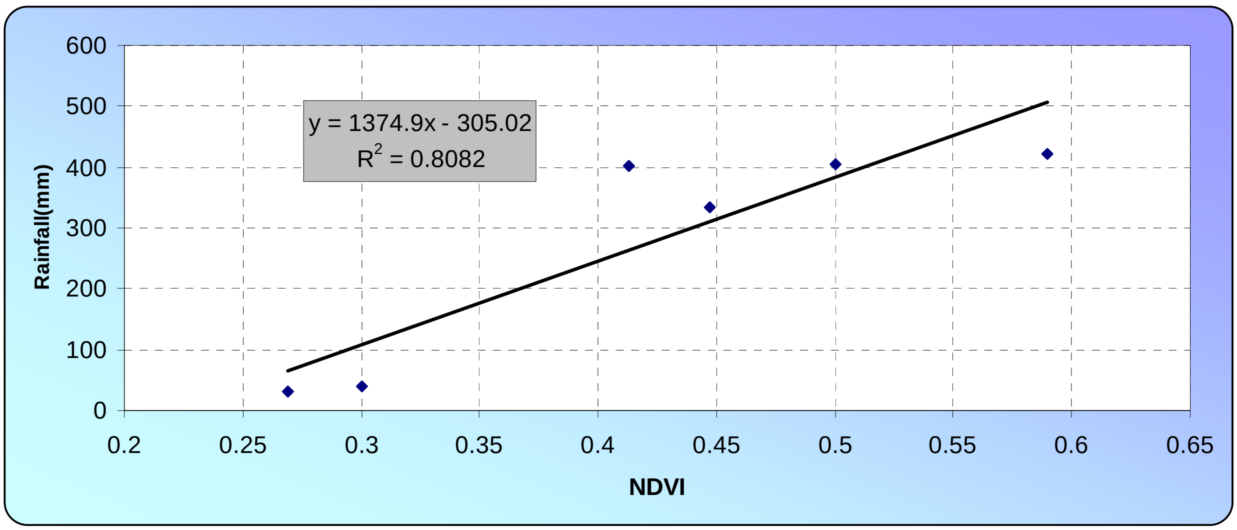


Figure 5.9 Graph showing the relationship between monthly NDVI and precipitation for Debub Wollo in 2000.

Zone Name	**R^2**
Debub Wollo	0.8082
Semien Shewa	0.7902
Semien Wollo	0.7876
Wag Himra	0.711

Table 5-2: Correlation coefficients showing the relationship between monthly NDVI and rainfall for 4 zones of Amhara Region.

The rainfalls lag period shows up to three month periods. This indicates the maximum time period for which an influence of rainfall on NDVI could be observed. This shows that there is a lag period in soil moisture and vegetation development. The average NDVI response from the districts will be influenced by land use and cropping pattern of the Zones under study.

5.3.2. CORRELATION BETWEEN NDVI AND PRODUCTION YIELD

Correlation between NDVI and annual crop production yield for all the districts of the "Amhara" region is examined based on the masks that delineate patterns of where these crops are produced. Relations between NDVI and annual production yield were analyzed using maximum NDVI over the growing season. There exists a strong correlation between maximum NDVI over the growing season and the total production yield for most of the districts in "Amhara" region. Table 5-3 shows the correlation coefficients for all the districts in the region.

Zone Name	**R^2**	**Zone Name**	**R^2**
Debub Wollo	0.7033	Semien Gonder	0.8487
Semien Wollo	0.7344	Debub Gonder	0.871
Wag Himra	0.7363	Mirab Gojjam	0.8477
Oromia	0.7181	Misrak Gojam	0.7243
Semien Shewa	0.7011	Agew Awi	0.6745

Table 5-3: Correlation coefficients between maximum NDVI and total production yield.

The relationship was established between maximum NDVI over the growing season and total production yield. Also, the NDVI values are obtained only for cultivated lands of each district. Herewith a graph showing the relationship between Maximum NDVI and total agricultural yield for Debub Wollo district is shown and such graphs for the other districts are presented in the Appendix-D.

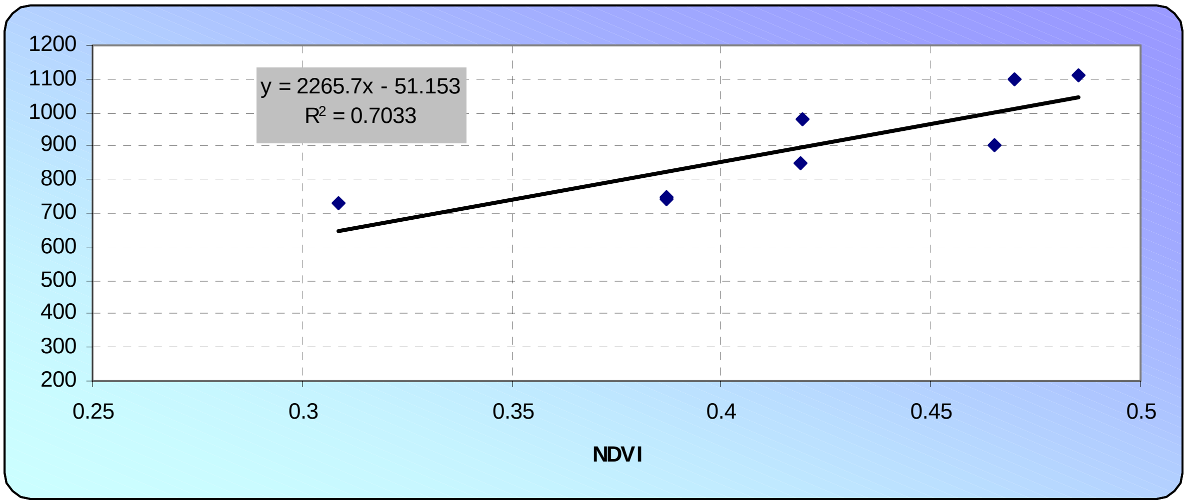


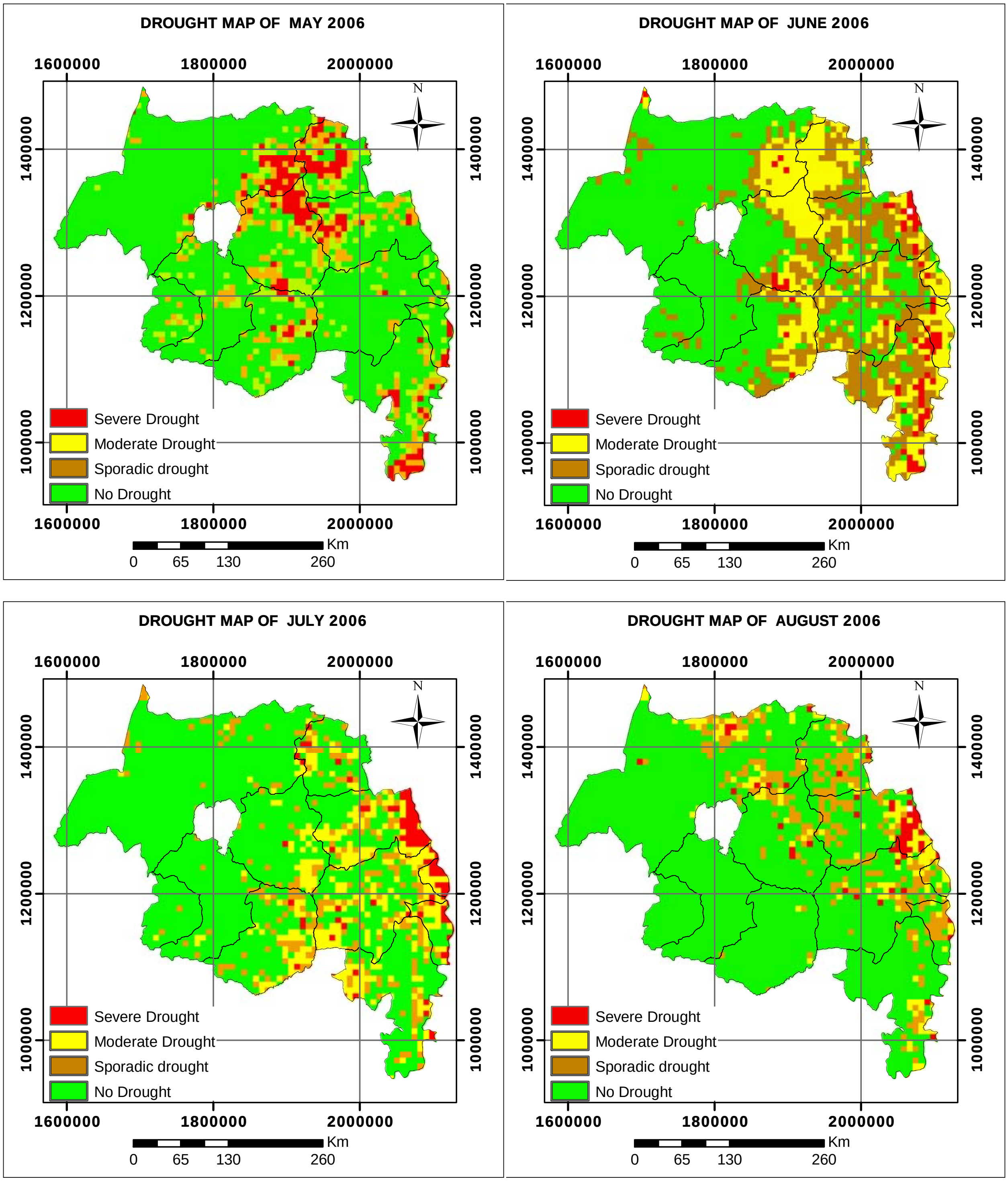
Figure 5.10: Graph showing the relationship between NDVI and Agricultural yield for the Debub Wollo

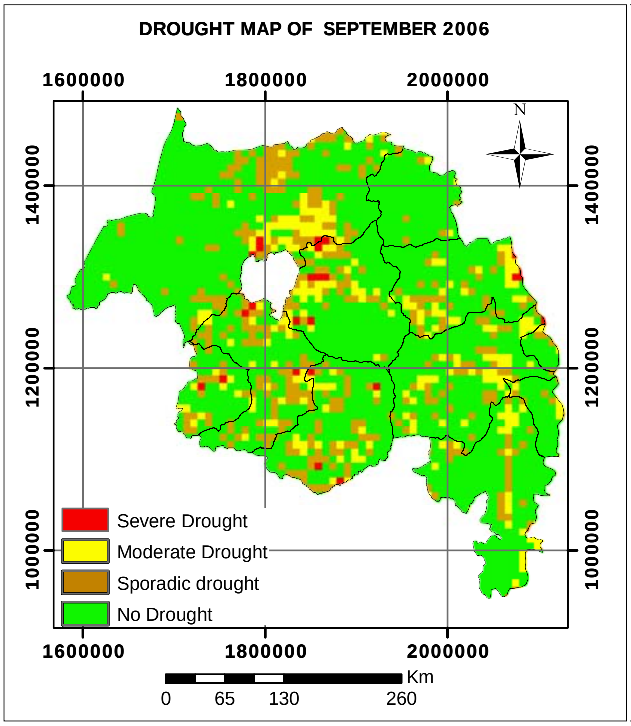
5.4. DROUGHT SEVERITY CLASSIFICATION

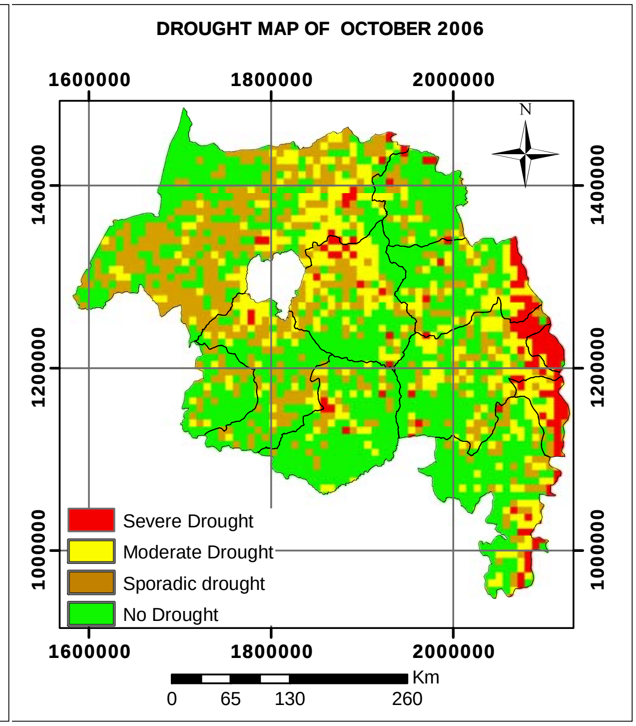
The drought map for the "Amhara region" during the main growing season (May to October) 2006 and the first five months of 2007 has been obtained on monthly basis by integrating all the drought-monitoring indices: Deviation of NDVI (DEV_{NDVI}), and Vegetation Condition Index (VCI) as where the ground truth data were obtained to validate the satellite derived results. To do so, first drought classification has been made based on the criterion suggested threshold values of each drought-index on monthly basis. Then, these maps were reclassified and overlaid using a software Arc Map GIS extension, Spatial Analyst.

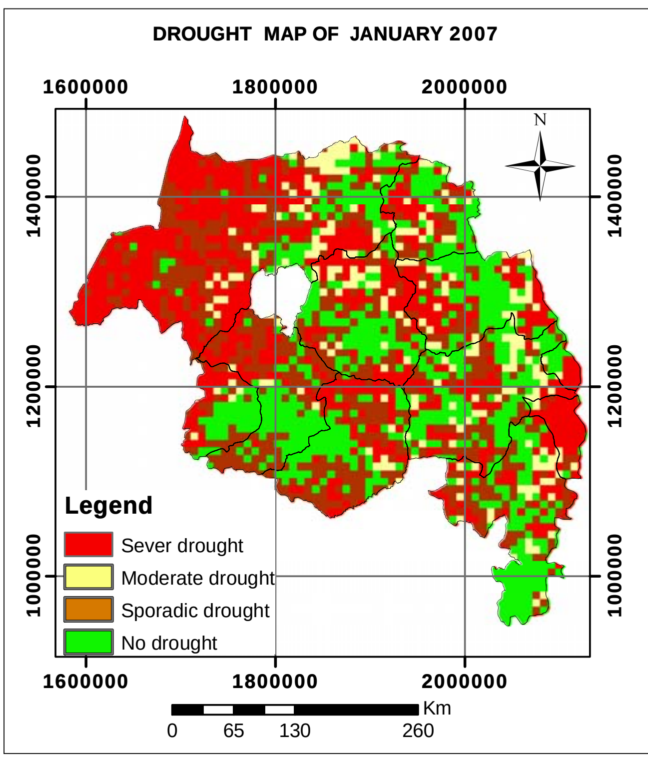
The final map was classified into non drought, sporadic drought, moderate drought and no drought classes based on the argument that a pixel has a drought and/or non drought condition for both two drought-monitoring indices. The thresholds used for reclassification for DEV are 0 to1: no drought, -0.1 to 0: sporadic drought, -0.1 to -0.15: moderate drought and greater than -0.15: severe drought. And for VCI above 50: no drought, 35 to 50 % moderate drought and below 35% severe drought (Kogan 1995). Similar methodology could also be applied to obtain a classified drought map for different years for the study area

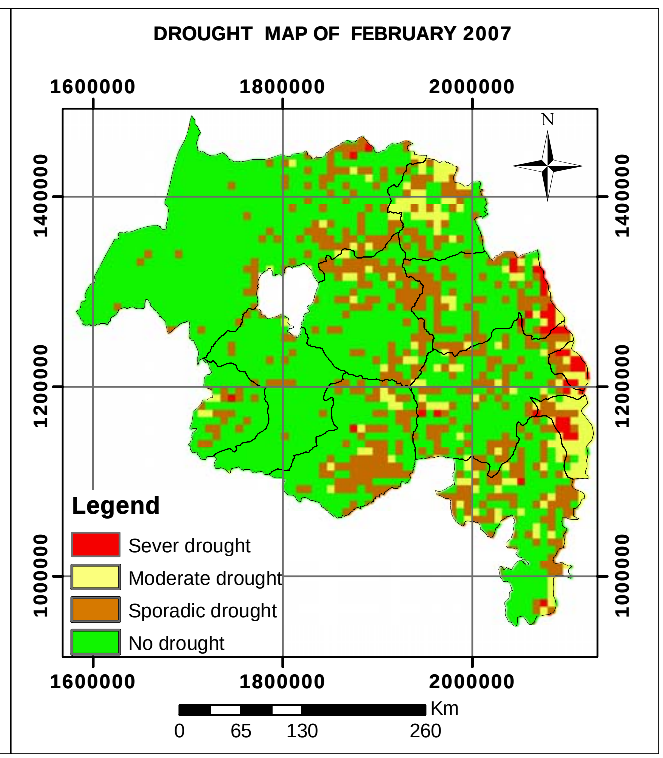
Figure 5.11 shows the drought map for the "Amhara region" 2006 and 2007.

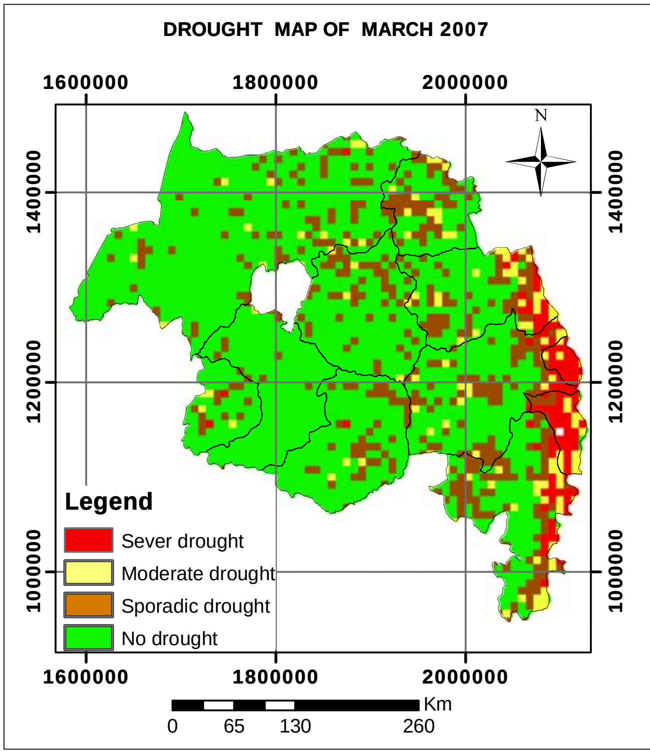



DROUGHT MAP OF SEPTEMBER 2006
1600000
1800000
2000000
1400000
1200000
1000000
N
Severe Drought
Moderate Drought
Sporadic drought
No Drought
Km
0
65
130
260

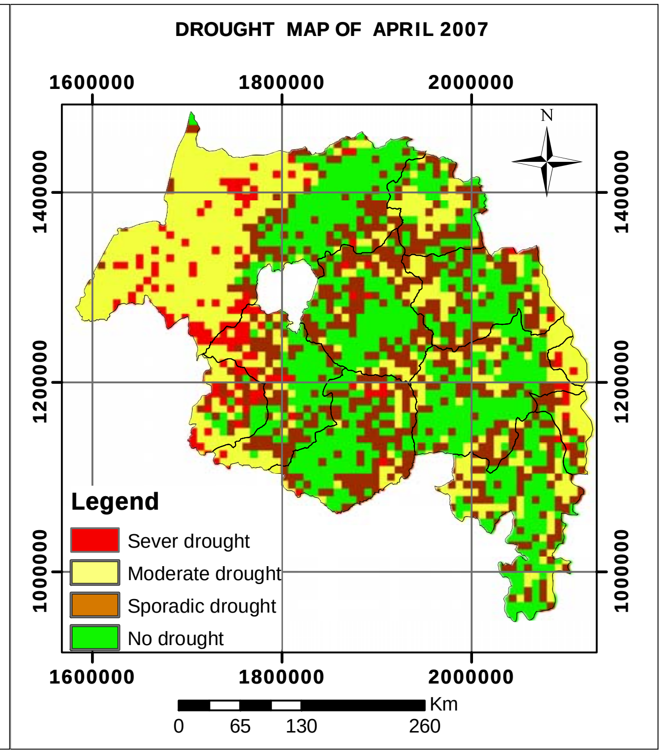

DROUGHT MAP OF OCTOBER 2006
1600000
1800000
2000000
1400000
1200000
1000000
N
Severe Drought
Moderate Drought
Sporadic drought
No Drought
Km
0
65
130
260


DROUGHT MAP OF JANUARY 2007
1600000
1800000
2000000
1400000
1200000
1000000
N
Legend
Sever drought
Moderate drought
Sporadic drought
No drought
Km
0
65
130
260

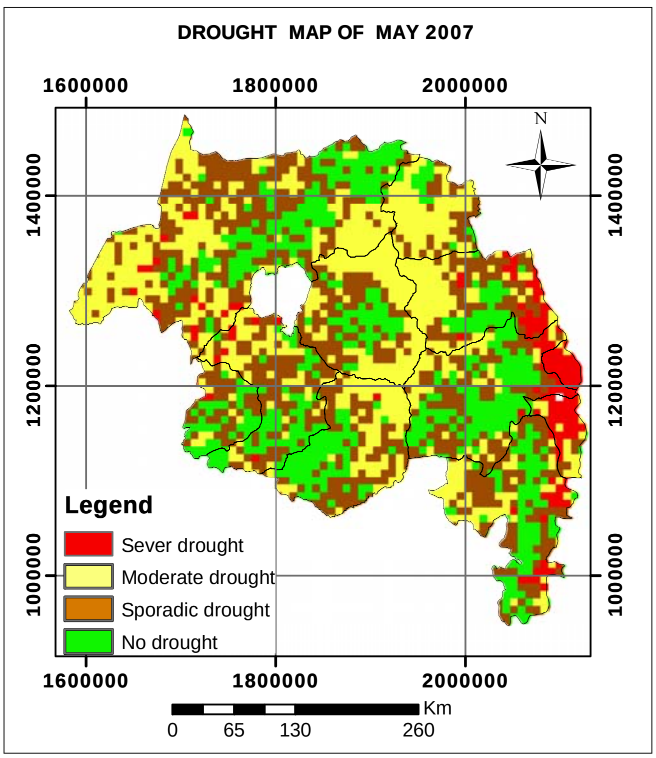

DROUGHT MAP OF FEBRUARY 2007
1600000
1800000
2000000
1400000
1200000
1000000
N
Legend
Sever drought
Moderate drought
Sporadic drought
No drought
Km
0
65
130
260



DROUGHT MAP OF MARCH 2007
1600000
1800000
2000000
1400000
1200000
1000000
N
Legend
Sever drought
Moderate drought
Sporadic drought
No drought
Km
0 65 130 260



DROUGHT MAP OF APRIL 2007
1600000
1800000
2000000
1400000
1200000
1000000
N
Legend
Sever drought
Moderate drought
Sporadic drought
No drought
Km
0 65 130 260



DROUGHT MAP OF MAY 2007
1600000
1800000
2000000
1400000
1200000
1000000
N
Legend
Sever drought
Moderate drought
Sporadic drought
No drought
Km
0 65 130 260

5.4. DELINEATION OF DROUGHT VULNERABLE AREAS

AVHRR images for several successive months from the beginning of 1981 were analyzed to establish how many Zones could have been identified as drought-hit using remote sensing information exclusively. For this, the DEV_{NDVI} and VCI values of all pixels in each Zone were calculated. The next step was to calculate the number of Zones in the region per each month, where monthly indices were below the drought thresholds. For the DEVNDVI the threshold was 0.0 and for VCI, where two thresholds were used, it was 50% and 35%. The first VCI threshold is normally perceived as the one below which the vegetation starts to lose its vigor, which is the first indication of an emerging drought. The second VCI threshold may be perceived as the beginning of a severe drought (Kogan 1995).

In Amhara Region, in the month of drought declaration (for July 1983, July 1991, July 1999 and July 2000), the number of Zones, which had their averaged indices values below the selected thresholds were 7, 10, 5 and 6, respectively indicating that the Region was already moving into a drought (although one Zone was found to be under severe drought conditions during July 1983).

As an example, figure 5.10 illustrates the distribution of the VCI values over the Amhara region. The low VCI values dominated over the region at July 1983 and became extremely low by July 1991.

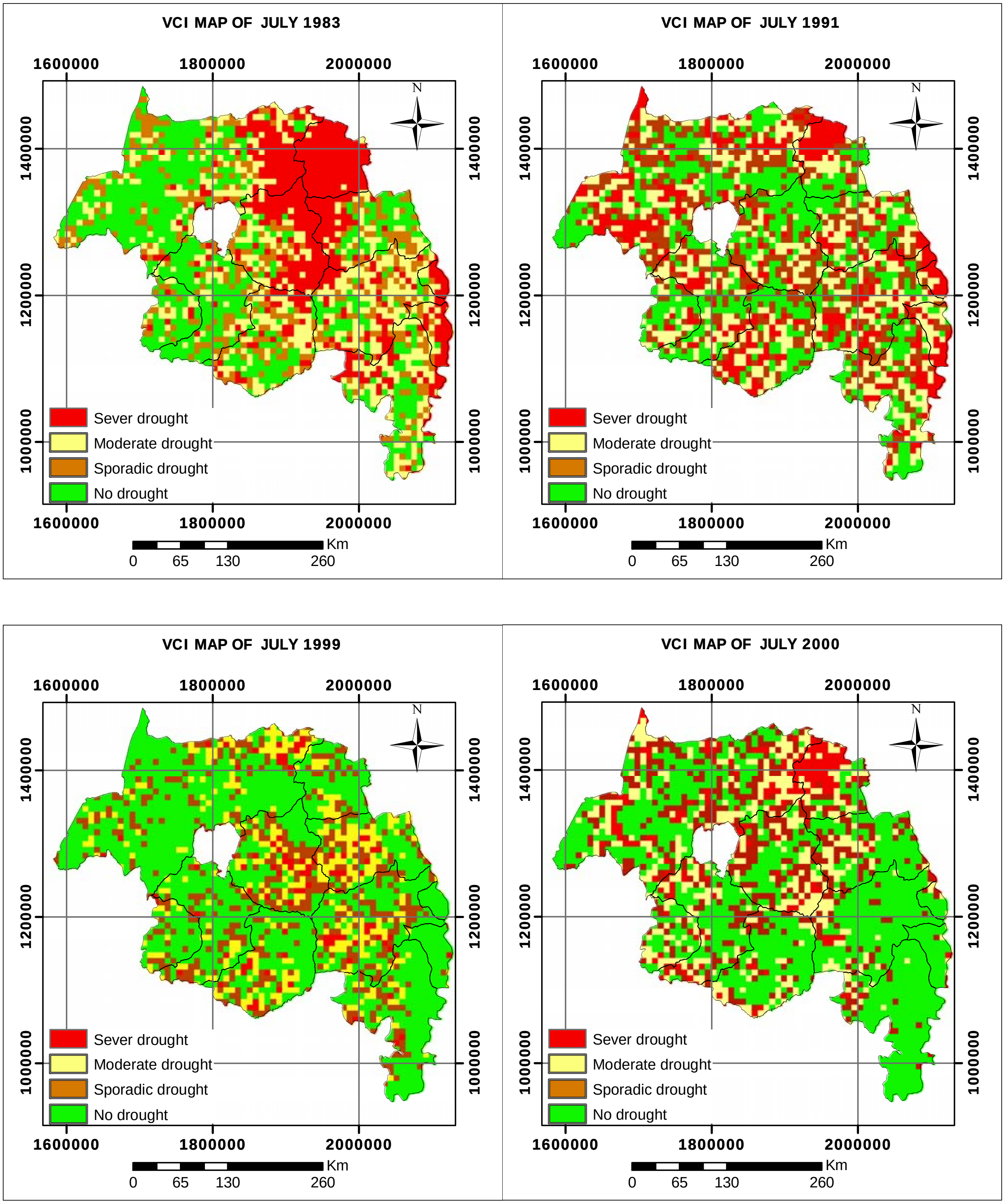


Figure 5-12 The VCI map for the "Amhara region" 1983, 1991, 1999 and 2000.

6. CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

The main objective of the study was to investigate the effectiveness of satellite derived indices as an indicator for drought assessment and identification of drought vulnerable areas. The temporal and spatial characteristics of drought can be detected, tracked and mapped from satellite data particularly that obtained from AVHRR and MODIS. The study suggested methods and techniques for delineating drought vulnerable areas and continuous drought monitoring by linking historical AVHRR sensor data with modern day MODIS sensor data. The methodology was tested for a study area in Amhara region. The results indicate that the two remote-sensing indices used, DEV_{NDVI}, and VCI are complementary and were found to be sensitive indicators of drought conditions.

It was concluded from the study that the temporal variations of NDVI are closely linked with precipitation and there is strong linear relationship between the two. And also a strong correlation has been observed between NDVI and agricultural production yield for most of the districts in “Amhara” region.

The satellite derived drought-monitoring indices have also been correlated with precipitation to see how vegetation stresses condition and consequently agricultural production yield is changing with the variability of rainfall. The result showed that the existence of a reasonably good relation between NDVI and rainfall variability over the growing season. A maximum correlation has been observed between NDVI and precipitation with a lag time of three months. Furthermore, a strong correlation also exists between the Vegetation Condition Index (VCI) and precipitation. These validation results of the satellite developed indices based on the ground data is vital for successful application of satellite derived indices for drought assessment and identification of drought vulnerable areas.

The study established and validated methods and techniques of drought assessment across two different sensors. It established reliable relationships between NDVI values derived from both sensors and created the options for the enhancement of existing free remote-sensing data. The best option incorporates the long-term NDVI characteristics calculated from AVHRR into MODIS at 500-m spatial resolution. This option is particularly attractive for the future drought monitoring, as it will have all the advantages of the better MODIS technology. The availability of MODIS data is guaranteed at least till 2018, with continuity missions planned with its successors NPP and NPOESS. Therefore, the AVHRR, MODIS-NPP-NPOESS data sets may effectively form one continuous data stream from 1982 to 2018, and possibly beyond. This would make it the single largest source of spatial data available for the region (and for the entire globe).

Thus, the satellite derived drought-indices can sufficiently identify and characterize the onset and severity of drought condition for different agro-climatologically homogeneous regions in combination with respective ground data. The results obtained from the satellite derived indices in this research are found to be complementary with each other, especially over the growing season and their deviation from the long-term mean can be used as a good indicator for identifying the drought and non-drought condition for near real time drought assessment. In Amhara Region, in the month of drought declaration (for July 1983, July 1991, July 1999 and July 2000), the number of Zones, which had their averaged indices values below the selected thresholds were 7, 10, 5 and 6, respectively indicating that the Region was already moving into a drought (although one Zone was found to be under severe drought conditions during July 1983).

The results of this study are being used for the development of a regional drought monitoring system. Considering the spread and frequency of droughts in the region on the one hand, and the lack of ground climate observations and technical capacity in the region to deal with droughts on the other, such a system could play an invaluable role for drought preparedness.

6.2 RECOMMENDATIONS

Even though the present work deals with satellite images, precipitation and agricultural production due to unavailability of ancillary data, still some of the portions which could not be handled and can be taken up in further research are listed below.

- Drought severity classes had been classified into non-drought and different drought conditions. However, the magnitude of drought severity varies within these categories and hence strategies for mitigation of its adverse impacts are different for different magnitude of drought severity. Therefore, it is essential to quantify the magnitude of drought severity into various degrees of drought classes.
- Drought from socio-economic aspect could not be studied. Besides delineating areas under drought condition, relevancy of risk assessment can be made more meaningful when the human population as well as livestock population under risk can be assessed. Therefore it is recommended to include the socio-economic data to better understand the effect of drought.
- Further more as the drought map gives the areas facing a high drought condition, a detailed study of these areas in terms of soil, water availability, temperature conditions, rainfall, crops grown, and the economic importance of the area can further help in preparing better management plans.

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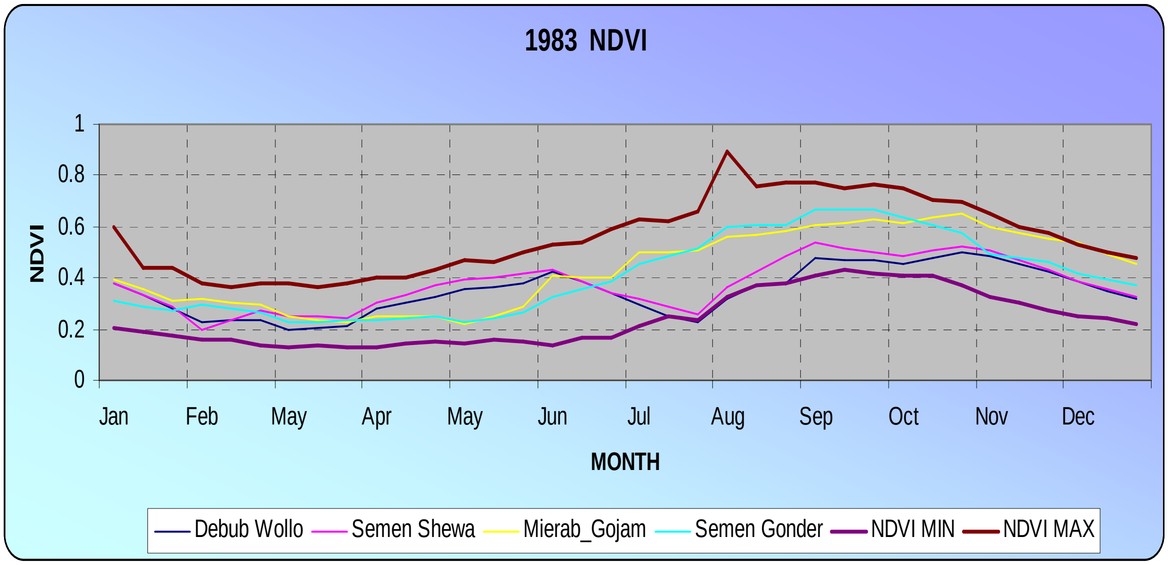
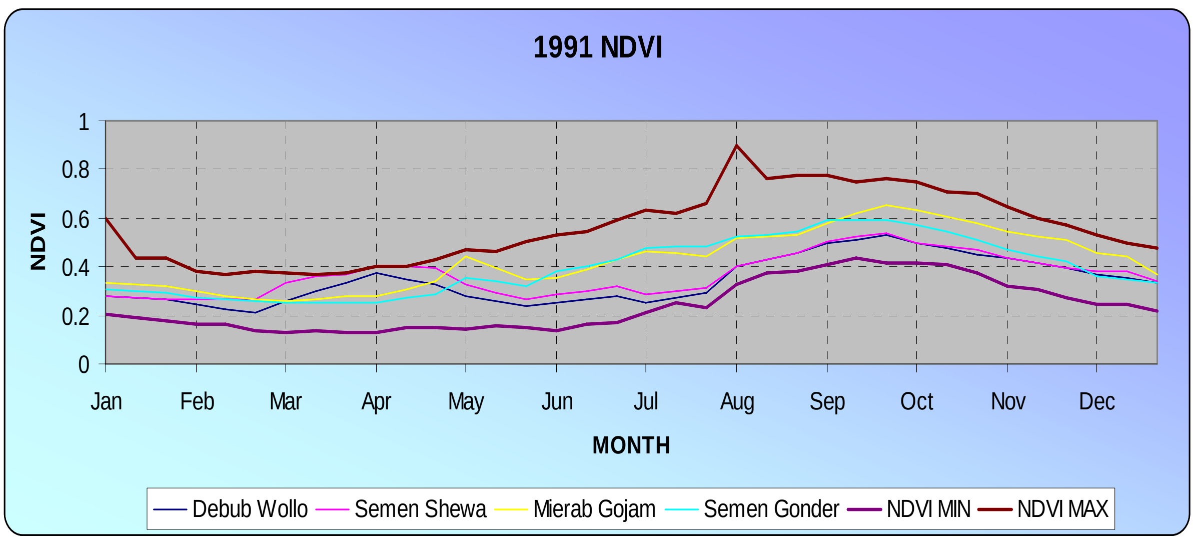
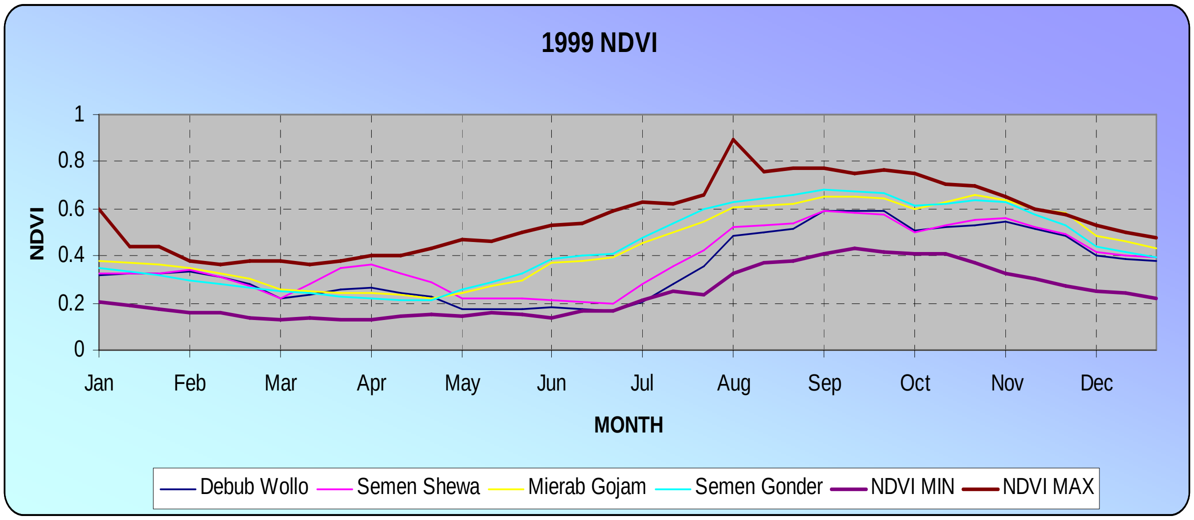
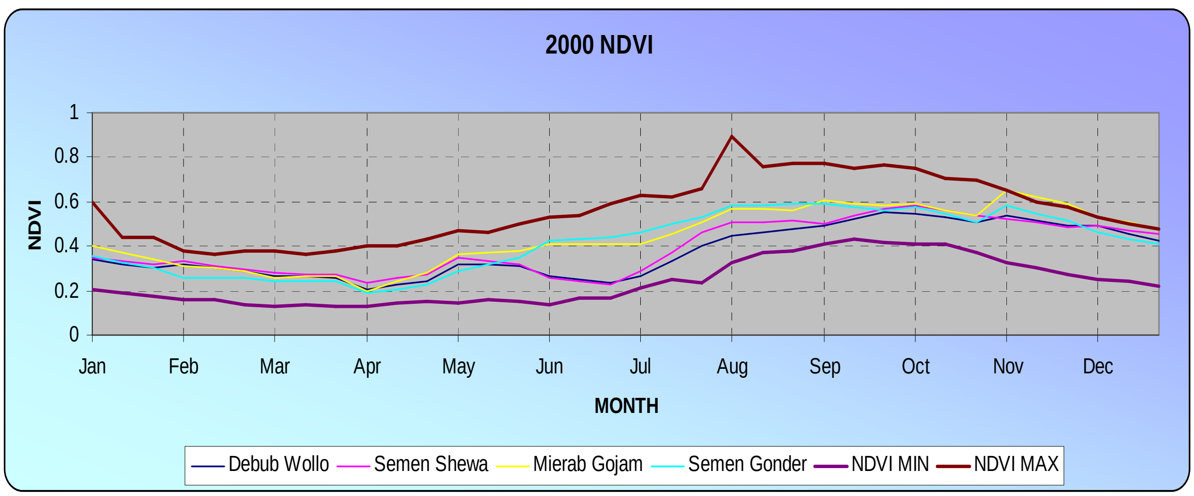
Appendices:

Appendix-A: Graphs showing absolute maximum, minimum and NDVI curves for the years 1983, 1991, 1999 and 2000 for selected Zones of Amhara region






1999 NDVI
NDVI
1
0.8
0.6
0.4
0.2
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
MONTH
Debub Wollo
Semen Shewa
Mierab Gojam
Semen Gonder
NDVI MIN
NDVI MAX


2000 NDVI
NDVI
1
0.8
0.6
0.4
0.2
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Jan
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May
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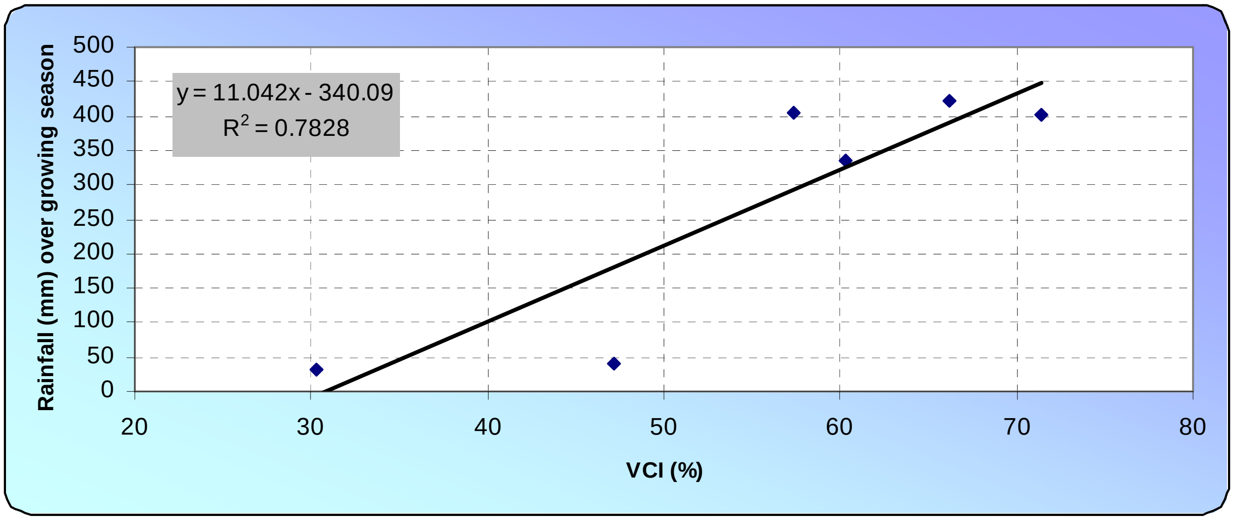
Sep
Oct
Nov
Dec
MONTH
Debub Wollo
Semen Shewa
Mierab Gojam
Semen Gonder
NDVI MIN
NDVI MAX

Appendix-B: Graphs showing correlation between VCI and precipitation and DEV_{NDVI} and precipitation



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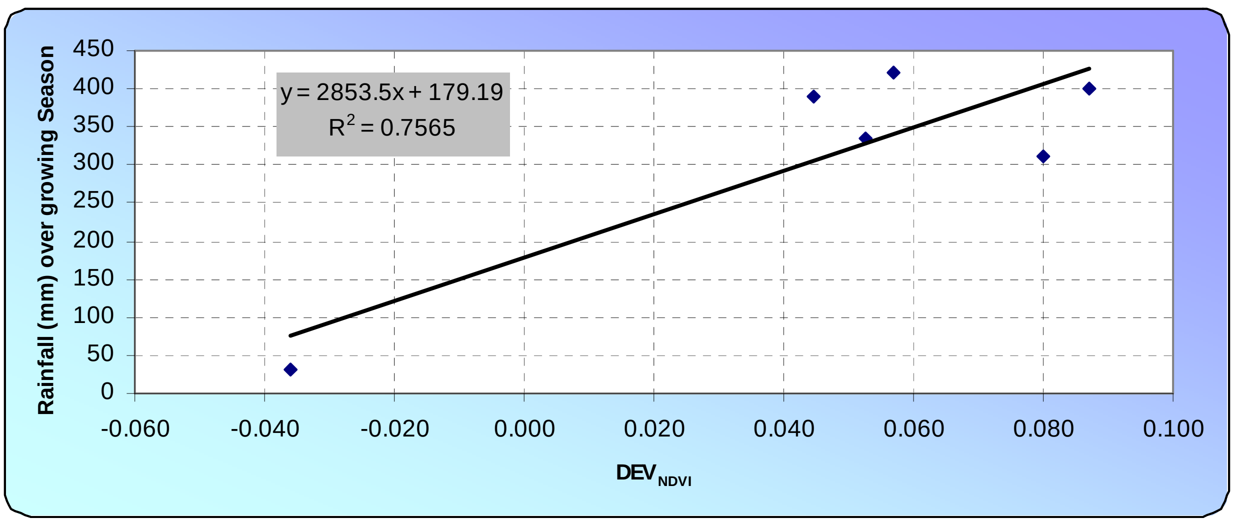
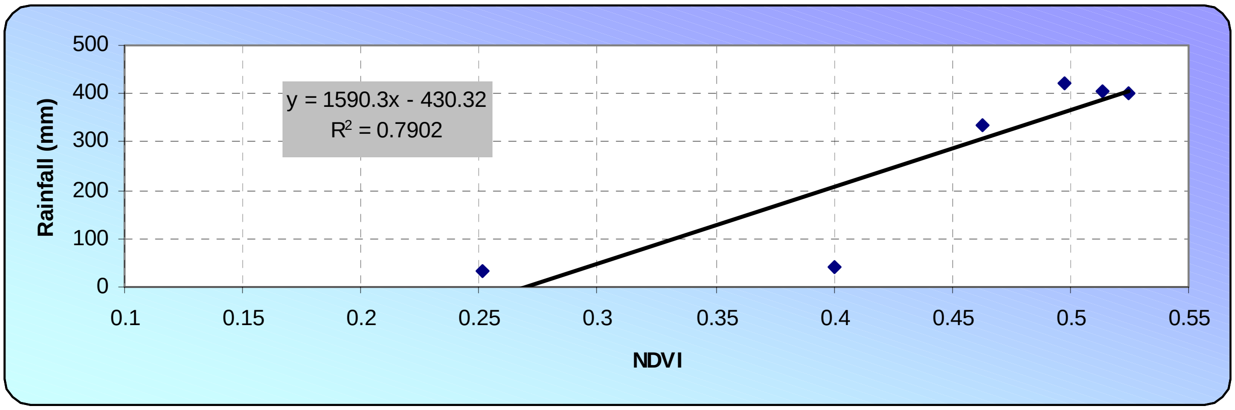


Semen Shewa

Appendix-C: Graphs showing correlation between NDVI and precipitation



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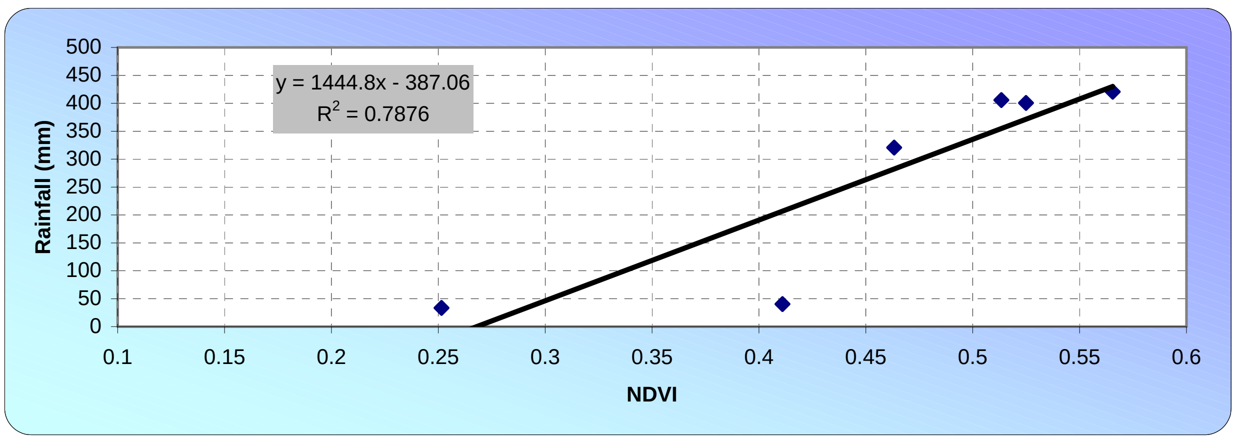

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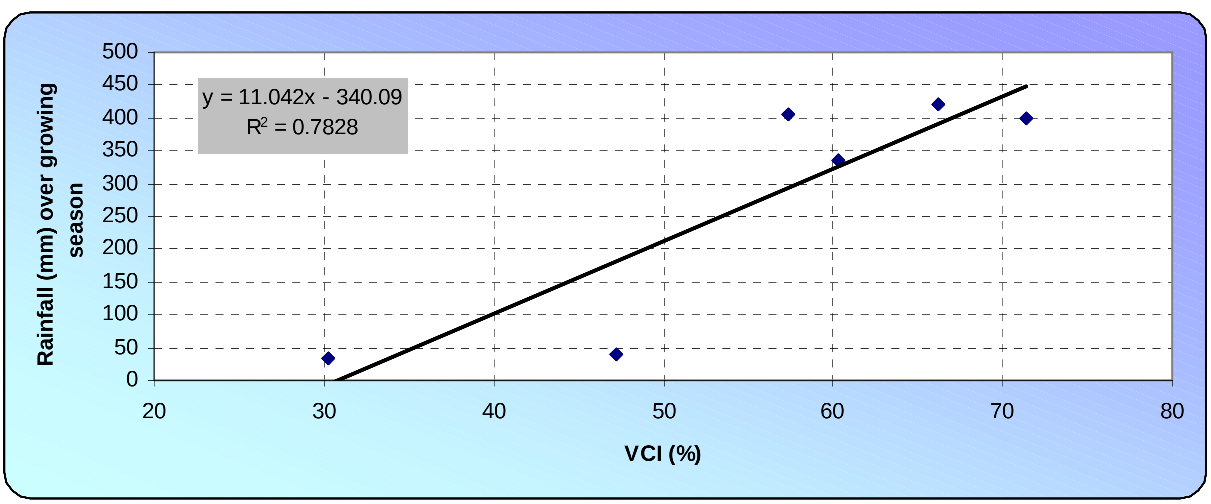
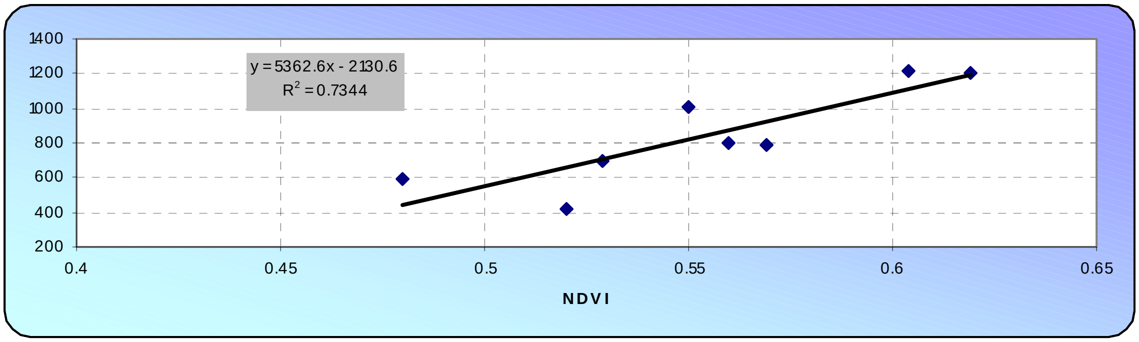


Wag Himra

Appendix-D Graphs showing correlation between NDVI and production yield



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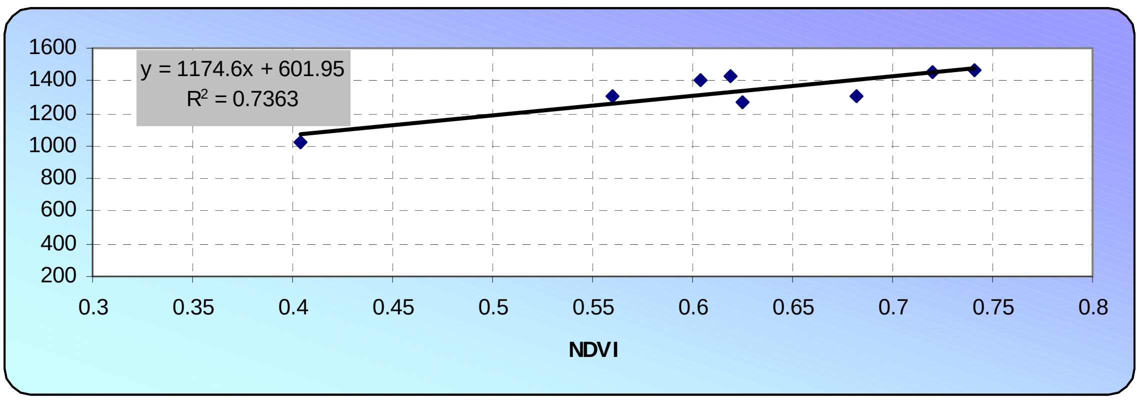

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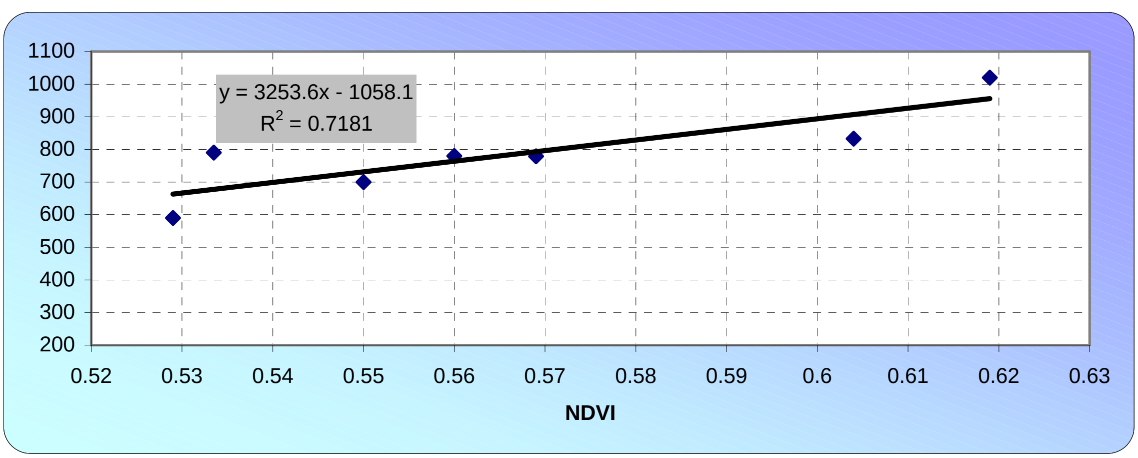
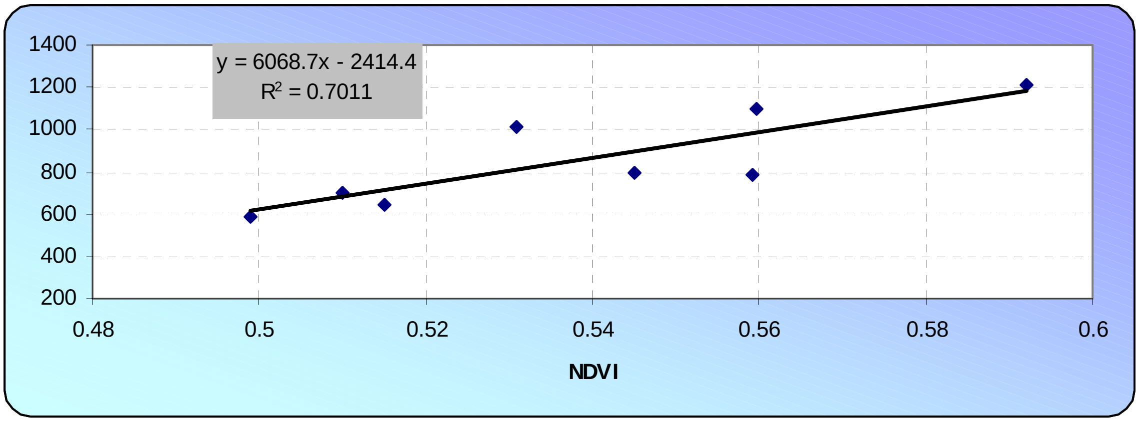


Oromia



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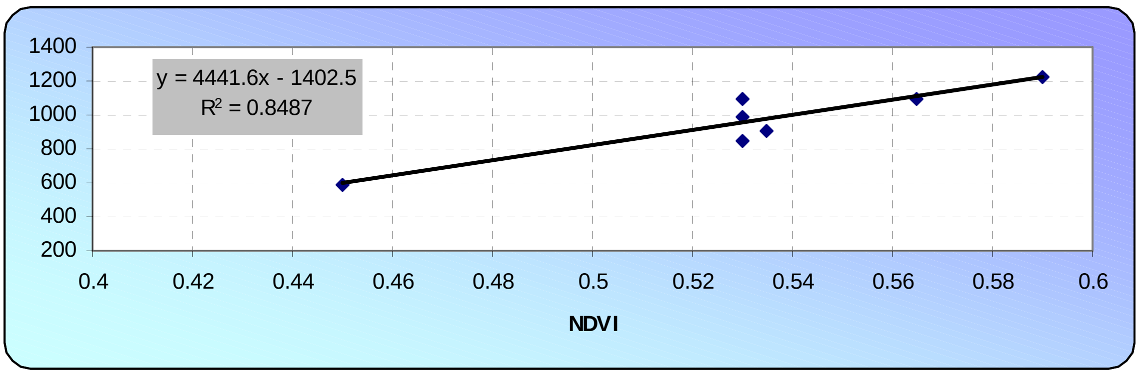

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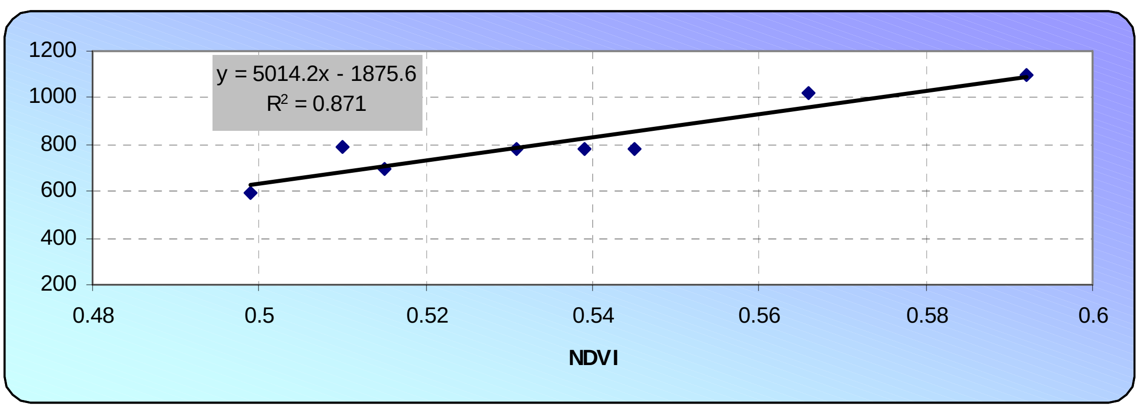

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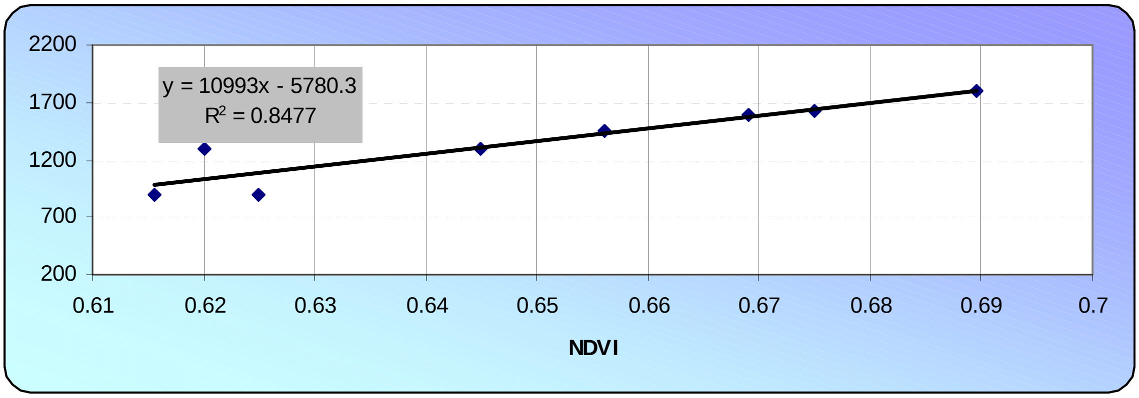

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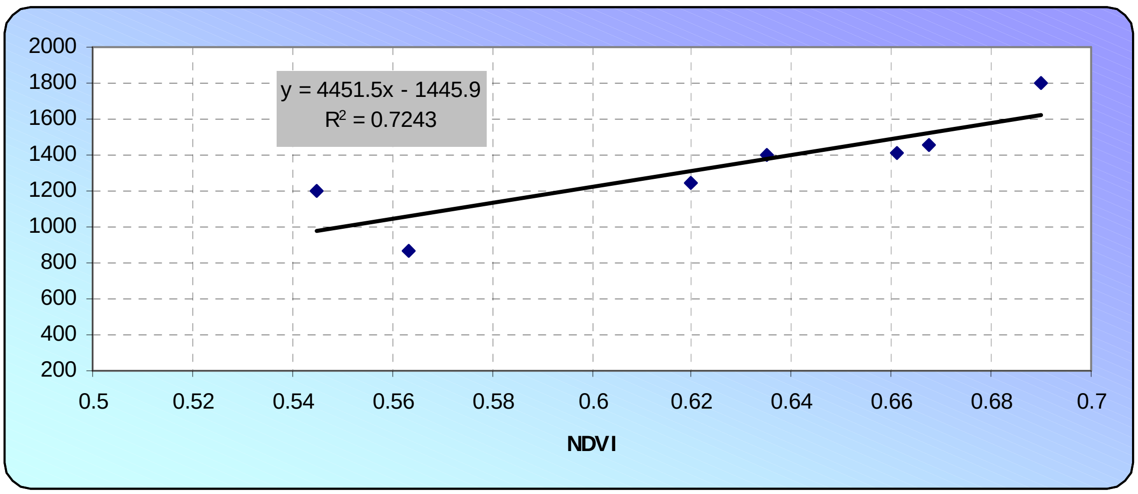

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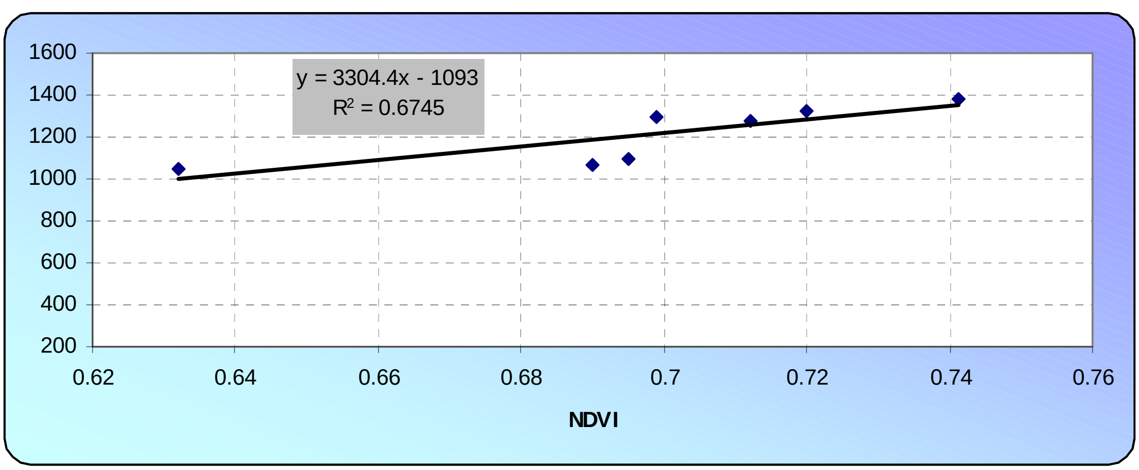

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