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Drought Risk Assessment using remote Sensing and GIS: A case study in Southern Zones, Tigray Region, Ethiopia

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.

By
LEGESSE HADISH

Under the guidance of

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JUNE 2010

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SCHOOL OF GRADUATE STUDIES

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Remote Sensing and GIS

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DECLARATION

I hereby declare that the dissertation entitled "Drought Risk Assessment using Remote Sensing and GIS: A case study in Southern zones, Tigray Ethiopia" has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2008-2010 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: June 10, 2010

(Legesse Hadish)

CERTIFICATE

This is certified that the dissertation entitled “Drought Risk Assessment using Remote Sensing and GIS: A case study in Southern zones, Tigray Ethiopia” is a bonafied work carried out by under my guidance and supervision. This is the actual work done by Legesse Hadish 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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Assistant Professor

Department of Earth Sciences
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Table of Contents Page

List of Figures

List of Tables

Acronyms

ARTEMI	Advanced Real Time Environmental Monitoring Information
AVHRR	Advanced Very High Resolution Radiometer
BOFED	Bureau of Finance and Economic Development
BoARD	Bureau of Agricultural and Rural Development
CSA	Central Statistics Agency
CCD	Cloud Cover Duration
CMI	Crop Moisture Index
DEVNDVI	Deviation of NDVI
DMCN	Drought Monitoring Centre Nairobi
DPPC	Disaster Prevention and Preparedness Commission
DSI	Drought Severity Index
EMSA	Ethiopian Meteorological Service Agency
EOS	Earth Observation System
EROS	Earth Resources Observation System
FAO	Food and Agricultural Organization of United Nation
FEWS	Famine Early Warning Systems
FFSP	Federal Food Security Program
GAO	United States Government Accountability Office
GI	Global Information and Early Warning System
GIS	Geographic Information System
GVI	Global Vegetation Index
HRV	Resolution Visible
IFRCARCS	International Federation of Red Cross and Red Crescent Societies
MODIS	Moderate Resolution Imaging Spectroradiometer
MOFED	Ministry of Finance and Economic Development
Mss	Millti Spectral Scanner
MVC	Maximum Value Composite
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference of Vegetation Index
NGO	Non-Governmental Organizations
NIR	Near Infra Red
NOAA	North Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity Index

SPI	Standard Precipitation Index
SPOT	Satellite Pour l' Observation de la Terra
SWSI	Surface Water Supply Index
TCI	Temperature Condition Index
TIR	Thermal Condition Index
TM	Thematic Mapper
UN	United Nations
VCI	Vegetation Condition Index
VGT-S10	10-day Synthesis Vegetation Products
VNIR	Visible and Near-Infrared
WFP	World Food Programme
WFS	World Food Summit
WMO	World Meteorological Organization
WSVI	Water Supply Vegetation Index

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(**Legesse Hadish**)

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. Drought causes loss of life, human and animal suffering and damage to economy and environment. The present study area is prone to extreme climate events such as drought. Successive years of low and erratic rainfall have left large areas of the southern zone in severe drought that resulted in crop failure, water shortage and has raised serious food security concerns in 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 investigation an effort has been made to derive drought risk areas facing agricultural as well as meteorological drought using an eight-year time series of decadal satellite SPOT NDVI (Normalized Difference Vegetation Index) and rainfall data (1998-2005) respectively. A deviation of the current NDVI with the long-term mean NDVI, and the Vegetation Condition Index (VCI) derived from the SPOT used in this study for drought detection, monitoring and real time prediction. In this study, it is indicated that large proportion of the area, i.e. 31.45% (3009km^2) is at moderate drought risk level, whereas 17% (1568km^2) of the area accounted for high drought risk. It is also shown from the result Enderta, Hintalo Wajirat, eastern part of Raya Azebo and southern part of Alamata Woredas were more susceptible to drought. 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. Moreover, SPOT NDVI at 1km by 1km resolution, which incorporates the long-term NDVI, is also the best option for drought risk assessment.

Keywords: Drought, NDVI, VCI, Risk assessment

1. INTRODUCTION

1.1 Background

Drought is a slow-onset, creeping natural hazard where the impacts are largely non-structural and spread over a larger geographical area than are damages from other natural hazards. The non-structural characteristics of drought impacts has certainly hindered the development of accurate, reliable, and timely estimates of severity and, ultimately, the formation of drought preparedness plans by most governments.

Drought risk is a product of a region's exposure to the climatic hazard; and its vulnerability to extended periods of water shortage (Wilhite, 2000). If nations like Ethiopia improve their understanding of the hazard and the factors that influence vulnerability. The impacts of drought, like those of other hazards, can be reduced through mitigation and preparedness.

In Southern zone of Tigray, where precipitation distributes unevenly in both spatial and temporal dimensions, more than 80% of the annual rainfall precipitation in the main rain season, usually known as Meher in local language that occur from June to September, leading to frequent occurrence of agro-drought in other months of the year. Successive years of low precipitation have left large areas of the southern Tigray in severe drought that resulted in crop failure, water shortage and has raised serious food security concerns for the region.

Generally, drought can be monitored through either ground observation or remote sensing. Ground observation with its limitation like relatively slows to get enough information for the whole region, needs a lot of labor to obtain the necessary information, and is very expensive to undertake it is a direct and accurate way for drought monitoring. As a contrast, remote sensing from space represents a fast and economic way of monitoring, but needs to elaborately develop an applicable approach for the region under study

1.2 Problem Statement

In Tigray, the conventional drought monitoring and early warning system is based on ground data collection and analysis so as to identify drought-prone areas. The system performed manually by the taskforce from government, NGO and UN agencies by DPPC as a leading organization of the team.

In country level “Meher” (summer rain that occur from June-September) season is selected to evaluate the performance and distribution (spatial and temporal) of rain, its impact on crop and livestock production, livelihoods and finally identify population needing food and non food relief assistance in every year due to drought and other disasters.

This assessment is intensive to cover all drought suspected areas and to identify the actual drought affected areas. In addition to this, data collection is done mostly by those who do not have training on the importance and technique of early warning. The post harvest assessment compiled mostly by Woreda agricultural experts and is not reliable for targeting food insecure areas. The regional and zonal level experts try to crosscheck the report at field. But there is no statistical method of area selection for the cross checking. Having seen the post-harvest assessment and other early warning reports, the relevant body decides the areas with food deficit and the number of beneficiaries at Woreda level. Generally, the system is subject to resource liquidation.

(Sharp 1997, cited in Devereuex, 2004) stated that in Ethiopia poor targeting system for food aid becomes a significant determinant of food insecurity. This indicates that some of the areas where the poor are living are missed during targeting. According to the seriousness of the case, it needs conscience result to save human life and mitigate the problem by identifying the most vulnerable areas. This is one of the problems encountered in Southern Tigray.

To avoid the above problem, it is better to use satellite sensor data which are consistently available, cost-effective and can be used to detect the onset of drought, its duration and magnitude. As timely information on the extent and severity of drought can limit impacts of drought-related losses, the near real time assessment through effective monitoring using SPOT image and satellite Rainfall data plays a significant role in mitigating its adverse impacts.

1.3 Objectives

Given the above stated problem, the following research objectives have been formulated to tackle the challenge:

The general objective of this research is to delineate drought risk areas using Remote Sensing and GIS techniques in south Gondar zone from the crop production (food availability) point of view.

1.3.1. General objective:

- To assess drought risk areas for the southern zone, Tigray Region using Remote Sensing and GIS.

1.3.2. Specific objectives:

- To prepare NDVI change map from normal year to drought year.
- To calculate the percentage of drought affected area by drought risk level.
- To show the effectiveness of satellite derived drought indices as an indicator for drought assessment.
- To identify the most draught vulnerable area.

2. LITREATURE REVIEW

2.1. Drought: Definition

Drought has 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.

Drought is a weather-related natural disaster. It affects vast regions for months or years. It has an impact on food production and it reduces life expectancy and the economic performance of large regions or entire countries. Drought is a recurrent feature of the climate. It occurs in virtually all climatic zones, and its characteristics vary significantly among regions. Drought differs from aridity in that drought is temporary; aridity is a permanent characteristic of regions with low rainfall.

Drought is an insidious hazard of nature. It is related to a deficiency of precipitation over an extended period of time, usually for a season or more. This deficiency results in a water shortage for some activity, group, or environmental sector. Drought is also related to the timing of precipitation. Other climatic factors such as high temperature, high wind, and low relative humidity are often associated with drought.

Drought is more than a physical phenomenon or natural event. Its impact results from the relation between a natural event and demands on the water supply, and it is often exacerbated by human activities. The experience from droughts has underscored the vulnerability of human societies to this natural hazard.

Drought definitions are of two types: (1) conceptual, and (2) operational. Conceptual definitions help understand the meaning of drought and its effects. For example, drought is a protracted period of deficient precipitation which causes extensive damage to crops, resulting in loss of yield.

Operational definitions help identify the drought's beginning, end, and degree of severity. To determine the beginning of drought, operational definitions specify the degree of departure from the precipitation average over some time period. This is usually accomplished by comparing the current situation with the historical average. The threshold identified as the beginning of a drought (e.g., 75% of average precipitation over a specified time period) is usually established somewhat arbitrarily.

An operational definition for agriculture may compare daily precipitation to evapotranspiration to determine the rate of soil-moisture depletion, and express these relationships in terms of drought effects on plant behavior. Operational definitions are used to analyze drought frequency, severity, and duration for a given historical period. Such definitions, however, require weather data on hourly, daily, monthly, or other time scales and, possibly, impact data (e.g., crop yield). Climatology of drought for a given region provides a greater understanding of its characteristics and the probability of recurrence at various levels of severity. Information of this type is beneficial in the formulation of mitigation strategies. The various types of droughts are listed below.

- **Meteorological drought**

Meteorological drought is defined on the basis of the degree of dryness, in comparison to a normal or average amount, and the duration of the dry period. Definitions of meteorological drought must be region specific, since the atmospheric conditions that result in deficiencies of precipitation are highly region specific. The variety of meteorological definitions in different countries illustrates why it is not possible to apply a definition of drought developed in one part of the world to another. For instance, the following definitions of drought have been reported:

- United States (1942): Less than 2.5 mm of rainfall in 48 hours.
- Great Britain (1936): Fifteen consecutive days with daily precipitation less than 0.25 mm.
- Libya (1964): When annual rainfall is less than 180 mm.
- Bali (1964): A period of six days without rain.

Data sets required to assess meteorological drought are daily rainfall information, temperature, humidity, wind velocity and pressure, and evaporation.

- **Agricultural drought**

Agricultural drought links various characteristics of meteorological drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so on. Plant water demand depends on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil. A good definition of agricultural drought should account for the susceptibility of crops during different stages of crop development. Deficient topsoil moisture at planting may hinder germination, leading to low plant populations per hectare and a reduction of yield.

Data sets required to assess agricultural drought are soil texture, fertility and soil moisture, crop type and area, crop water requirements, pests and climate.

- **Hydrological drought**

Hydrological drought refers to a persistently low discharge and/or volume of water in streams and reservoirs, lasting months or years. Hydrological drought is a natural phenomenon, but it may be exacerbated by human activities. Hydrological droughts are usually related to meteorological droughts, and their recurrence interval varies accordingly. Changes in land use and land degradation can affect the magnitude and frequency of hydrological droughts.

Data sets required to assess hydrological drought are surface-water area and volume, surface runoff, stream flow measurements, infiltration, water-table fluctuations, and aquifer parameters.

- **Socioeconomic drought**

Socioeconomic definitions of drought associate the supply and demand of some economic good with elements of meteorological, hydrological, and agricultural drought. It differs from the other types of drought in that its occurrence depends on the processes of supply and demand. The supply of many economic goods, such as water, forage, food grains, fish, and hydroelectric power, depends on the weather. Due to the natural variability of climate, water supply is ample in some years, but insufficient to meet human and environmental needs in other years.

Socioeconomic drought occurs when the demand for an economic good exceeds the supply as a result of a weather-related shortfall in water supply. The drought may result in significantly reduced hydroelectric power production because power plants were dependent on stream flow rather than storage for power generation. Reducing hydroelectric power production may require the government to convert to more expensive petroleum alternatives, and to commit to stringent energy conservation measures to meet its power needs.

The demand for economic goods is increasing as a result of population growth and economic development. The supply may also increase because of improved production efficiency, technology, or the construction of reservoirs. When both supply and demand increase, the critical factor is their relative rate of change. Socioeconomic drought is promoted when the demand for water for economic activities far exceeds the supply. Data sets required to assess socioeconomic drought are human and animal population and growth rate, water and fodder requirements, severity of crop failure, and industry type and water requirements.

analyzed from Figure 2.1

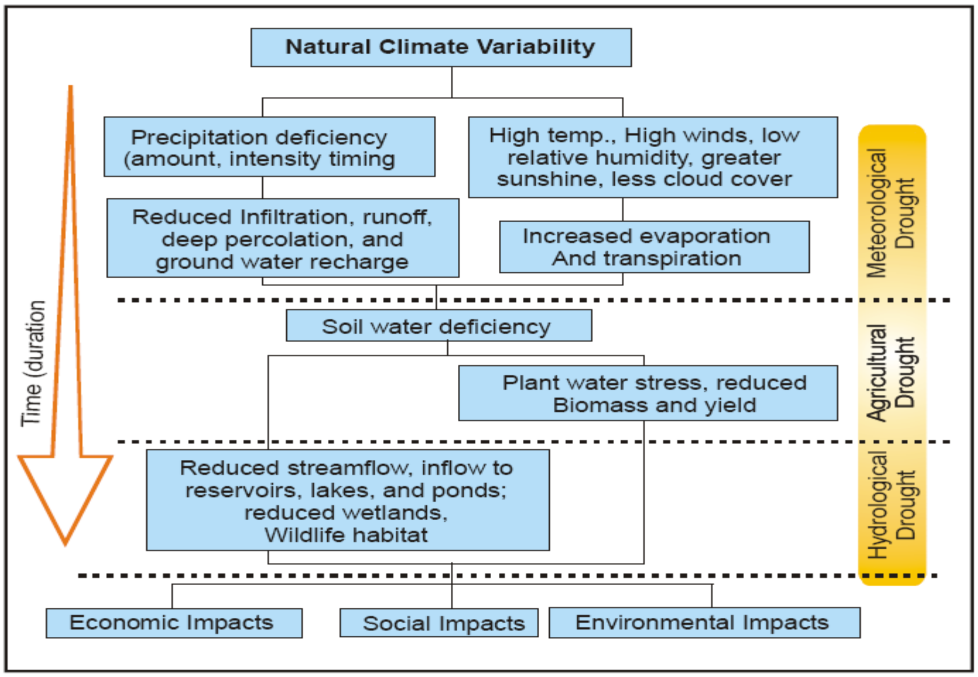

Figure2.1: Relationship between the drought types
(Source: National Drought Mitigation Centre)

2.2 Impacts of Drought

The impacts of a drought can be economic, environmental or social. Drought produces a complex web of impacts that spans many sectors of the economy and reaches well beyond the area experiencing physical drought. This complexity exists because water is integral to society's ability to produce goods and provide services. Impacts are commonly referred to as direct and indirect. Direct impacts include reduced crop, rangeland, and forest productivity, increased fire hazard, reduced water levels, increased livestock and wildlife mortality rates, and damage to wildlife and fish habitat. The consequences of these direct impacts illustrate indirect impacts. Remote sensing and GIS technology significantly contributes to all the activities of drought management

(Jeyaseelan, 2003). For example, a reduction in crop, rangeland, and forest productivity may result in reduced income for farmers and increased prices for food and timber, unemployment, reduced expenditures, migration, and disaster relief programs.

2.3 Drought Risk Management in Ethiopia and Tigray Region

Many of the food emergencies in Ethiopia are induced by drought. There is complex interaction between drought and food insecurity. Drought is the most common form of environmental risk leading to food insecurity (Devereux, 2004). It is only in poor countries that drought turns into famine, often resulting in population displacement, suffering, and loss of life (Shah et al., 2008). The Cyclical drought has tremendous impact on long term food security. This is because of the fact that recovery from previous crisis is cut short by the next drought (GAO, 2002).Since the entire agricultural activity of Ethiopia is associated with the behavior of rainfall, drought should be given an important attention and its impact should not be divorced from the societal context (Wilhite, 1993 cited in Birhanu Gedif, 2009).

The occurrence of drought and famine in Ethiopia is dated back to 253 BC. The records of drought periods are indicated in different literatures including religious books. However the years 1066-70, 1071-72, 1252, 1272-73, 1274-1275, 1435-36, 1454, 1468, 1562, 1800, 1826-29, 1835, 1836-1837, 1872, 1888-90 (the great Ethiopian famine), 1891-1892, 1895-1900, 1913-1914, 1921-22, 1932-34, 1953-58, 1964-66, 1969, 1971-1972, 1975-1976, 1978-1979, 1982, 1983-1984, 1999-2000, 2002-2003 and 2008-2009 are as being the major drought years among others recorded (Glantz, 1987, Teshome, 2006 and USAID, 2007).(www.fao.org/drought%20 report%20 2008)

It seems that the frequency of drought and number of affected population increases through time. There have been deaths from drought affected population in the recent past in the country shows in Table 2.1

Table 2.1: Drought affected population

S.No	Year	Affected population	Human loss	Remark
1	1972/1973	1.9 million	250,000	
2	1983/1984	8 million	1 million	
3	1999/2000	10.6 million	Excess	No data is available
4	2002/2003	>13 million	No major deaths	The advancement in early warning and contingence planning reduces death
5	2007/2008	8 .6 million	No major deaths	

Source: USAID (2007)

Since drought as a disaster, is a determinant factor for food insecurity (particularly in rain fed agriculture dependent population), there is an immediate operational need to keep in tracks of drought conditions for monitoring and prediction. It is a regular feature of Ethiopian weather pattern disrupting cropping operations, which results in reduced amount of income from the sector and food insecurity if it persists for a considerable period of time (Almayehu Kassa, 1993). In addition to the reduction of crop yield, drought is associated with pest infestation and diseases (Chopra, 2006). That is why the Government of Ethiopia focuses on reducing the countries. Vulnerability to drought and other natural calamities in its poverty reduction strategy (MOFED, 2002).Sometimes, there would be drought even if the area is green, usually called green drought. It is a type of drought condition associated with apparent ample rainfall but reduced agricultural productivity because of poor timely rains or ineffective precipitation. The characteristics of drought are distinctly regional reflecting unique meteorological, hydrological, agricultural and socio-economic characteristics (Wilhite, 1993 cited in Birhanu Gedif, 2009).Satellite based drought watch system will serve this goal With the help of environmental satellite, drought can be detected 4 to 6 weeks early and delineated more accurately, and its impact on agriculture can be diagnosed far in advance of harvest, which is the most vital for food security (Kogan, 1990)

Several indices have been developed for the quantification of drought (based on the type of drought). Conventional methods of drought monitoring suffer from limitations with regard to timeliness, objectivity, unreliability, and inadequacy, but satellite sensors provide spatial information on vegetation stress caused by drought conditions. This shows that a comprehensive study on drought can be conducted using satellite sensors.
Different types of drought require different drought indicators. In agricultural drought monitoring, the most suitable indicators needed are the factors that are responsive to rainfall data and satellite images as a result moisture deficit has critical relation with crop water requirements and it is important in assessing the impact of drought on crops. The choice depends on hydro-climatology of the region, the type of drought, the vulnerability of society, the purpose of the study and the available data (Narendra, 2008).

Tigray region particular in the Southern zones has suffered from a number of severe droughts and associated famines, and chronically food-insecure. Below-averaged belg, rains season (February-May) coupled with delayed and sporadic meher/Summer, or the main rains (June- September) have led to widespread food insecurity in the study areas.

The lack of sufficient precipitation during the belg season failed to replenish water sources. In addition, given the poor performance of the meher rains, and agricultural areas, particularly the lowlands and midlands of the study areas. USAID's Famine Early Warning Systems Network (FEWS-NET) estimates that overall crop production in1999, 2000, 2002-2003 and 2008-2009 as to be observed between 8-10% below average. Erratic rainfall patterns have characterized the four years. In these the belg rains (secondary rains that occur from February through May) have also failed to produce much precipitation although little precipitation at the end of March. The belg rain which normally begins in February and peak in mid April is important and the study area is dependent on them for the production of short cycle crops. They are also significant in terms of the coming meher (main rains that occur from June through September) 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.

2.4 Remote Sensing and GIS

The detection, monitoring and mitigation of disasters require gathering of rapid and continuous relevant information that are not effectively collected by conventional methods. Remote sensing tools and techniques make it possible to obtain and distribute continuous 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, whilst an aircraft can give a more detailed analysis of a smaller area, if a specific need occurs. The spectral bands used by these sensors cover the whole range between visible and microwaves.

Rapid developments in computer technology and the Geographical information Systems (GIS) help to process Remote Sensing (RS) observation from satellites in a spatial format of maps – both individually and along with tabular data and "crunch" them together to provide a new perception – the spatial visualization of natural resources. The integration of information derived from RS techniques with other datasets – both in spatial and non-spatial formats provides tremendous potential for identification, monitoring and assessment of droughts and floods (Johnson et al., 1993).

For an accurate assessment of the occurrence, extent and severity of drought, it is necessary to get a correct picture of the spatial and temporal distribution of a number of meteorological, hydrological and surface variables. Space observation having this potential has made a significant contribution in this field. The satellite sensors that have the capability to retrieve surface parameters with high spatial and temporal resolutions over large areas have provided a comprehensive view of the situation.

For example, the multi-spectral mode is more adapted for characterizing vegetation: canopy density, photosynthetic activity, water stress, fire activity, vegetation moisture, ratio dead to live plant materials and distributions of bare ground. The number of spectral bands of a multi spectral sensor ranges from just a few (i.e. SPOT satellites) to more than 200 bands on hyper spectral spectrometers. Spectral bands in the visible (blue to red wavelengths), near infrared (NIR) and short wave infrared (SWIR) are particularly interesting for monitoring vegetation. The bandwidth of satellite sensors is generally around 100 nm but some low or medium resolution sensors such as MODIS (500 and 1000 m) or MERIS (350 m) present narrower bands (10 to 30 nm) more adapted to the retrieval of certain biophysical features. The thermal infrared domain (TIR) is used for studying water fluxes between vegetation and atmosphere, for estimating the evapotranspiration of vegetation canopies and for detecting water stress. Several TIR spectral bands are necessary for separating temperature and emissivity and for correcting atmospheric effects.

Remote sensing and GIS can successfully contribute to monitoring and assessment of process changes in ecosystem (Kienberger et al., 2002). GIS in drought assessment helps to create spatial digital database to hold meteorological information and generate thematic layers that represent spatial distribution of drought for both Standardized Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI). Using GIS, we can delineate areas with high drought risk using SPI and NDVI and compare the results from both models (Nezar et al., 2004).

2.5 Ground based and Satellite-derived Drought Indices

Drought monitoring mechanism exists in most of the countries based on ground based information on drought related parameters such as rainfall and weather, crop condition and water availability, etc. There are several indices that measure how much precipitation for a given period of time has deviated from historically established norms. Agricultural and hydrological indices are also widely used in addition to meteorological index. Meteorological and hydrological drought indices include Standardized

Precipitation Index (SPI). Palmer Drought Severity Index (PDSI) and Surface Water Supply Index (SWSI), respectively. Whereas agricultural drought indices include Crop Moisture Index (CMI), Grassland Curing Index and Grazing Potential and Rangeland Suitability Model. However, these ground based drought indicators have major drawbacks of lack of spatial details as well as they are dependent on data collected at ground stations which sometimes are sparsely distributed affecting the reliability of the drought indices. (Brown and Reed *et al*., 2002).

Earth observations from satellite are highly complementary to those collected by *in-situ* systems. Satellites are necessary for the provision of synoptic, wide-area coverage and frequent information required for spatial monitoring of drought conditions. The present state of remotely sensed data for drought monitoring and early warning is based on rainfall, surface wetness, temperature and vegetation monitoring. (NDVI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) are some of the extensively used vegetation indices.

2.5.1 Satellite-derived Drought Indices

2.5.1.1 The Convenience of NDVI for Drought-Risk Assessment

The vegetation condition reflects the overall effect of rainfall, (soil moisture, weather and agricultural practices) and the satellite based monitoring of vegetation plays an important role in drought monitoring and early warning.

When drought exists, due to notable reduction of the rainfall, the capacity of vegetation to carry out the photosynthesis is reduced. This occurrence is demonstrated by the spectral response to the EMR falling up on them. Thus, the response of the green vegetation (in a good physiological and healthy state) is characterized by a substantial absorption in the red region and a large reflection in the infrared region in the electromagnetic spectrum. Unhealthy, aged or stressed vegetation increase its reflection in the red region of the spectrum and decrease in the infrared region of the spectrum.

NDVI was first suggested by (Tucker, 1979) as an index of vegetation health and density (Sharma, 2006). The NDVI is currently the only operational, global-based vegetation index utilized. This is in part, due to its 'rationing' properties, which enable the NDVI to cancel out a large proportion of signal variations attributed to calibration, noise, and changing irradiance conditions that accompany changing sun angles, topography, clouds/shadow and atmospheric conditions (Jeyaseelan, 2003). NDVI for a given season can serve as an indicator of drought severity by inferring deficiencies in photosynthetic capacity in drought years as contrasted with other years (Wilhite, 1993). It is related to the Photo- Synthetically absorbed radiation by examining the ratio of reflected infrared to red wave length and is an excellent measure of vegetation health. Healthy plants have high NDVI value because of their high reflectance of infrared light, and relatively low reflectance of red light.

$$\mathbf{NDVI = (NIR-RED) / (NIR+RED)}$$

Where, NIR and RED are the reflectance in the near infrared and red bands of the EMR. 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 (Roy *et al*., 2003).

However, NDVI uses only two bands and is not very sensitive to the influences of soil background reflectance at low vegetation cover, and has a lagged response to drought because of lagged vegetation response to developing rainfall deficits due to residual moisture stored in the soil. Previous studies have shown that NDVI lags behind antecedent precipitation by up to 3 months. The lag time is dependent on whether the region is purely rain fed, fully irrigated, or partially irrigated. The lag time will be shorter in areas which are dependent up on rainfall. NDVI itself does not reflect 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 (DEVNDVI). This deviation is calculated as the difference between the NDVI for the current time step and a long-term mean NDVI for that month for each pixel (Sharma, 2006):

$$\mathbf{DEVNDVI = NDVIi - NDVI_{mean}}$$

Where, NDVIi is the NDVI value for month i (current NDVI) and $NDVI_{mean}$ is the long-term NDVI for the same month. When DEVNDVI is negative, it indicates below-normal vegetation condition/health and, therefore, suggests a prevailing drought situation. Thenkabail et al., (2002) said that 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/year. This indicator is widely used in drought studies. 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 (Thenkabail *et al*., 2002). So in low vegetation cover conditions, deviations may be less well correlated to changes in vegetation cover.

2.5.1.2. Vegetation Condition Index (VCI)

VCI is an indicator of the status of the vegetation cover as a function of minimum and maximum NDVI encountered for a given ecosystem over many years. It shows, effectively, how close the current month's NDVI is to the minimum NDVI calculated from the long-term record of Remote Sensing images. VCI enables to separate the short-term signal from the ecological signal. VCI is defined as:

$$\mathbf{VCIj} = \frac{\mathbf{(NDVIj - NDVImin)}}{\mathbf{(NDVImax - NDVI\ mean)}} * \mathbf{100}$$

Where, NDVImax and NDVImin are calculated from long-term record for a particular month and j is the index of the current month. The condition of the ground vegetation presented by VCI is measured in percent. For example the VCI values around 50% reflect fair vegetation conditions. (Sharma, 2006) indicated that the VCI values between 50 and 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. The VCI values below 50% indicate different degrees of a drought severity (Kogan, 1995 cited in Sharma, 2006) illustrated that the 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%. The VCI value close to 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 point to drought development.

These studies suggest that VCI captures rainfall dynamics better than the NDVI particularly in geographically non-homogeneous areas. Also, VCI values indicate how much the vegetation has advanced or deteriorated in response to weather. It provides better understanding of assessment of drought spatial characteristics, as well as its duration and severity in good agreement with precipitation patterns (Chopra, 2006). Areas with different values of NDVI will have similar VCI values. VCI provides accurate information not only for the cases with well defined, prolonged, widespread, and intensive droughts, but also for localized, short term and poorly defined droughts (Wilhite, 1993).

2.6 Drought Indices

Drought Indices are continuous functions of rainfall /or temperature, river discharge or other measurable variables. Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better studied than others for certain use (Amare Degefaw, 2007). There are a number of indices to track and define drought. No one definition covers all possible forms of drought and no one index can possibly capture all the various definitions. The turning point in the evaluation of drought indices is back to the 1960s, when Palmer (1965) devised PDSI. Following new technological innovations we have now many more indices available aiming at monitoring and predicting the onset, intensity, duration and spatial extent of drought.

2.6.1 Drought Indices Derived From Meteorological Data

Rainfall is an important meteorological parameter which influences the type of vegetation in a region. Drought indices 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 long-term rainfall records are often available. Rainfall data alone may not reflect the spectrum of drought-related conditions, but they can serve as a pragmatic solution in data poor regions. Meteorological data based indices include Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI) and Standardized Precipitation Index (SPI).The simplest drought index is the deviation from a normal precipitation, which is called rainfall anomaly (Dunkel *et al.,* 2005, Cited in Birhanu Gedif, 2009).

Meteorological stations provide weather information on daily basis or several times a day for environmental monitoring purpose, including drought watch. But, they are not sufficient to characterize regional drought. Its weather parameters are physical in nature and are not sufficient to characterize agricultural drought and its impact on vegetation (Wilhite, 1993). These types of data are used to calibrate the drought situation result from satellite image based drought delineation. Observations from satellite images provide more timely information and better spatial coverage.

2.6.2 Drought Indices derived from Remote Sensing data

Utility of remote sensing data in drought assessment has long been proven. It is far superior to conventional methods at an optimal spatial extent. Remote Sensing technology in its current state of art can help in predicting, mitigating and monitoring of drought. Data from various satellites can be utilized for this purpose irrespective of the perspective that a researcher has towards drought, whether it is agricultural, meteorological or hydrological. It enables to understand the manifestations of drought in a larger area more directly than through conventional methods, and of all, in less time consuming manner (Sharma, 2006). The drought prone area or risk zone identification is usually carried out on the basis of historic data analysis of rainfall or rainfall and evapotranspiration and the area of irrigation support. The conventional methods lack identification of spatial variation and does not cover man's influence on land-use changes.

Remote Sensing based method for identification of drought prone-areas uses historical vegetation index data derived from satellite images. It provides spatial information on drought-prone areas depending on the trend in vegetation development and frequency of development (Jeyaseelan, 2003). Drought indicators calculated from satellite-derived surface parameters have been widely used to study droughts. (NDVI) and (VCI) are of extensively used vegetation indices.

2.6.3 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is a way of measuring drought that is different from the Palmer drought index (PDI). Like the PDI, this index is negative for drought, and positive for wet conditions. But SPI is a probability index that considers only precipitation, while Palmer's indices are water balance indices that consider water supply (precipitation), demand (evapotranspiration) and loss (runoff).

The wide variety of disciplines affected by drought, its diverse geographical and temporal distribution, and the many scales drought operates on make it difficult to develop both a definition to describe drought and an index to measure it. Many quantitative measures of drought have been developed in the United States, depending on its effects, the region being considered, and the particular application. Several indices developed by Palmer, as well as the (SPI), are useful for describing the many scales of drought (NOAA Satellite and Information Service, 2008).

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" (Amare Degefaw, 2007). The classification of SPI Value is illustrated in Table 2.2

Table 2.2: Standardized Precipitation Index values

SPI Values	
2.0+	Extremely wet
1.5 to l.99	Very wet
1.0 to 1.49	Moderately wet
-.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1,5 to -1.99	Severely dry
-2 and less	Extremely dry

Source: (Chopra, 2006)

SPI was developed in Colorado by McKee *et al.,* (1993) cited in Chopra, (2006) to quantify the precipitation scarcity for multiple time scales which reflect the impact of drought on the availability of different water resources. SPI is considered as the most simple and recent drought index as it only requires rainfall data (Nezar *et al.,* 2004).

2.6.4 Palmer Drought Severity Index (PDSI)

In 1965, Palmer developed an index to "measure the departure of the moisture supply" (Palmer, 1965). Palmer based his index on the supply and demand concept of the water balance equation, taking into account more than only the precipitation deficit at specific locations. The objective of the Palmer Drought Severity Index (PDSI), as this index is now called, was to provide a measurement of moisture conditions that were "standardized" so that comparisons using the index could be made between locations and between months (Palmer, 1965).

The PDSI is a "meteorological" drought index and responds to weather conditions that have been abnormally dry or abnormally wet. When conditions change from dry to normal or wet, for example, the drought measured by the PDSI ends without taking into account stream flow, lake and reservoir levels, and other longer-term hydrologic impacts (Karl and Knight, 1985). The PDSI is calculated based on precipitation and temperature data, as well as the local Available Water Content (AWC) of the soil. From the inputs, all the basic terms of the water balance equation can be determined, including evapotranspiration, soil recharge, runoff, and moisture loss from the surface layer. Human impacts on the water balance, such as irrigation, are not considered. Complete descriptions of the equations can be found in the original study by Palmer (1965) and in the more recent analysis by Alley, (1984).

The Palmer Index varies roughly between -6.0 and +6.0. Palmer arbitrarily selected the classification scale of moisture conditions based on his original study areas in central Lowa and western Kansas (Palmer, 1965). Ideally, the Palmer Index is designed so that a -4.0 in South Carolina has the same meaning in terms of the moisture departure from a climatologically normal as a -4.0 in Idaho (Alley, 1984). The Palmer Index has typically been calculated on a monthly basis, and a long-term archive of the monthly PDSI values for every Climate Division in the United States exists with the National Climatic Data Center from 1895 through the present.

The advantage of the Palmer Index is that it is standardized to local climate, so it can be applied to any part of the country to demonstrate relative drought or rainfall conditions. The disadvantage is that it is not good for short term forecasts, and is not particularly useful in calculating supplies of water locked up in snow, so it works best east of the Continental Divide. Palmer classification is illustrated in Table 2.3

Table 2.3: Palmer Classification

Palmer Classification	
4.0 or more	Extremely wet
3.0 to 3.99	very wet
2.0 to 2.99	moderately wet
1.0 to ,1.99	slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to -0.49	near normal
-0.5 to -0.99	incipient dry spell
-1.0 to -1.99	mild drought
-2.0 to -2.99	moderate drought
-3.0 to -3.99	severe drought
4.0 or less	extreme drought

2.6.5 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 *et al*., 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. Nemani, et al. (1992) (Cited in Chopra, 2006) 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 favorable moisture conditions over a particularly wet or dry month even in the middle of a serious long-term wet or dry period.

2.6.6 Surface Water Supply Index (SWSI; pronounced "swage")

According to (Shafer and Dezman, 1982 cited in Enatagegnehu Tarekegn, 2008) SWSI was to complement the Palmer Index for moisture conditions across the state of Colorado. The Palmer Index is basically a soil moisture algorithm calibrated for relatively homogeneous regions, but it is not designed for large topographic variations across a region and it does not account for snow accumulation and subsequent runoff. Shafer and Dezman, (1982) designed the SWSI to be an indicator of surface water conditions and described the index as "mountain water dependent", in which mountain snowpack is a major component.

The objective of the SWSI was to incorporate both hydrological and climatological features into a single index value resembling the Palmer Index for each major river basin in the state of Colorado (Shafer and Dezman, 1982). These values would be standardized to allow comparisons between basins. Four inputs are required within the SWSI: snowpack, stream flow, precipitation, and reservoir storage. Because it is dependent on the season, the SWSI is computed with only snowpack, precipitation, and reservoir storage in the winter. During the summer months, stream flow replaces snowpack as a component within the SWSI equation.

2.6.7 Deciles

A simple meteorological index is the rainfall deciles, in which the precipitation totals for the preceding three months are ranked against climatologic records. If the sum falls within the lowest decile of the historical distribution of 3-month totals, then the region is considered to be under drought conditions (Kininmonth *et al*., 2000). The drought ends when: (i) the precipitation measured during the past month already places the 3-month total in or above the fourth decile, or (ii) the precipitation total for the past three months is in or above the eighth decile.

The first decile is the precipitation amount not exceeded by the lowest 10% of the precipitation occurrences. The second decile is the precipitation amount not exceeded by the lowest 20% of occurrences. These deciles continue until the rainfall amount identified by the tenth decile is the largest precipitation amount within the long-term record. By definition, the fifth decile is the median, and it is the precipitation amount not exceeded by 50% of the occurrences over the period of record. The deciles are grouped into five classifications.

. Table 2.4 presents the classification of drought conditions according to deciles.

Decile Classifications	
Deciles 1-2: lowest 20%	Much below normal
Deciles 3-4 : next lowest 20%	Below normal
Deciles 5-6: middle 20%	Near normal
Deciles7-8: next highest 20%	Above normal
Deciles 9-10: highest 20%	Much above normal

Source: h ttp://drought.unt.edu/whatis/indices.htm,March 2010

The advantage of the decile approach is its computational ease, but its simplicity can lead to conceptual difficulties. For example, it is reasonable for a drought to terminate when observed rainfall is close to or above normal conditions. But minor amounts of precipitation during periods in which little or no precipitation usually falls, can activate the first stopping rule, even though the amount of precipitation is trivial and does not terminate the water deficit. A supplemental third rule, that considers the total precipitation since the beginning of drought, may be used (Keyantash and Dracup, 2002). According to this rule, if the total precipitation exceeds the first decile for all drought months, then the meteorological drought may be considered terminated.

2.7 Relationship between NDVI and SPI

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 (infrared reflectance (IR)-red reflectance (R)/ (IR+R) and rainfall (Li *et al.,* 2002). Many studies have focused on the relationship between the NDVI and rainfall.

The study focused on three major areas namely relationship between NDVI and SPI at different time scales, response of NDVI to SPI during different time periods within a growing season and regional characteristics of the NDVI-SPI relationship. The relationship between vegetation and moisture availability was clarified by analyzing the covariance of NDVI and SPI time series with the scatter plots and Pearson correlation analysis. It was found that NDVI response is not sufficiently sensitive to 1 or 2 month SPI and the scales longer than 6 months tend to reduce the co-variation of SPI and vegetation vigor. It was fond that the 3-month SPI has the highest correlation to the NDVI, because the 3-month SPI is best for determining drought severity and duration. Also it was found that seasonality has a very significant effect on the relationship between the NDVI and SPI.

A study was carried out by Chaudhari and Dadhwal (2004) to quantify the impact of drought on production of Kharif and Rabi crops using SPI. SPI were computed at monthly (SPI 1), bimonthly (SPI 2) and tri-monthly (SPI 3) time scales with the suggested Pearson type III distribution. SPI values were then classified into seven categories suggested by Hayes et al., (1999). Correlation coefficients were computed between state-wise production of major Kharif crops (1980-2001) and SPI values (SPI1, SPI2 and SPI3). Production forecasts using SPI3 showed good agreement with the statistics from state department of agriculture, thereby suggesting that SPI at different time scales can be used as a predicator of regional crop production in India.

3. MATERIALS AND METHODS

3.1 Description of Study Area

Southern administration zone is in Tigray National Regional State and it is located 660km north of Addis Ababa and 120 km south of Mekele. It is geographically located 12° 15'and 13° 41' north latitude and 38° 59'and 39° 54'east longitude, constituting an area of 9446km^2. It shares common border with eastern Tigray zone in the north, Amhara regional state from the south and west, Afar Regional state from the east. The study area has a total population of 1,004,558 and rural population of 879,745 and composed of eight Woredas (CSA, 2007).

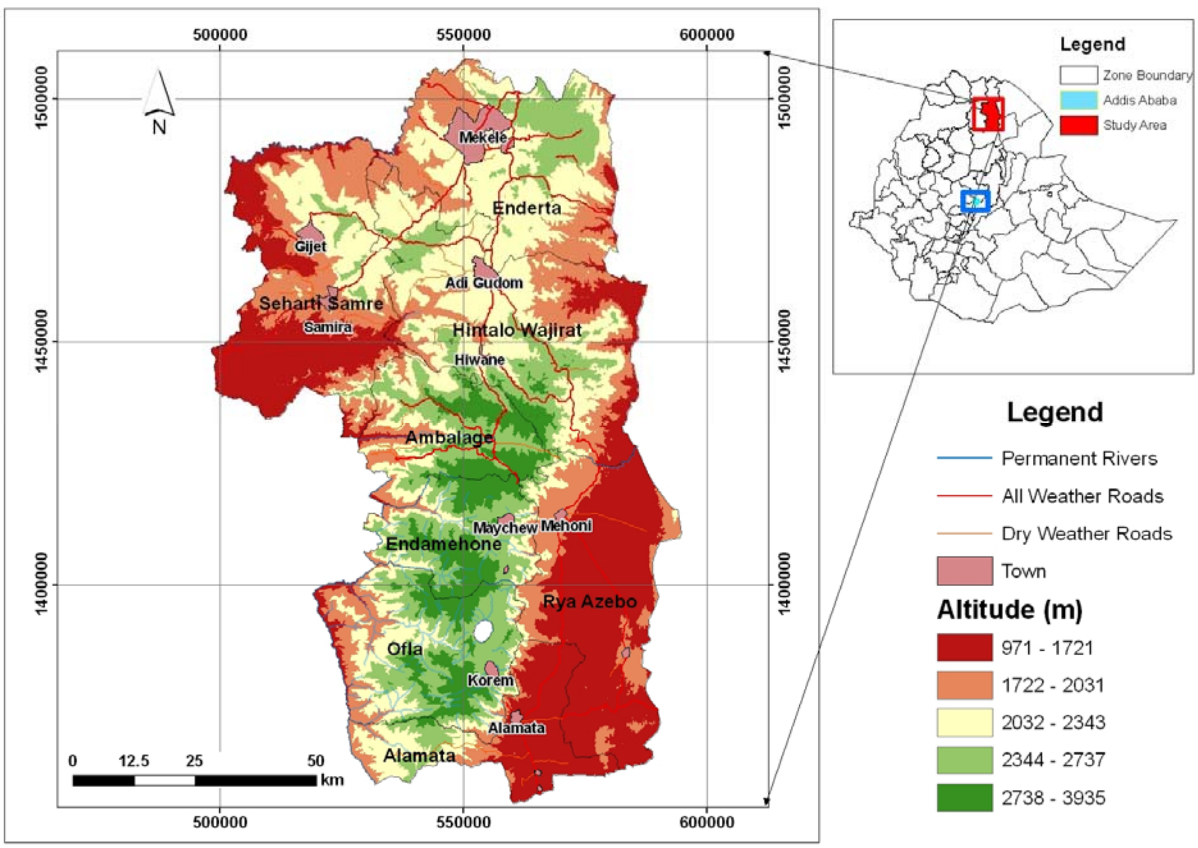

Figure 3-1: Study area Map

3.1.1 Major Economic Activities

Crop production in the study area is cereal dominated. Cereals account for 84 per cent of the cultivated land, while oil crops and pulses constitute 9 and 7 per cent, respectively

(BoARD, 2000). A review of the area under different crops for the past 5-6 years shows that sorghum, barley and teff are the three most import cereal crops in the study area, in terms of area coverage. Like in other parts of the region, the farming techniques used by most farmers are traditional and the dominant farming system is crop-livestock mixed farming. Livestock also constitute an important part of the rural economy of the region, the zone as well as the Woredas of the study area.

3 .1.2 Topography

Centuries of erosion, deforestation and overgrazing have left the southern Zone with dry and treeless plains, hills and plateau. Nevertheless, the Zone has an amazing landscape of chains of mountains ranging from 2,737-3,935 meters altitude. Mount Amba Alagi, which is the highest peaks of the Wajirat Mountains also found in this Zone.

3.1.3 Climate

The climatic variables of the Study are highly governed by the topography of the area (mainly altitude). Mean annual temperature of this part of the area ranges from 12.5^{o} to 25^{o}. The highest mean monthly wind velocity of Raya Valley as estimated from the average of Maichew and Kobo stations is about 227km/day in the month of July and a minimum of 118km/day in December. The average monthly relative humidity as observed at Mehoni and Maichew stations ranges from a minimum of 44 % in June to a maximum of 68% in August.

3.1.4 Rainfall

The area is characterized by a bimodal rainfall pattern with a short rainy season “Belg” from February to March and a long rainy season “Kiremt” from June to September with a peak in August. The spatial distribution of rainfall is mainly governed by variation in altitude accordingly there are three distinct areas with significant variation in the annual total rainfall. The annual average rainfall of these areas (highland, midland and lowland) ranges from 700 mm to 1000 mm 400 mm to 900 and 650 mm to 750 mm, respectively. The rainfall pattern in the area is relatively erratic and unpredictable. The climatic variables of the study area are presented in Figure 3.2

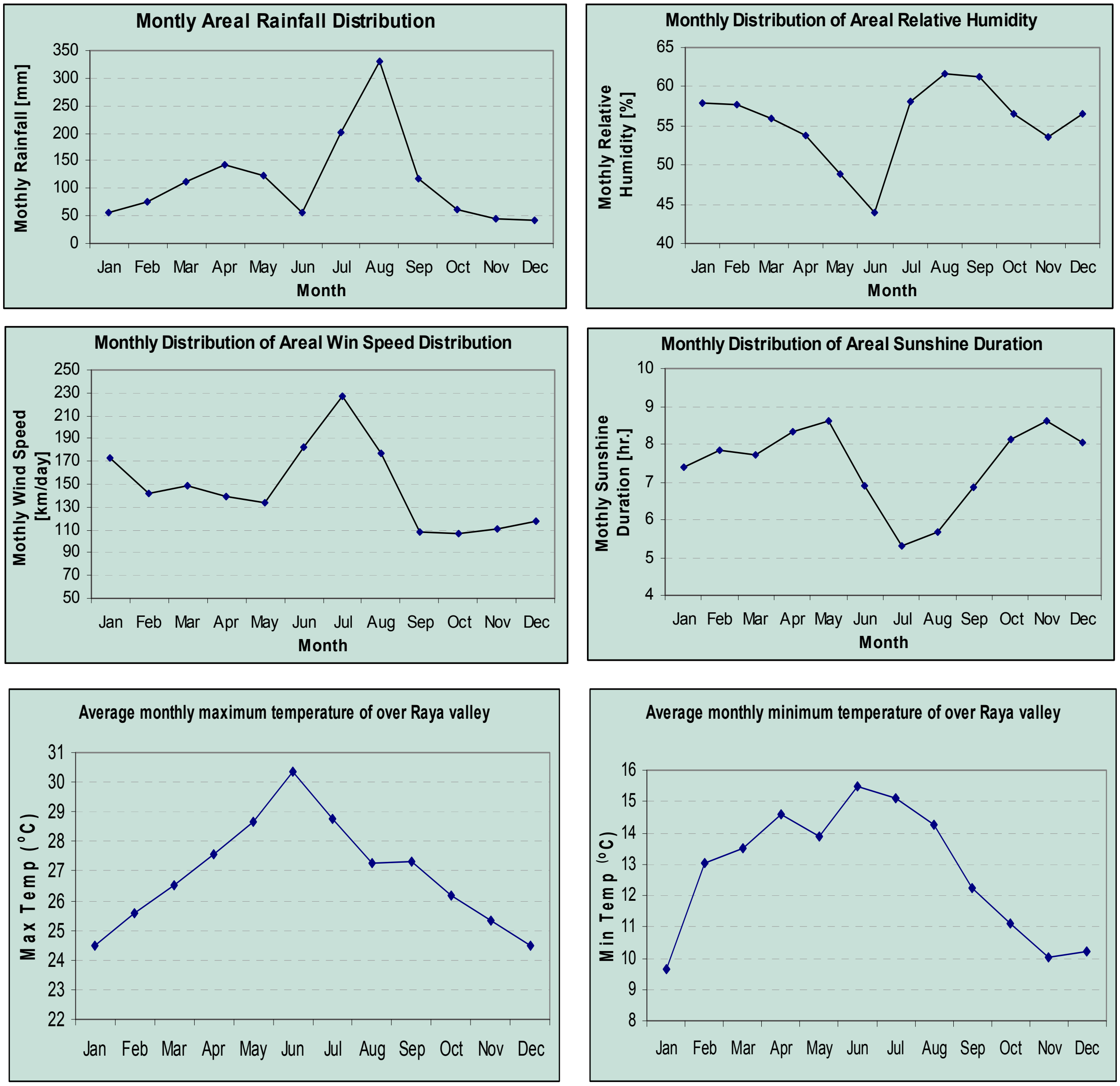

Figure 3.2: Climatic Variables of the Study Area

3.1.5 Lakes

Lake Hashenge, which is found in the Zone, is an interesting area for observing birds and for fishing.

3.1.6 Livestock

The State claims to have about 1,387,888 domestic animals of which 621,481 are cattle, 460,350 are sheep and goats,365,832 are hen and 77,139 are pack animals.

Source: http://www.ethiopar.net/type/English/basinfo/regninfo.htm

3.2. Data Acquisition

3.2.1 SPOT Vegetation data

SPOT Vegetation NDVI products have also been downloaded for the continent Africa (1998-2005) and southern zone NDVI values are extracted out. The vegetation data contains all products, including high level products, derived from the vegetation instrument on board the SPOT satellite. The vegetation 10-day synthesis archive is freely accessible through the website of the vegetation programme directly via the free S10 distribution server: http://free.vgt.vito.be. The vegetation instrument is dedicated to the daily observation of terrestrial ecosystems and the biosphere, particularly for addressing global change and environmental issues. The vegetation instrument observes the whole earth every day because of its large field of view, and is an essential tool for studies on global vegetation. Ten-day composite data were constructed by selecting pixels with the maximum NDVI during the period. Selecting pixels with the maximum NDVI reduces cloud cover and water vapour effects that strongly reduce NDVI. There are three 10-day composite per month in this data set, from the first of the month to the 10, from the 11th to 20th, and from 21 to the end of the month. The last compositing period can vary from 8-11 days, depending upon the number of days in the month. The image projection is Albers Equal Area Conic.

VGT-S10 products (ten day synthesis) are compiled by merging segments acquired in ten days. All the segments of this period are compared again pixel by pixel to pick out the best reflectance values aggregated in a dekadal basis, 36 dekadal images were stacked together for a single year. In order to obtain actual NDVI values each dekadal layer should be rescaled by multiplying raw data with 0.004 and subtract 0.1, i.e., (**Value*0.004) -0.1.**

- NDVI time series between April 1998 and December 2005 (3 composites per a month,

36 layers per year, except for 1998, with 1km resolution) is collected from *http://free.vgt.vito.be* web site

A dekade is one third of a month. These are:

- Dekad-1: The first 1-10 days in the month.
- Dekad-2: 11-20 days
- Dekad-3: 21-days to end of the Months.

The dekadal data were combined into monthly, seasonal and yearly totals. The images have a geometrical resolution of 1km by 1km and serve as inputs into the modeler.

The image inputs rescaled to get corrected NDVI values ranging from -1 to +1 by using the following formula from the ERDAS' modeler maker icon.

(**Image*0.004)-0.1** (Eq. 3.1)

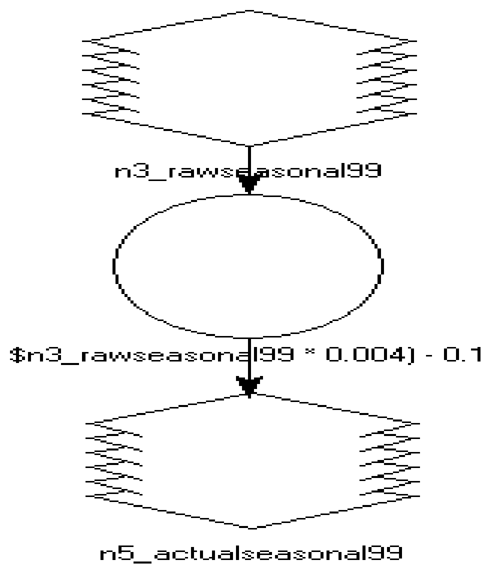

Figure 3.3: Modeler for corrected SPOT NDVI Value

3.2.2 Rainfall Data Acquisition

3.2.2.1 Satellite Rainfall Data

Eight years rainfall satellite data (1998-2005) were acquired from an organization called Famine Early Warning Systems Network ("FEWS NET") .The data were extracted using WINDISP 5.1 software, developed by FAO, ARCVIEW 3.2a.

The outputs of extracted data were dekadal composite that covered the whole Woredas of Ethiopia. Out of this the 8 Woreda's data of the study area were selected and used for this purposes. The rainfall satellite data were used as an alternative substation of weather station data due to missing of functional weather station in the study areas.

3.2.3. Ancillary data

3.2.3.1. Land-cover map

A generalized land cover map of the study area was prepared. It was extracted from the land cover map of the zone. The generalized land-cover map presents quite a large number of different land cover types: lakes, open forest, shrub, shrub with cactus, small holding Agricultural Field and Urban area, Artificial Lake, Open Forest, and Swampy Areas. It is being used to extract cultivated areas of the southern zone which is the main concern in computing the NDVI values.

Figure 3.4 shows a generalized land-cover map of the Study Area. It is reclassified in to eight, dominantly Small holdings Agricultural Field 57.6%, moderately Shrub 23.9%, Shrub with Cactus 15.6% and the remaining 2.9% are (Artificial Lake, Hashenge Lake, Open Forest and Swamp Areas).

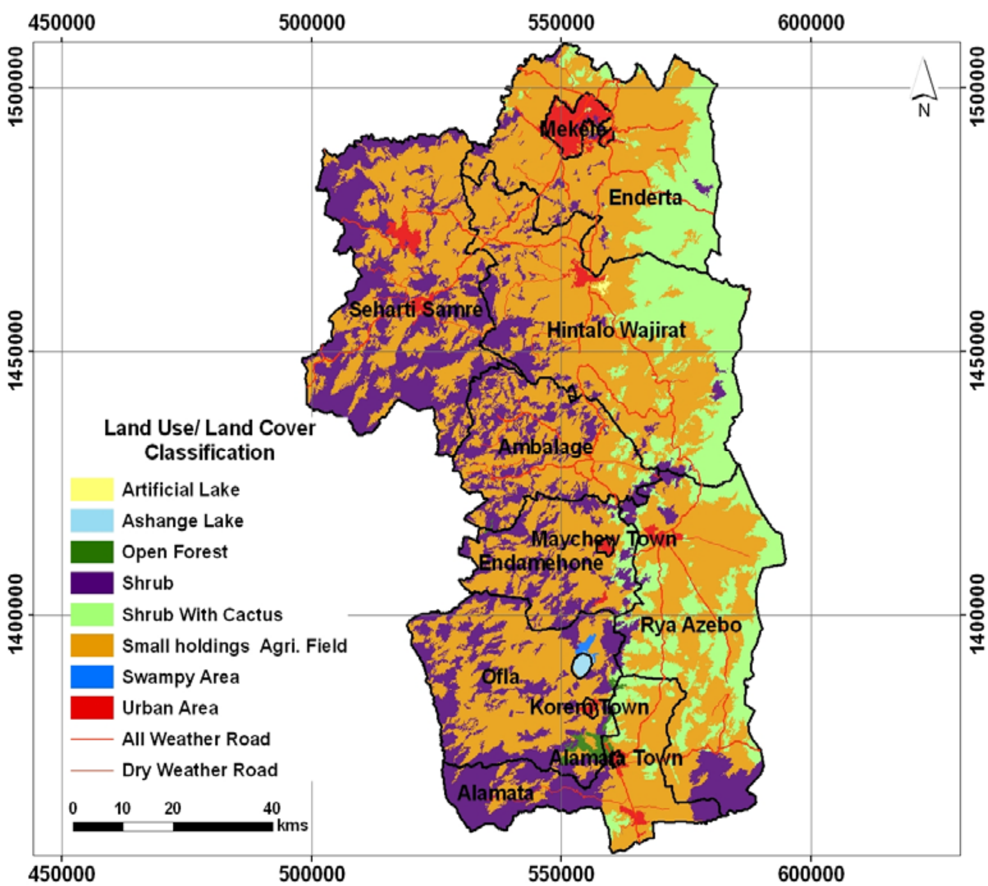

Figure 3.4: Land-Use/Land-Cover Map

3.2.4 Meteorological Data

Apart from the agricultural production yield data, rainfall data were collected from 11 stations which are distributed unevenlyin the zone. The data source is the Ethiopian Meteorological Service Agency (EMSA).

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

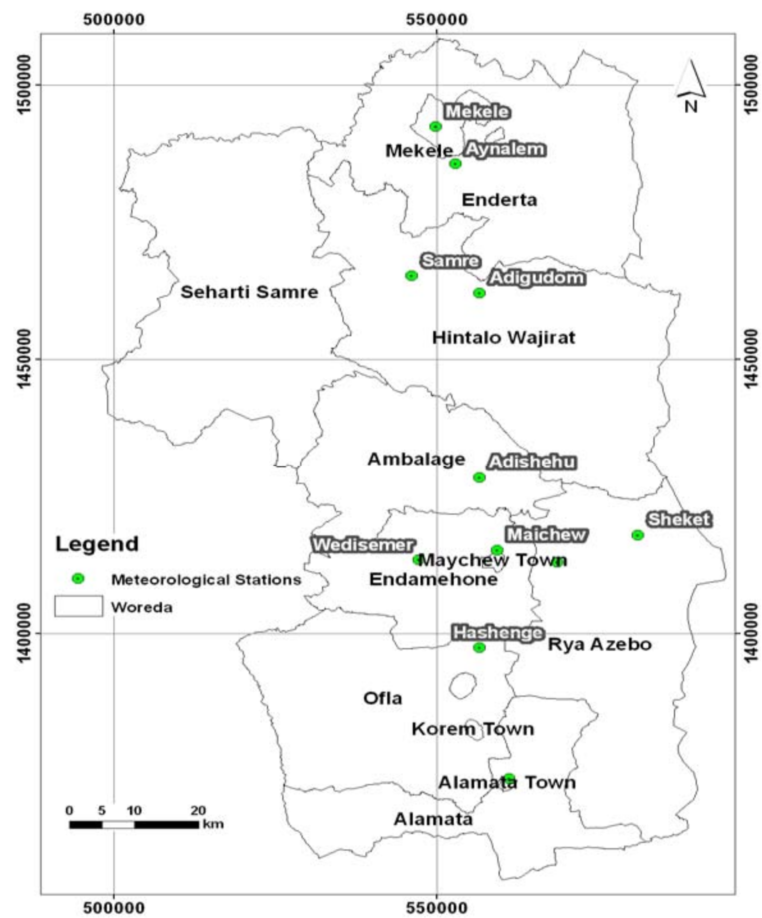

Figure 3.5: meteorological stations

3.3 Methods

Data were collected from different sources to achieve the indicated objectives. All are analyzed and interpreted in the ERDAS 9.1, ARC VIEW 3.2a, ArcGIS 9.2 and IDRISI environment.

SPOT-4 and rainfall dekadal data are aggregated in to monthly basis for seasonal drought map generation. Rainfall data (mean seasonal), land-use/land-cover from LAND SAT Images and southern zone shape file (CSA); finally the drought layers were weighted and overlaid for generating Drought severity class map.

The following diagram shows the overview of methods which are applied in this study.

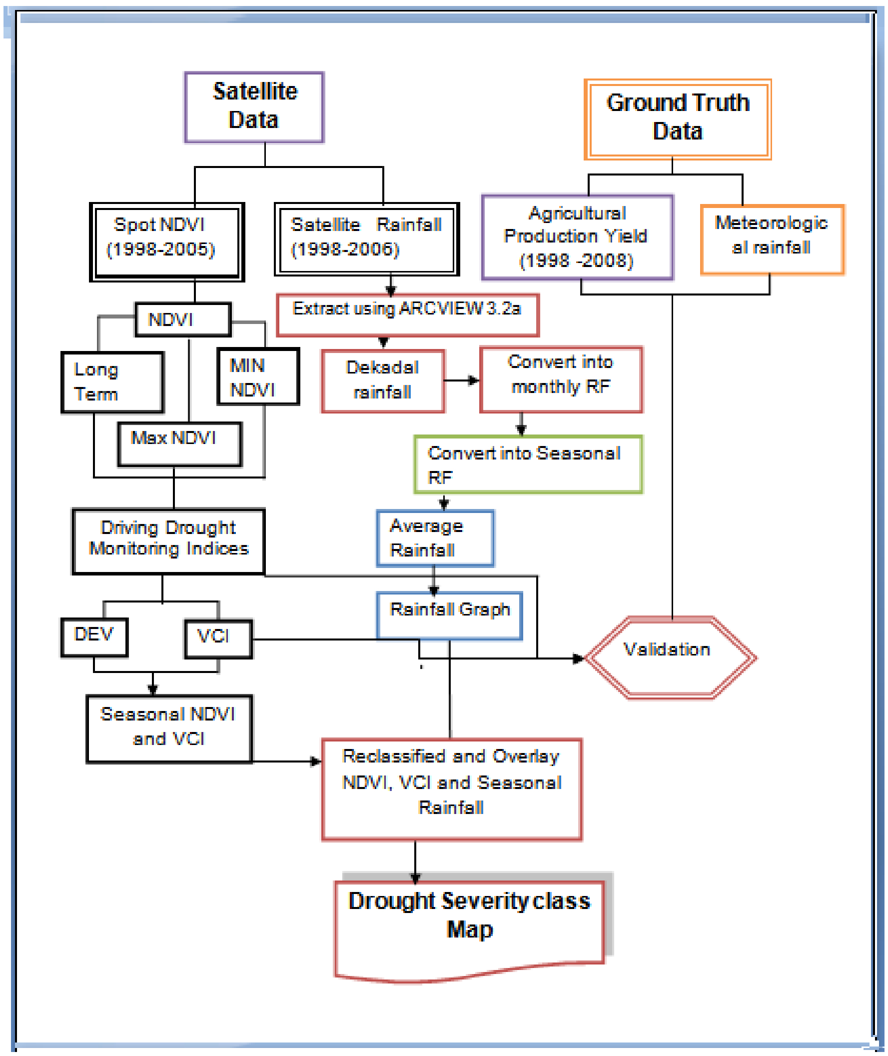

Figure 3.6: Conceptual work flows.

4 DROUGHT INDEX GENERATION PARAMETERS

4.1. Drought Detection

The development of a near real-time drought monitoring system integrates satellite-based Vegetation condition variables (NDVI) and climate-based drought variables and index. A drought variable can be defined as a prime variable responsible for drought effects, therefore it must be considered as a key element in detecting and monitoring activities. The determinant variable for the meteorological drought is precipitation, whereas for agricultural drought the governing variables are soil moisture and several measures of vegetation conditions and growth. Drought indicators are variables used to describe the beginning, magnitude, duration, severity, and the spatial extent of drought events. Commonly used indicators are based on meteorological, hydrological and agricultural variables. Finally, drought triggers are threshold values of an indicator that allow to detect a drought event and its level. Drought levels are categories of drought, with nomenclature such as "mild, moderate, severe, extreme drought" (Birhanu Gedif, 2009).

The drought detection and monitoring systems allow mainly delivering maps that show the areas where the vegetation is subject to water stress or affected by drought. This gives information about the crop condition of an area. Therefore, in areas where agriculture is the main activity of the population, cyclic drought prevalence determines their food security. The agriculture of South Tigray zone in particular and the country in general is very important for food self-sufficiency, and food production is highly dependent on drought or rains.

For this study, indices for drought monitoring are derived from SPOT NDVI raw data from SPOT 4 VEGETATION System and Rainfall Data. The vegetation systems observe the Earth at a resolution of 1km, with a swath width of nearly 2250km. This gives almost daily access to any point on the earth surface. These characteristics suit the observation and study of seasonal evolutions in the biosphere and its processes. The indices from SPOT-4 NDVI image were measures of vegetation condition by exploiting the unique spectral signatures of canopy elements in the RED and NIR portions of the spectrum (CNES) (*http://sirius-ci.cst.cnes.fr:8080/).*

A SPOT Vegetation NDVI product has been collected for East Africa (1998-2005) and the Southern zone NDVI data was extracted out. The vegetation 10-day synthesis (S10) archive was freely accessible through the website of the vegetation programme directly via the free S10 distribution server (http://free.vgt.vito.be), which was not directly compatible with ERDAS and ArcGIS. The vegetation instrument dedicated to the daily observation of terrestrial ecosystems and the biosphere, particularly for addressing global change and environmental issues. There are three 10-day composite per month in this data set, from the first of the month to the 10th, from the 11th to the20th, and from the 21st to the end of the month. The last compositing period can vary from 8-11 days, depending upon the number of days in the month.

NDVI were calculated from two bands, the near-infrared (NIR) and RED wavelengths, using the following algorithm:

NDVI = (NIR - RED) / (NIR + RED)

Where, **NIR** and **RED** is the reflectance in the near infra-red and red bands, respectively. NDVI is a nonlinear function that ranges between -1 and +1. However, in practice, NDVI measurements generally range between -0.1 and +0.7. Cloud, water, snow, ice and non-vegetated surfaces have negative NDVI values. Bare soils and other background materials produce NDVI values ranging from -0.1 to +0.1. The NDVI values for vegetation are positive and range from 0.1 to 0.7, with low values indicating poor vegetation conditions and possibly unfavorable weather impacts, with values greater than 0.5 indicating healthy vegetation conditions. Lower NDVI values are indicators of prevalence of drought condition (Prathumchai *et al.,* 2001).

Table 4.1 Remote sensing data, indices and thresholds relevant to drought assessment use in the study

Drought index	Band or index used to compute the index SPOT	Range	Normal	Severe drought	Healthy vegetation
1. Normalized difference vegetation index (NDVI	Band 1 (0.58-0.68μm) Band 2 (0.73-1.10μm)	-1 to +1	Depends on the location	-1	1
2. Drought severity index (DEV_{NDVI})	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	0 to 100 %	50%	0%	100%

4.1.1. Driving Agricultural drought

A Normalized Difference Vegetation Index (NDVI)

NDVI has been tested by various scientists on its ability to predict drought and serve as a proxy to rainfall data. It has been used to detect drought in various parts of the world in the recent decade (Gurusamy, 2006). There are two characteristics of NDVI that make it ideal for vegetation monitoring.

1. No other surface exhibits higher NDVI values than healthy vegetated surfaces and
2. When vegetation vigor changes due to the nature of vegetation growth and development or environmental induced stress such as drought, the NDVI also changes.

Therefore, the NDVI does have paramount potential in drought detection (Beyene, 2007). Researchers indicated that NDVI has a three months lagged response to drought. However, it has a shorter lag time in areas where there is greater dependence on rain-fed agriculture. The complete analysis of NDVI for drought detection requires the identification of length of growing period (LGP), which includes start of apparent growing season, peak of the growing season (where the maximum NDVI value is observed) and harvesting period (where the NDVI value starts to decrease). In the summer season care should be taken whether there is flood during the growing season in the study area or not. The NDVI value in flooded areas is usually lower than the normal. This could not be taken as an indicator of drought prevalence.

The raw data from SPOT VEGITATION system should be rescaled to +1 and -1. The raw data is digital number for a pixel plus certain coefficients and ranges from 0 to 255. The relation between the digital numbers and the real NDVI is expressed as:

Actual NDVI = Coefficient **a***Digital Number plus coefficient **b**.

= **a***DN + **b**

Coefficient **a** = 0.004

Coefficient **b** = -0.1

Therefore the actual NDVI can be calculated from the raw data as:

(Raw data pixel Value*0.004) - 0.1

Since the impact of drought on crop production is important for this study, seasonal NDVI maps for eight years were generated from the raw data. The length of growing season in the study area ranges between May to September. The long term seasonal average also calculated in a similar manner. To derive seasonal NDVI images the dekadal images were stacked for months of growing period and then their average was taken.

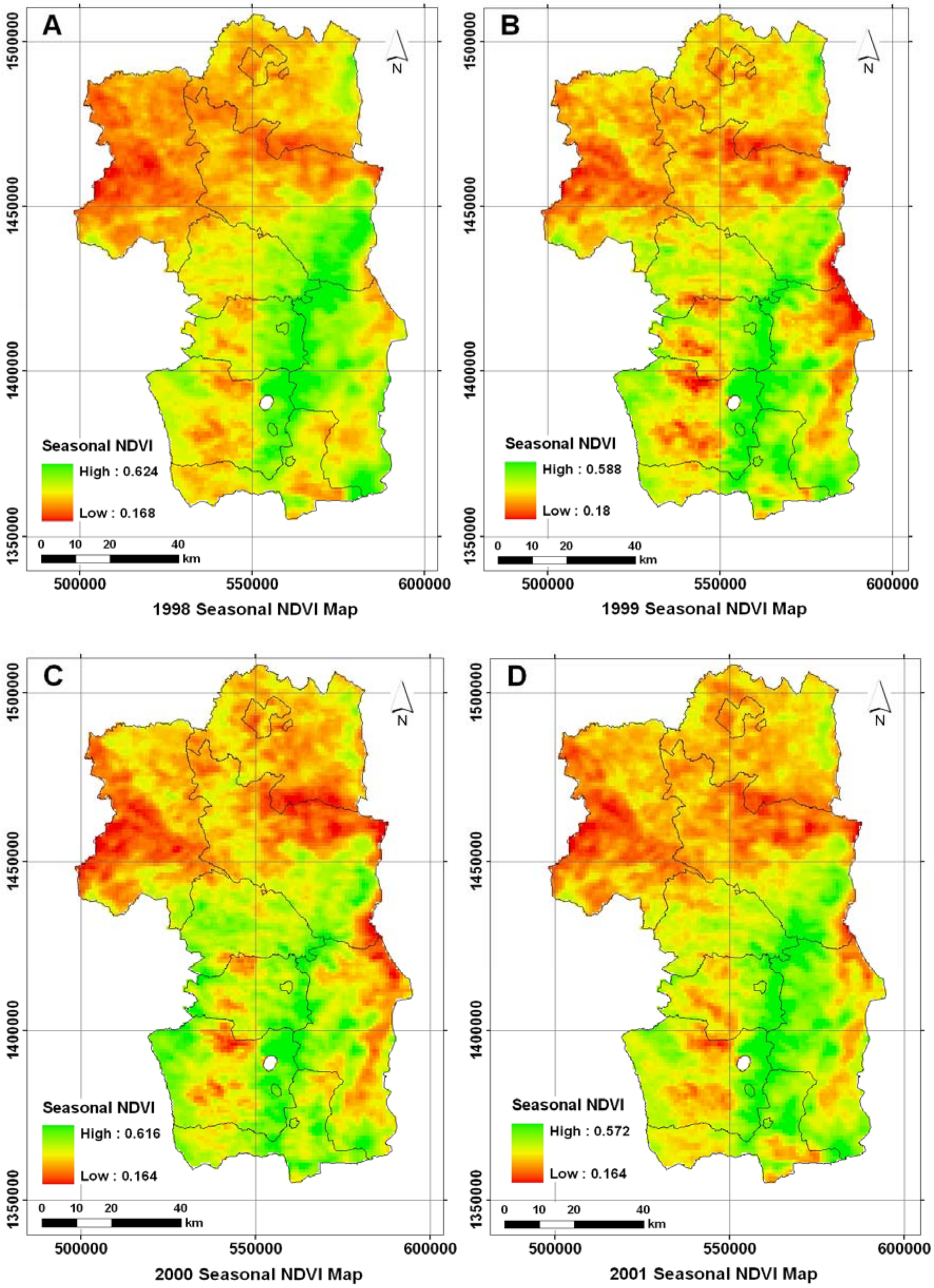

Figure 4.1: Drought map for the southern zone Seasonal (May-September) NDVI (A, B, C, D,)

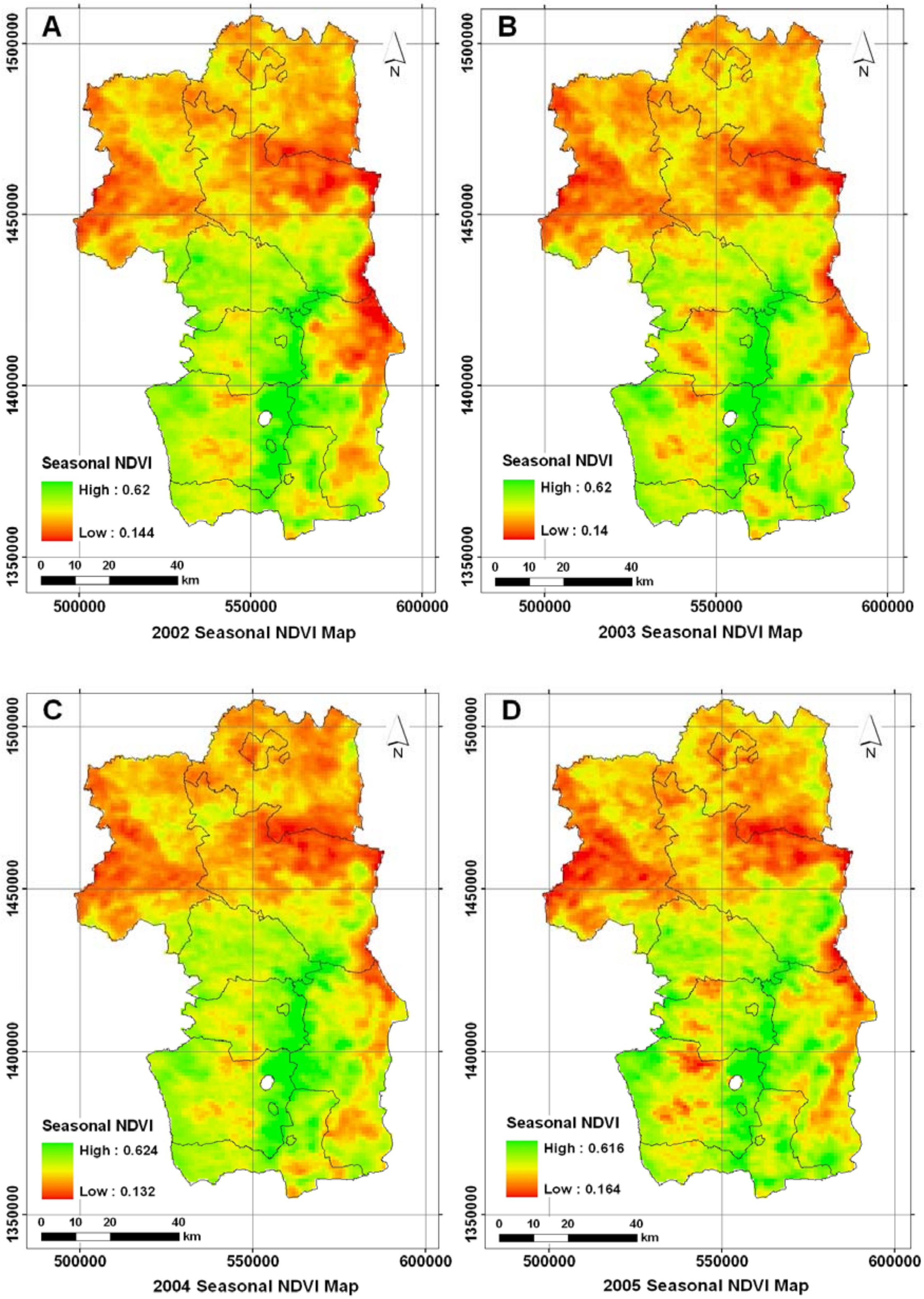

Figure 4.2: Drought map for the southern zone Seasonal (May-September) NDVI (A, B, C, D)

B. NDVI deviation

NDVI by itself does not reflect the severity and level of drought. The severity of drought can 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).

DEVNDVI = NDVIi - NDVI mean, i

Where, **NDVIi** is the current NDVI for month ***i*** and **NDVImean**, ***i*** is the long term mean NDVI for a calendar month, ***i***. When **DEVNDVI** 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 is. In general, the departure from the long-term mean can be used effectively as one of the drought indicators as it would reflect the conditions of healthy vegetation in normal and wet years (Thenkabail 2004).

Table 4.2: Drought severity class

SEVERITY	DEVIATION
Extreme drought	<-0.25
Severe drought	-0.1 to -0.25
Moderate drought	0.1 to -0.1
Mild drought	0.1 to 0.25
No drought	>0.25

Source: *(Song, 2004)*

NDVI deviation is produced for each month and months with low NDVI deviation values were taken for the purpose of comparison in Figure 4.3

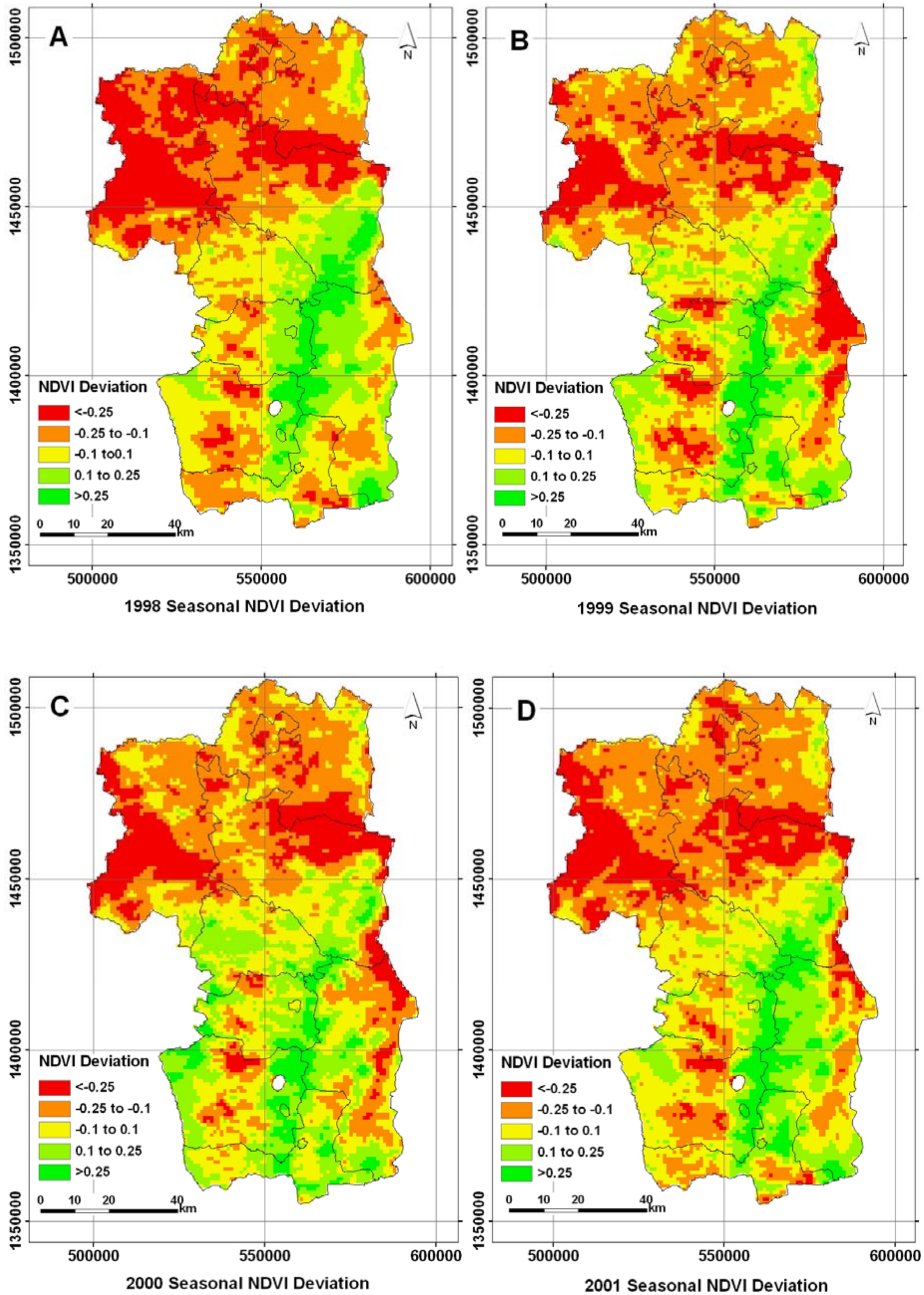

Figure 4.3: The NDVI deviation map for the Southern Zone (A, B, C, D)

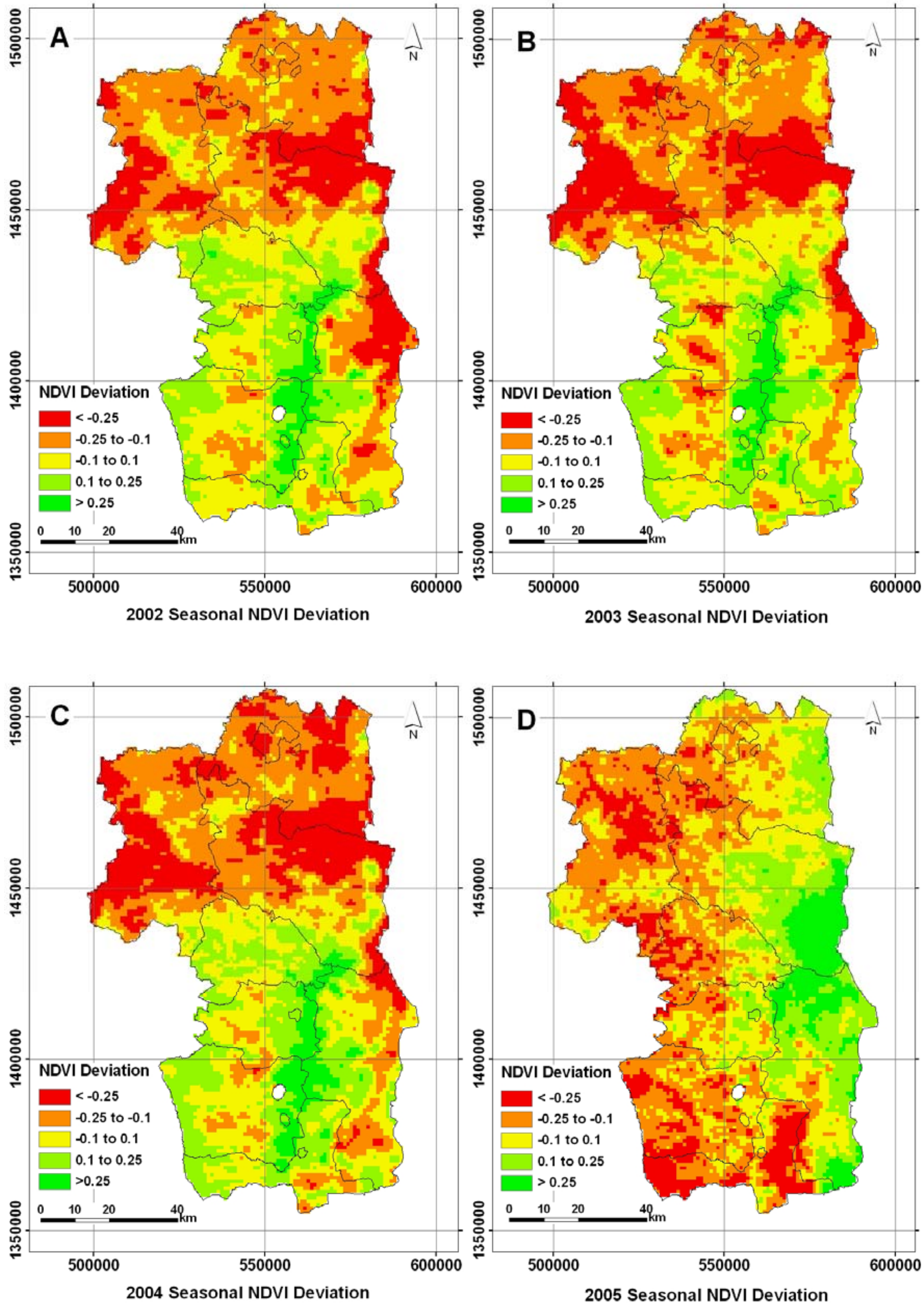

Figure 4.4: The NDVI deviation map for the Southern Zone (A, B, C, D)

C. Végétation Condition Index (VCI)

VCI effectively shows how close the NDVI of the current month was to the minimum NDVI calculated from the long-term record. It indicates how much the vegetation has advanced or deteriorated in response to weather. VCI measured in percent has provided an assessment of spatial characteristic of drought, as well as its duration and severity and were in good agreement with precipitation patterns (Chopra, 2006). It is an indicator of the status of the vegetation cover as a function of the NDVI minima and maxima encountered for a given ecosystem over many years. It normalizes the NDVI (or any other vegetation index) and allows for a comparison of different ecosystems. Therefore, it is a better indicator of water stress conditions than the NDVI (Kogan, 1995). VCI is dependent up on the number and quality of images available for the calculation of the absolute minimum and maximum.

The MNDVI is defined as the maximum NDVI for all time intervals of the MVC (maximum value composite) in a year or a month. The seasonal MNDVI was found to be a reliable indicator of variations that can affect the state of vegetation cover and crop condition. The NDVImax can be described by the following expression:

$$\mathbf{MaNDVIi = Max\ \{NDVIi_{13},\ NDVI\ i_{14} \ldots NDVIi_{27}\}}$$
$$\mathbf{MiNDVIi = Min\ \{NDVIi_{13},\ NDVI\ i_{14} \ldots NDVIi_{27}\}}$$

Where, **MNDVIi** and **MiNDVIi** is maximum and minimum Normalized Difference Vegetation Index of year *i*, **$NDVIi_{13}$** represents the first 10-day NDVI composites image of May, **$NDVIi_{27}$** is the third 10-day NDVI composite data of September. Note that; there were only 27 dekadal (10-day) NDVI composites in 1998 unlike other years. This is because of the fact that acquisition of VGT-S10 data started from April 1998

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 (dekade) 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. The VCI value close 0% (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 index captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas. Not only permits the description of land cover and spatial and temporal vegetation change, but also allows quantifying the impact of weather on vegetation. It also makes 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. VCI is a pixel-wise normalization of NDVI useful for making relative assessments (e.g. pixel specific) of changes in the NDVI signal by filtering out the contribution of local geographic to the spatial variability of NDVI. The VCI measures how weather conditions have influenced the relative vigor of the vegetation with respect to the ecologically defined limits.

This index is most useful during the growing season because it is a measure of vegetation vigor. When the vegetation is dormant (not in the summer season), the VCI cannot be used to measure moisture stress or drought. Interpretation of the VCI may be more complicated than other drought indices because it provides an indirect measure of moisture (drought) conditions. Anything that stresses the vegetation including insects, disease, and lack of nutrients will result in decreases in plant growth and therefore lower VCI values. Also, areas that have significant irrigation may not respond to precipitation deficiencies (Quiring et al. 2003).

For the purpose of delineating agricultural drought, a seasonal VCI value was generated for eight years. According to Kogan (1997), different degrees of drought severity are indicated by VCI below 50% and VCI of 35% is a threshold for extreme drought. Further classified the VCI values below 35% arbitrarily for east Africa as:

1. 50% to 100%, normal to above normal condition (wet);
2. <50% to 35%, moderate drought;
3. <35 to 20% severe drought;
4. <20% to 0% very severe drought

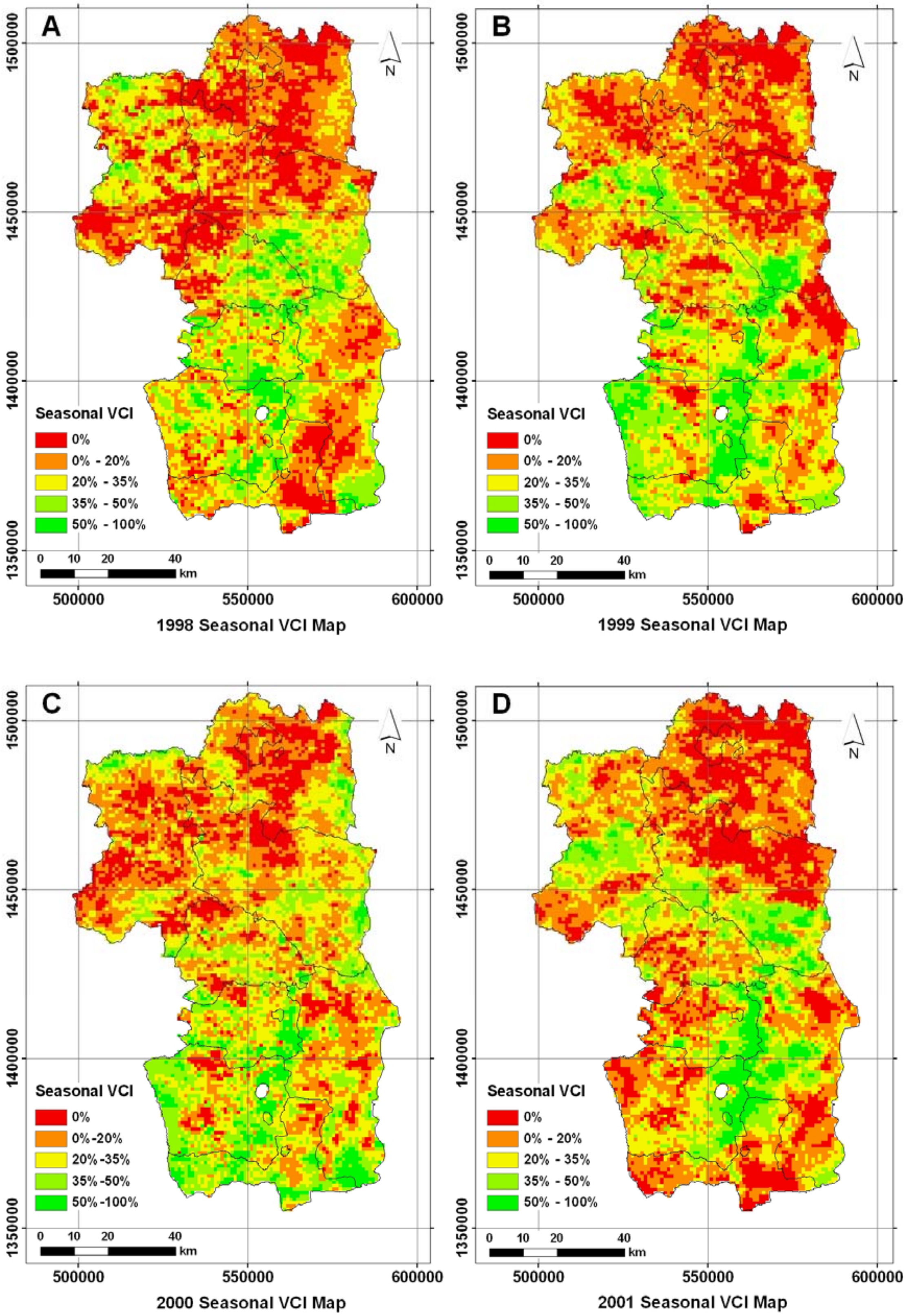

Figure 4.5: Vegetation Condition Index (VCI) for the Southern Zone (A, B, C, D).

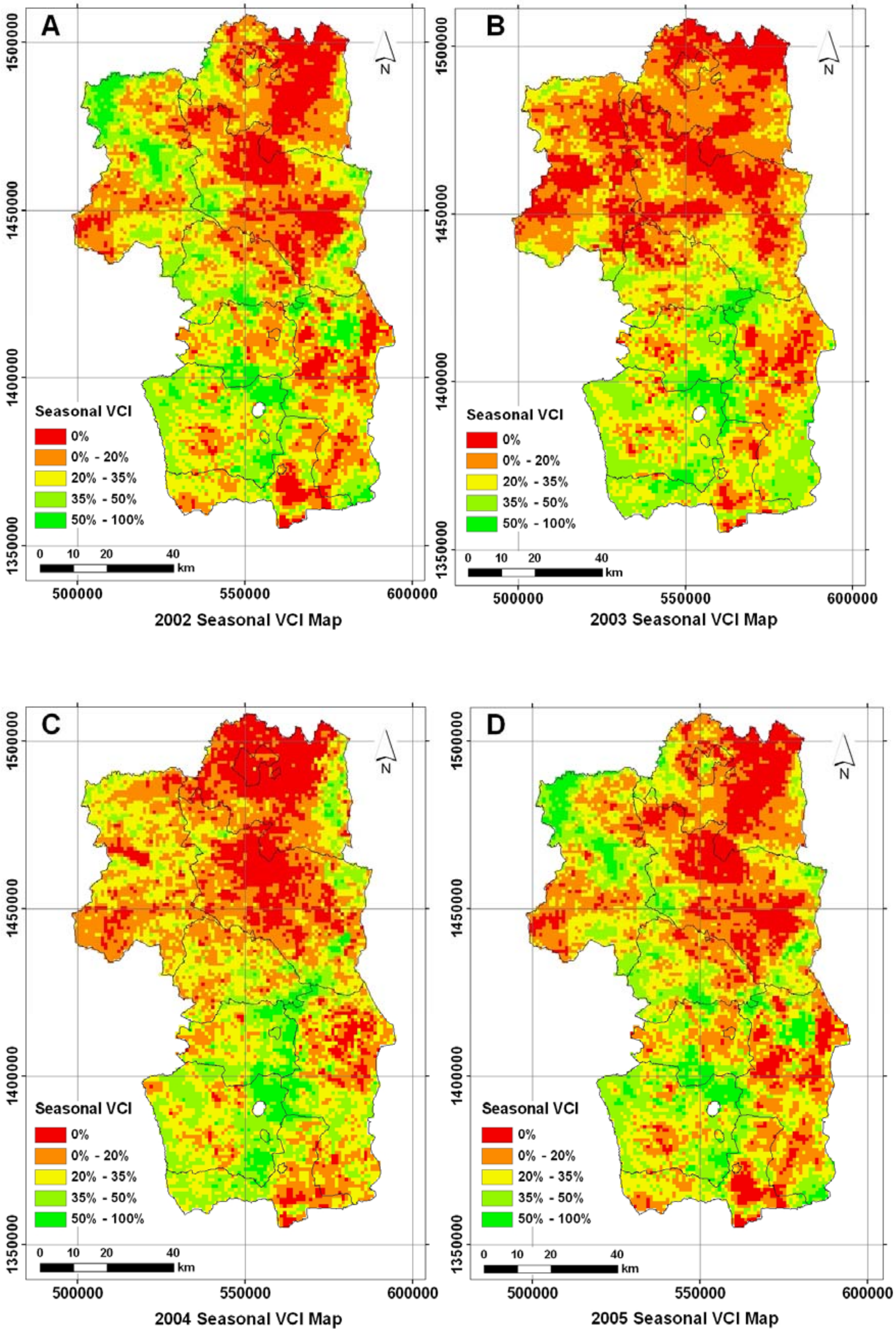

Figure 4.6 Vegetation Condition Index (VCI) for the Southern Zone (A, B, C, D).

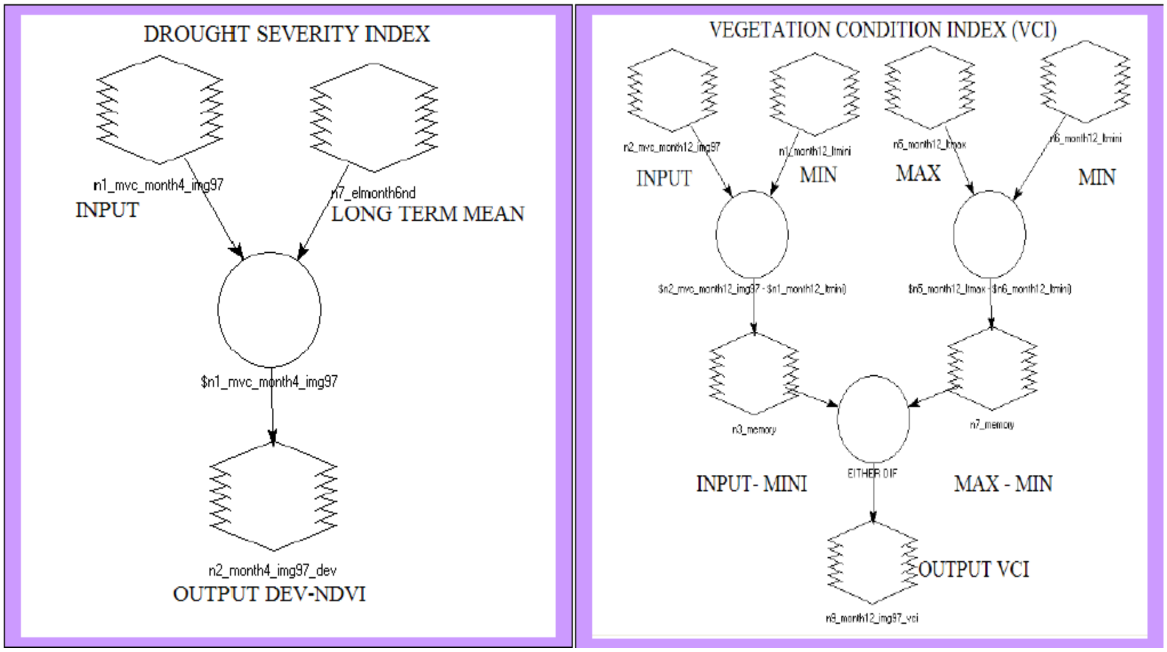

Figure 4.7 The model that used to drive the map of DEVNDVI and VCI of study area

4.1.2. Driving Meteorological drought

Rainfall (Precipitation) Anomaly

Meteorological drought indicates the deficiency of rainfall compared to normal rainfall in a given region.

Rainfall anomaly, expressed in percentage, when was computed from 1998 - 2005 for the months of May, June, July, August and September of the growing season to generate meteorological drought maps. Rainfall anomaly was computed as:

$$\mathbf{RFA\ i = [(RF\ i - RF\mu) / (RF\mu)]*100}$$

Where, RFAi is rainfall anomaly for i^{th} year, RFi is seasonal rainfall for i^{th} year and, RFμ is mean seasonal rainfall. They were multiplied by 100 to normalize the result.

Meteorological drought is defined as a situation when the seasonal rainfall received over an area is less than 75% of its long-term average value. Recently 63% is taken as a threshold for drought severity, (Dunkel, 2005). It is further classified into slight drought when rainfall is 25% less than the normal, moderate drought when rainfall is 50% less than the normal and severe drought when rainfall is 63% less than the normal (WMO, 1975).

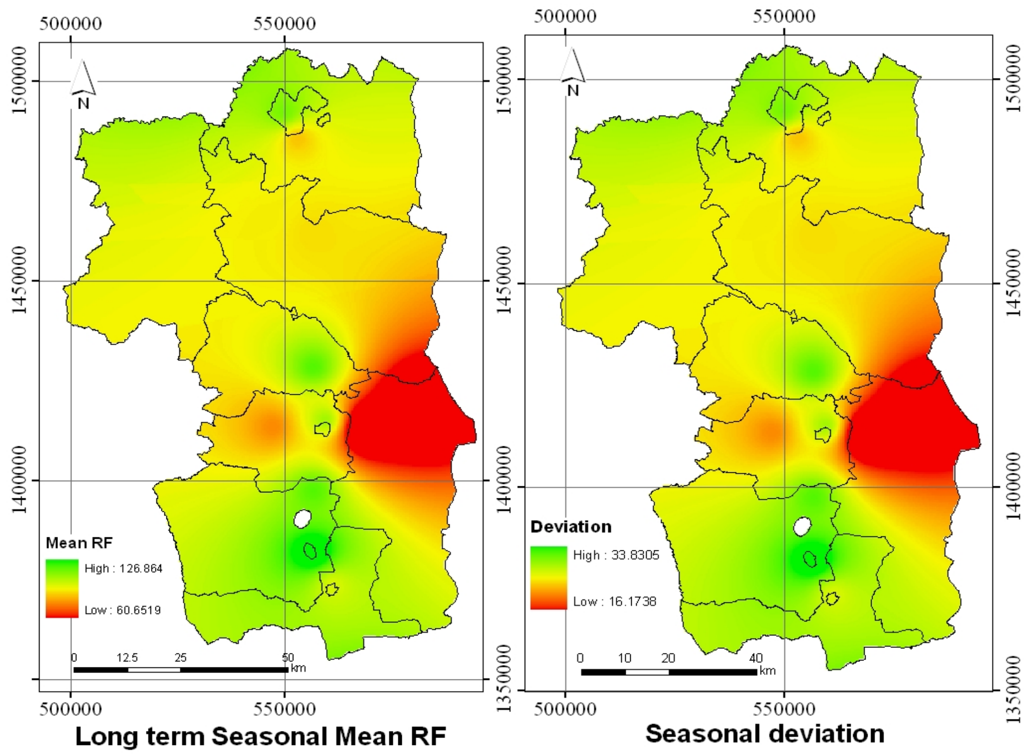

Figure 4.8: Long terms seasonal mean RF and Seasonal Deviation

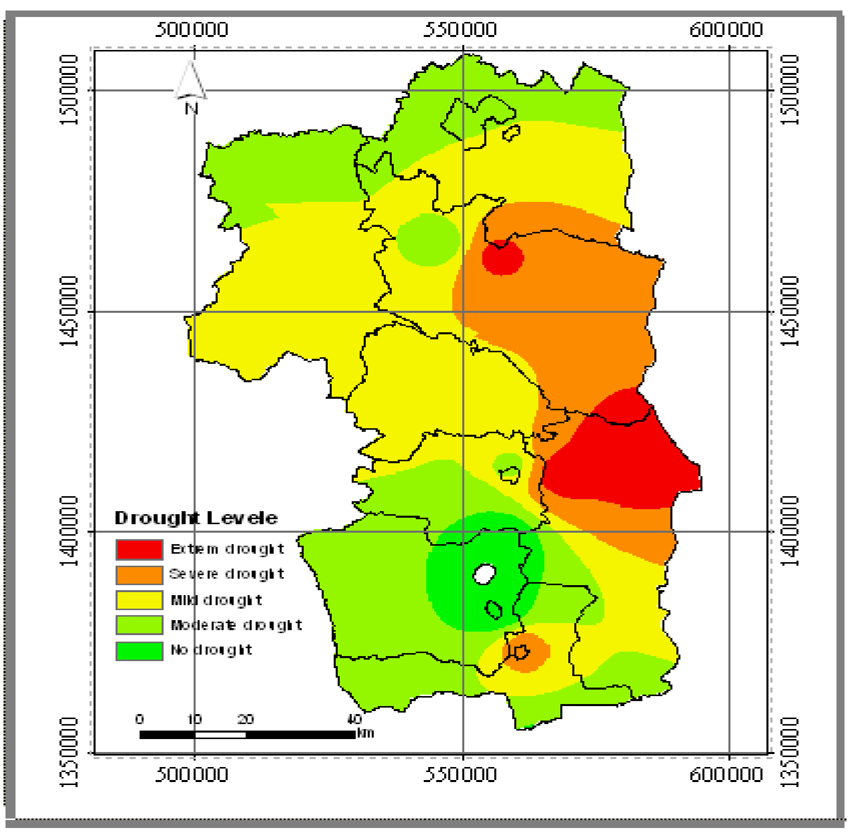

Figure 4.9*: Meteorological drought* map

The unevenly distributed stations hinder the accuracy of meteorological drought map. The Rainfall anomaly index gave an approximate picture of the meteorological drought prevailing in the study area. For example the western, northern and eastern parts of the study area was affected by drought, but as identified in Fig 4.9 the map depicts the existence of enough moisture for crop production. As a result, did not use this factor as a layer in the derivation of the final drought map.

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 seasonal means indicate the condition of ground vegetation month-by-month and allow dry and wet months in different parts of the Woredas to be identified. Figure 5.1 and 5.2 shows the long-term NDVI conditions (Seasonal mean NDVI for each year) and relative to it, the driest (1998, 2000, 2002 and 2004) and relatively the wet (2005) years' NDVI values for each year for the entire study area. Averaging of NDVI values over the entire study area was done primarily to illustrate that, the zone was dry during the main rainy season (from May to September) in 1998, 2000 and 2004 The differences between the long-term NDVI means and the NDVI values in specific year are the deviations of NDVI (DEVNDVI).

Most of the pixels in the study area have persistent shades of red, indicative of the negative deviation from NDVI mean Fig. 5.3. It can be seen how a major drought-affected area is developing from May to September in the southern Zone. The drought onset, magnitude and duration/persistence can be monitored at a scale of Woreda, or a single pixel level (1km by1km) with SPOT data using the series of consecutive images

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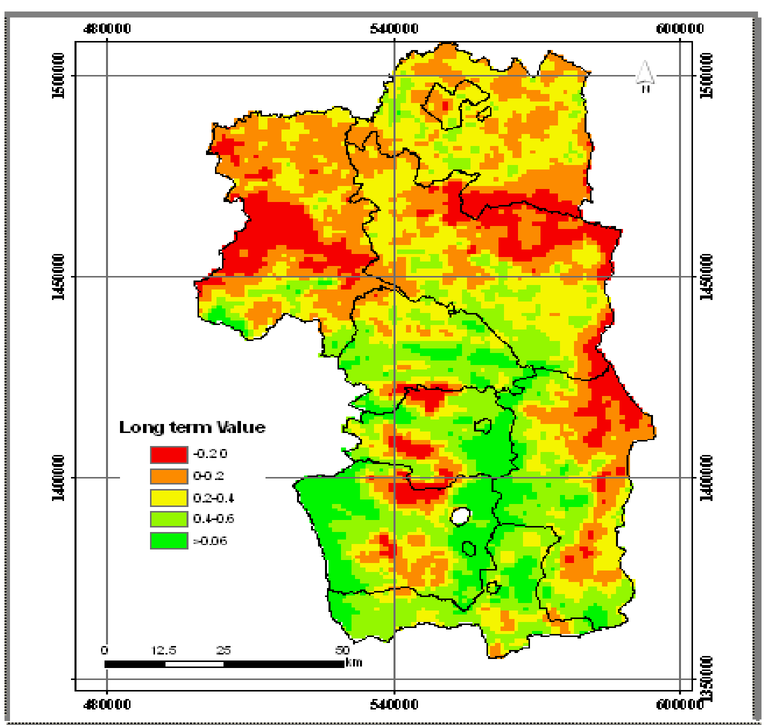


Figure 5.1: Long term NDVI (August)

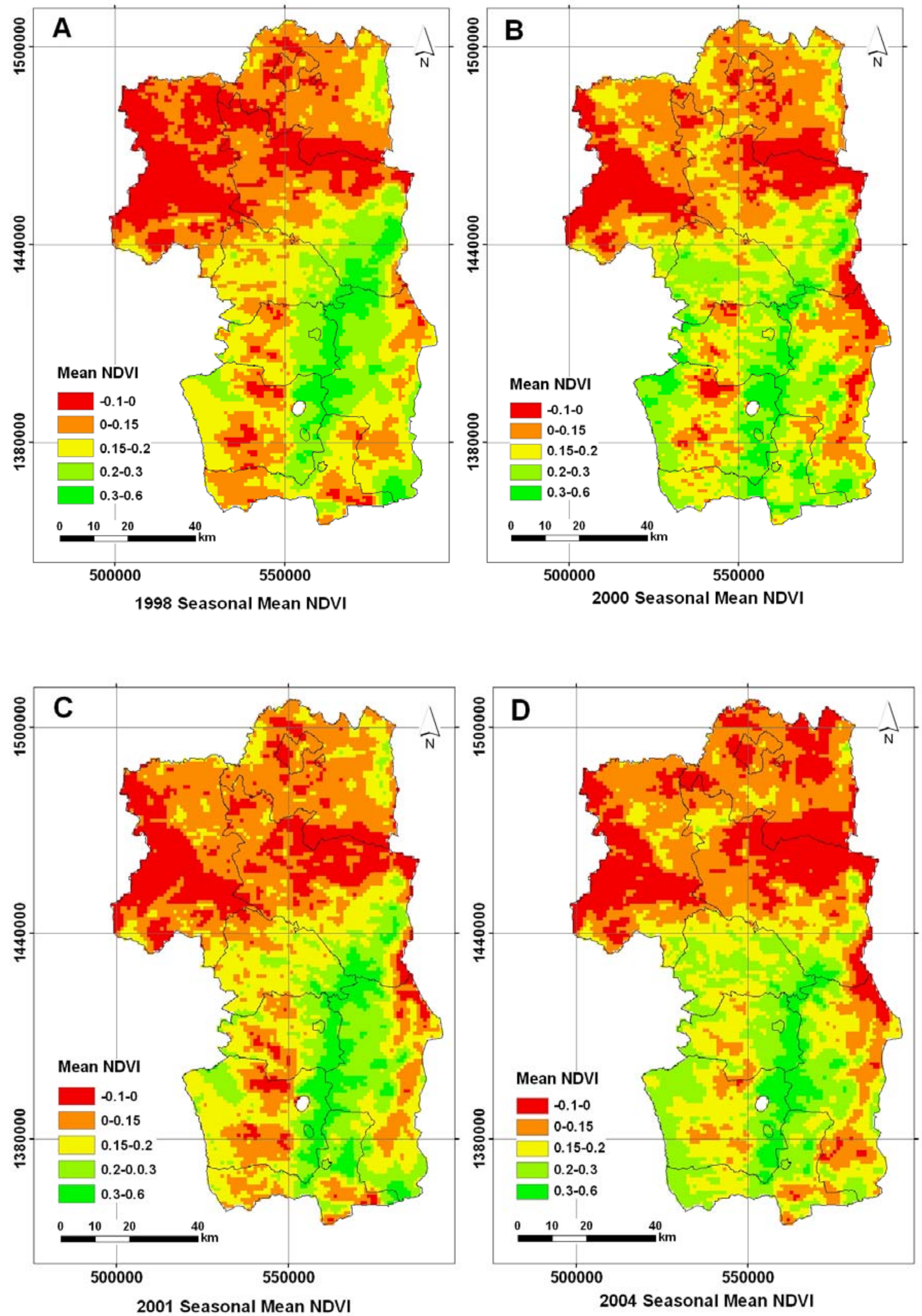


Figure 5.2: Seasonal Mean NDVI (A, B, C, D)

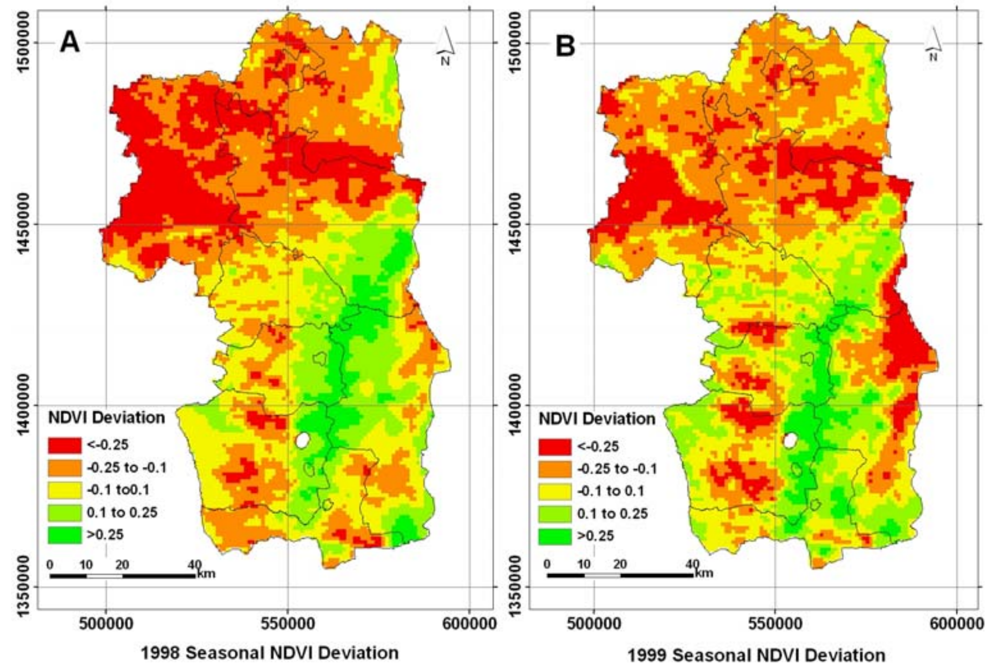


Figure 5.3: Seasonal NDVI Deviation (A, B)

The vegetation levels (measured in terms of NDVI) are normally higher in the highlands of Endamehoni, Hintalo Wajirat,Amba Alage and Ofla as a whole when compared with Seharti Samire, Enderta, and Raya Azebo Woredas (Figure 5.4). There is also a clear seasonality fluctuation in NDVI within and across seasons. The pattern of fluctuations is however very different between the four Woredas. The Southern Zone vegetation is rainfed and NDVI follows predominantly uni-modal vegetation condition cycle, determined by precipitation.

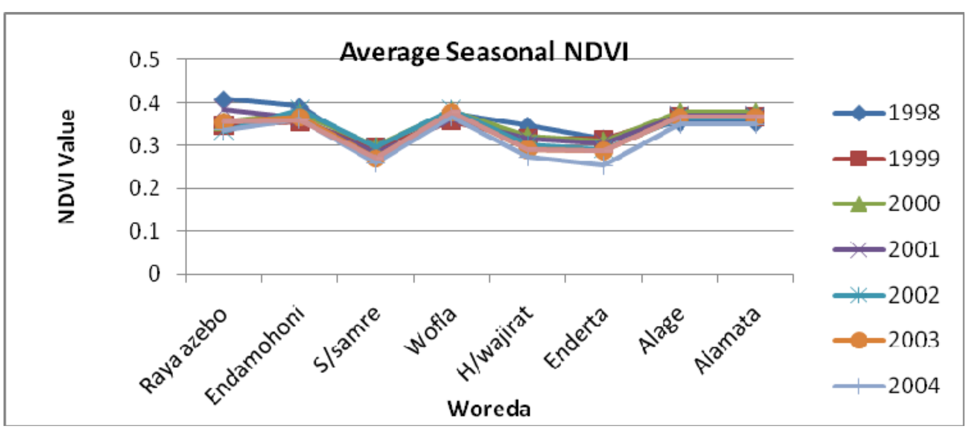


Figure 5.4: **The NDVI variability for Southern zone over 8 years**

The variability of two drought-related indices (DEV_{NDVI}, and VCI) for the period of 1998-2005 (containing a few successive droughts) is illustrated in Figure 5.5 using Seharti Samre, Enderta and Hintaro Wajirat Woredas as example. The DEV_{NDVI} abave 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. 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 May to September (1998-2005) were predominantly a continuous drought in Seharti Samre, Enderta and Hintaro Wajirat Woredas, 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.

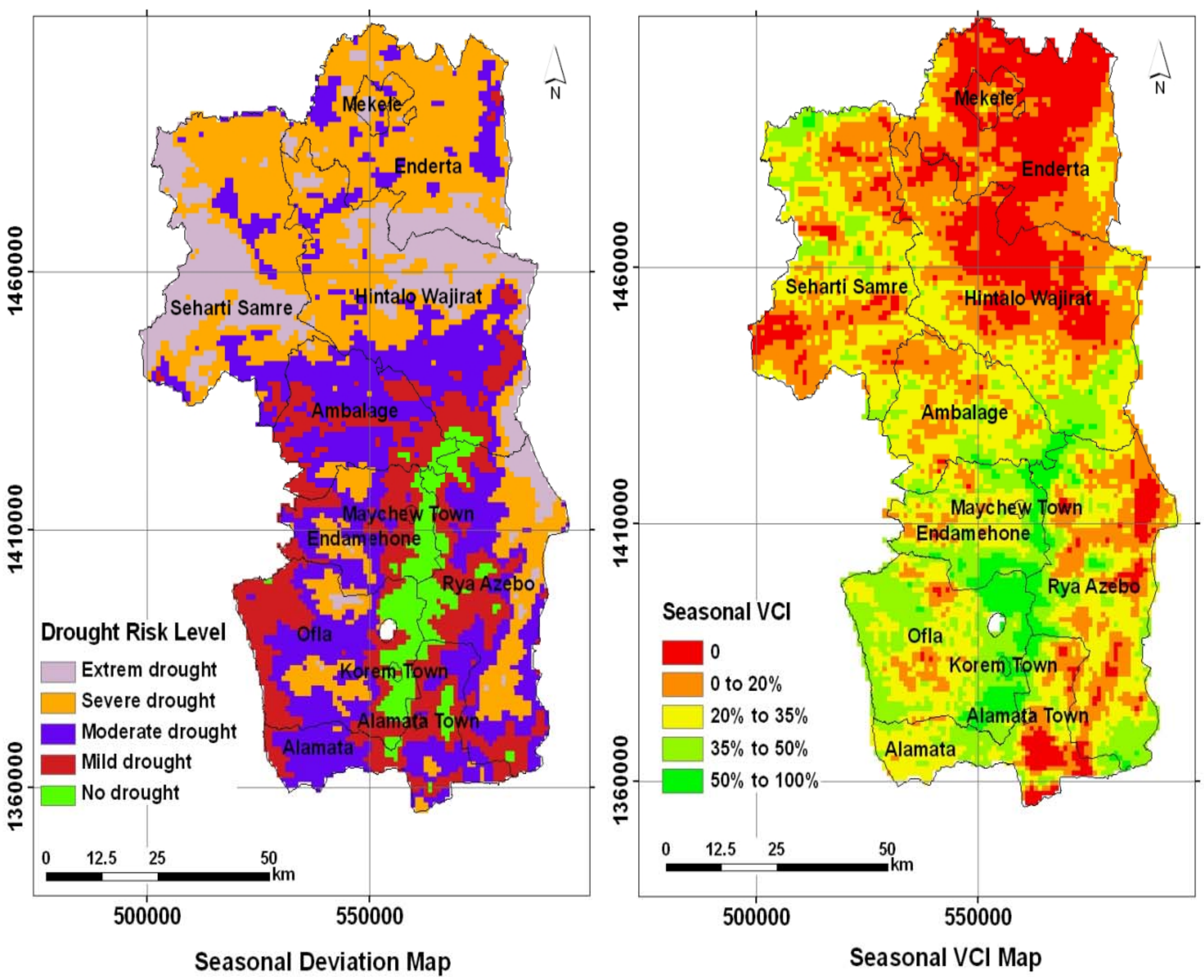


Figure 5.5: Drought map generated from seasonal NDVI deviation and Vegetation condition *Index* (VCI)

Table 5.1: *Number of drought affected Woredas*

Description	1998	1999	2000	2001	2002	2003	2004	2005
Very severe drought affected woreda	3	3	2	3	4	2	3	3
Severe drought affected woreda	4	4	3	5	4	2	4	3
Sum of affected woreda	3	4	4	3	4	4	4	5

Table 5.2: *Number of drought affected Woredas using Vegetation Condition Index (VCI)*

Description	1998	1999	2000	2001	2002	2003	2004	2005
Very severe drought affected woreda	3	3	3	2	2	3	4	2
Severe drought affected woreda	4	2	3	5	2	3	4	
Sum of affected woreda	3	5	3		4	2		6

Even though there is data inconsistence on yearly crop production, this can be validated by the yearly crop production of each Woreda in the following selected years in which there exists data.

Table 5.3: *Yearly crop production*

Woreda	1998	1999	2000	2003	2004	2005
S/Samre	1321746	1521746	1378178	2120586	2632411	404648
Enderta	361735	1136275	1099627	3028977	2250489	401136
H/Wajirat	1332250	1432379	1342757	2023365	1168960	295326
Ambalage	1020712	1120313	1037557	1565317	2204146	172462
Endamehoni	857585	869534	532560	985755	1096837	141871
Raya Azebo	3257161	3457161	4452192	5061466	4528575	655851
Alamata	1305568	1405068	1271189	1603056	2284487	135254
Wofla	1916851	1935432	1963181	1207171	1033207	209311

The total crop production in 2005 was the lowest of all years under study. Other things being constant, this was because of the severe drought condition in 2004 during the growing season. In general Enderta and Hintalo Wajirat areas are highly affected by drought conditions in the given eight years.

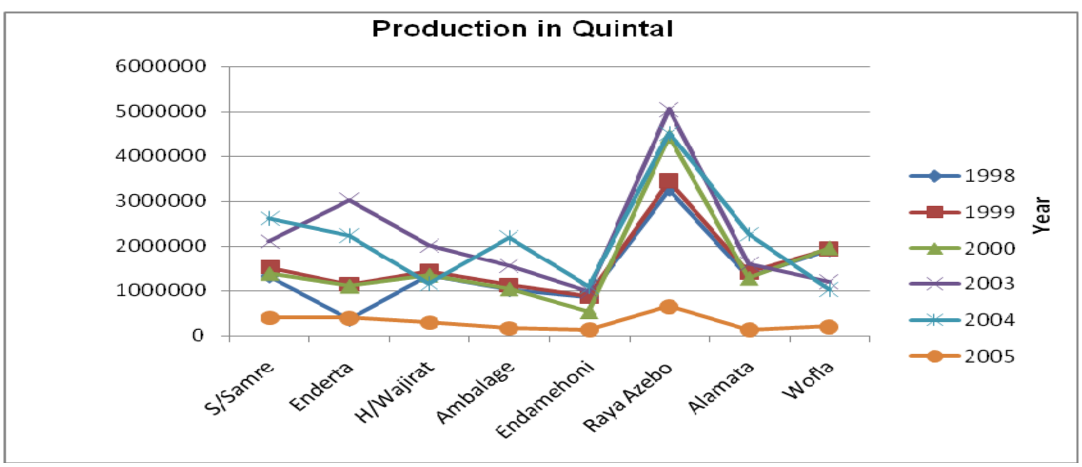


Figure 5.6: Production in Quintal (1998_2005)

5.2 Relationship of Seasonal Rainfall and NDVI

The analysis was done on the change of vegetation cover due to seasonal variation of rainfall by using data and NDVI images of past eight years (1998-2005).The study area is characterized by high land and lowlands. The flat plains and plateau are under intensive cultivation of crops. The mountains are mostly covered with natural vegetation (shrub) thus, according to the result; the seasonal NDVI was computed for the month's May, June, July, August and September.

As seen in the Fig.5.7 there was failure of seasonal rain in 2000 compared with that of the other years in almost all Woredas of the zone and followed by 2004.In contrary, 2005 seasonal rain was good in most parts of the study area, but production is low in all Woredas. The failure of seasonal rain indicated high probability of drought occurrence in years 2000, 2002 and 2004. In general; Ofla, Endamehoni, Amba Alage and Hintalo Wajirat Woredas very close to highland had relatively better rains for all study years.

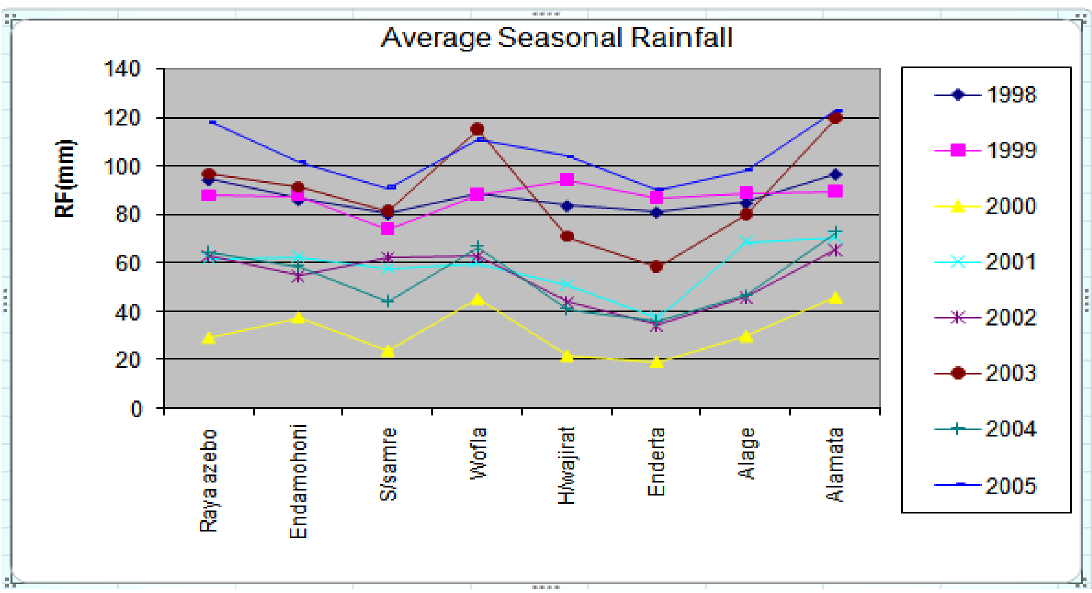


Figure 5.7: Average Seasonal NDVI chart

Fig.5.7 relates the seasonal rainfall situation with NDVI value. According to Fig. 5.8, 2000 and 2004 Average seasonal NDVI value was lowest compare to the 2005 mean NDVI. Therefore, it can be concluded that 2000 and 2004 was drought year as the rainfall and NDVI value of the lowest when compared to that of all the other studied years. Thus, this indicated that there was extreme drought in the study area in 2000 and 2004.

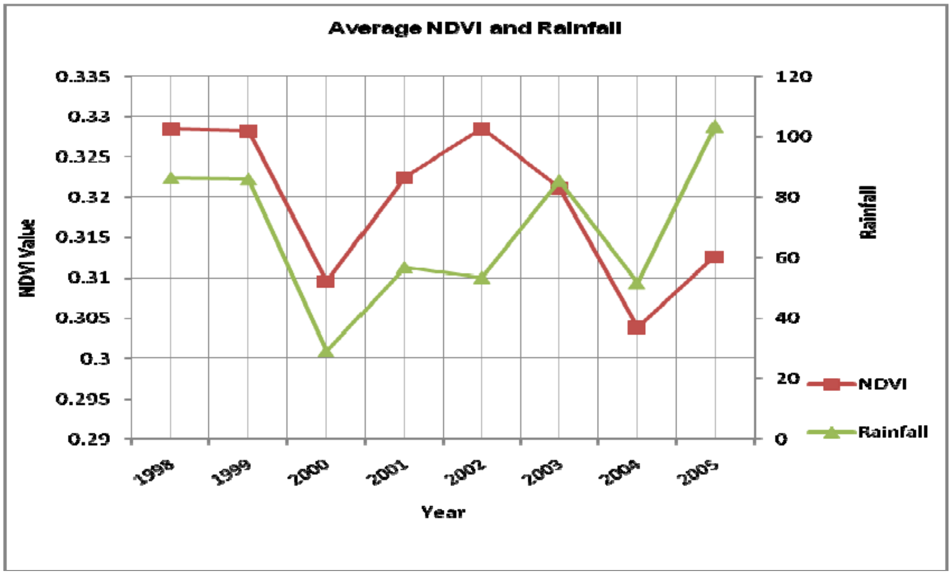


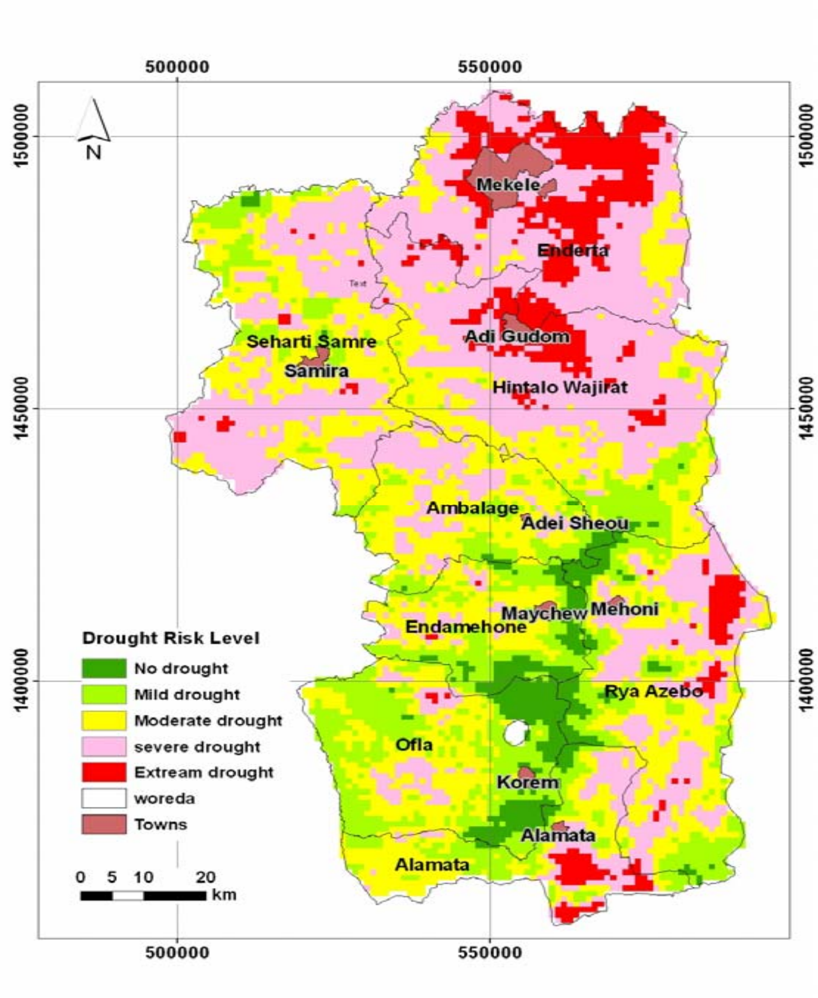
Figure 5.8: Average NDVI and Rainfall

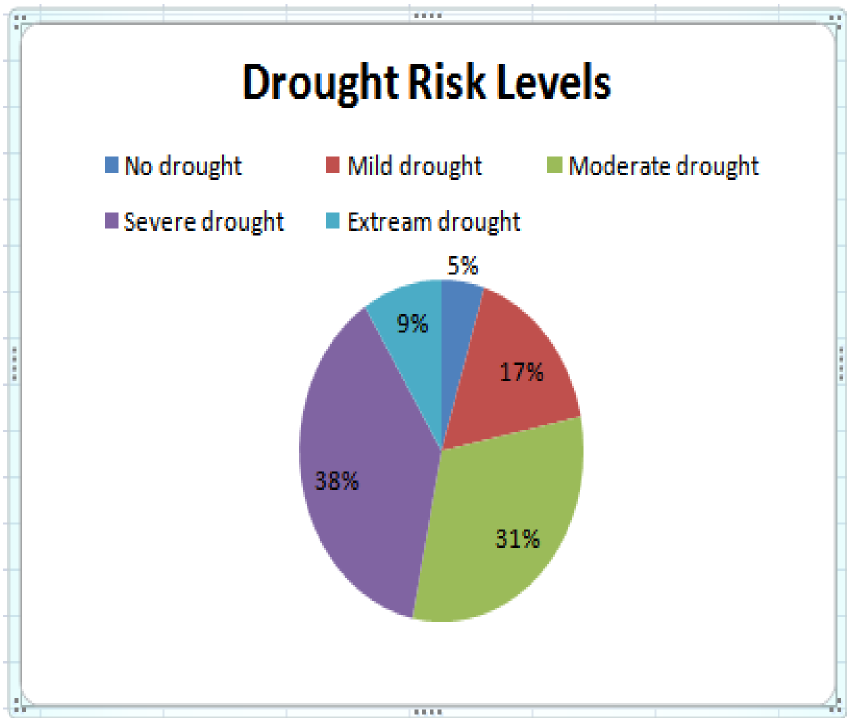
5.3 Identification of Drought Risk Area

The conventional methods of drought risk area identification are usually based on the collection and analysis of ground data such as rainfall and evaporation and irrigation area coverage. It lacks identification of spatial variation. The remote sensing based method identification of drought risk areas (Jeyaseelan, 2002) uses historical vegetation index data derived from NOAA satellite series and provides spatial information on drought risk area depending on the trend in vegetation development, frequency of low development and their standard devotions. Drought is a normal, recurrent feature of climate and occurs in all climatic zones, although its characteristics vary significantly from one region to another the analysis of NDVI temporal images was used to arrive at the agricultural drought, while the ancillary data of rainfall was utilized in determining the meteorological drought. Both types of drought were then combined to arrive at risk arising out of them. It covers description of the relationship established between rainfall and vegetation.

The degree of NDVI change was different across the different categories of drought risk level, as identified by this study. The highest NDVI changes were witnessed in areas classified as being very high drought risk. While low drought risk areas experienced a lower NDVI changes. Moderate drought risk areas were observed with moderate NDVI change values.

Prathumchain *et al.,* (2001) used Weighting System and multi-criteria assessment to determine drought risk areas for the Central Plain of Thailand by participating experts in meteorology, soil science and agriculture within MOSTE. However, in this current study, weighting system and multi-criteria assessment were not used to identify drought risk area. The primary reason for this was lack of data on certain parameters such as rangeland area, water resource in cubic meter and livestock population by Woreda. However, this study identified drought risk areas using the change of NDVI, VCI and rainfall in the predominant drought types were classified into "high drought risk", "moderate" and "low drought risk" Woreda of the study area.





Figur: 5.9: Drought Risk Map

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The temporal and spatial characteristics of drought can be detected, tracked and mapped from satellite data particularly that obtained from the Satellite Rainfall data. Based on the analysis for the "Southern" Zone which is found in the Tigray Region, this study shows the drought condition scenario can be constructed from the deviation of Normalized Difference Vegetation Index (NDVI) from its long-term mean, the Vegetation Condition Index (VCI) and Satellite Rainfalls.

These eight years' seasonal pattern of rainfall and NDVI (1998- 2005) indicate that the northern, western and eastern parts of the study area has low rainfall distribution during farming season as well as has low NDVI value. The highland part of the study area has relatively better rain and NDVI value. Thus, it can be said that NDVI and rainfall have strong relations. SPOT4 images are used in comparative analysis of the trend of derived NDVI of a given year relative to the trend in a normal year for spatial and temporal as well as continuous drought risk assessment and area delineation.

Accordingly, NDVI change map of the zone was prepared and calculated the percentage of the NDVI change. The moderate drought risk category accounted for 31.85% of the land (3009km^2). The result of the study illustrates that agricultural condition could be used as an indicator for drought condition of an area. The result shows a decrease in NDVI in 2000 and 2004 which was related to the reduced rainfall quantity in both seasons (belg and meher)of the year. Thus, NDVI could be used as the main indicator to assess drought. According to the results, the relationship between drought risk levels and NDVI changes were considered into three drought risk levels (extreme, severe and moderate drought risk levels). There was significant relation between NDVI change and drought risk level. Areas with low NDVI change are identified as low drought risk. Relatively, areas with high decrease in NDVI are expected to be areas with high drought risk. This change may be explained by the fact that extreme drought risk areas account for 457km^2 (9.4% of Enderta and Hintalo Wajirat). The larger proportion of the drought risk (Enderta,Hintalo Wajirat Seharti Samre, Raya Azebo and Alamata Woredas) wetre moderate drought risk level which accounted for 3009km^2 (31.45%) and Enderta, Hintalo Wajirat, Raya Azebo and Alamata Woredas were severe drought risk areas accounted 1568km^2 (17%).

In this study, Enderta and Hintalo Wajirat Woredas were more susceptible to drought. 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.

A maximum correlation has been observed between NDVI and precipitation with a lag time of three weeks. Furthermore, a strong correlation also exists between the 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 best option incorporates the long-term NDVI characteristics calculated from SPOT NDVI at 1km by 1km resolution. This option is particularly attractive for the future drought monitoring, as it will have all the advantages of the better SPOT NDVI technology. 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 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

Based on the findings the researcher would like to suggest the following:

- 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.

- Further researches are needed to improve the findings from this by incorporating other factors determining drought risk area. Having made the system reliable it could be scaled up at regional or national level with a web based GIS as is common in Middle East and Far East Countries
- From the entire work it is found that the north, Eastern and western part of Southern Zone are moisture stress areas as is indicated by the greenness indices, which are therefore made the area susceptible to drought. This finally resulted in low agricultural products, the major cause for food insecurity. It is evident that the drought in 2000 and 2004 caused low crop production, hence food shortage in 2001 and 2005.

- The main objective of the study was to assess drought risk area from the crop production perspective using SPOT-4 NDVI data and other ancillary data. It was found that drought affected areas with severe (17%) and very severe (9.4%), moderate (31.45%), mild drought (37.98%) are no drought areas (4.85%). Hence, People living in the area are generally food in secure.

- The respective Zonal and Regional offices can predict drought before their occurrences. For this activity SPOT-4 NDVI or NOAA images of the respective area should be accessed by those offices from Global Information and Early Warning System (GIEWS) or Advanced Real Time Environmental Monitoring Information System (ARTEMIS) of the FAO Environment and Natural Resources Service.

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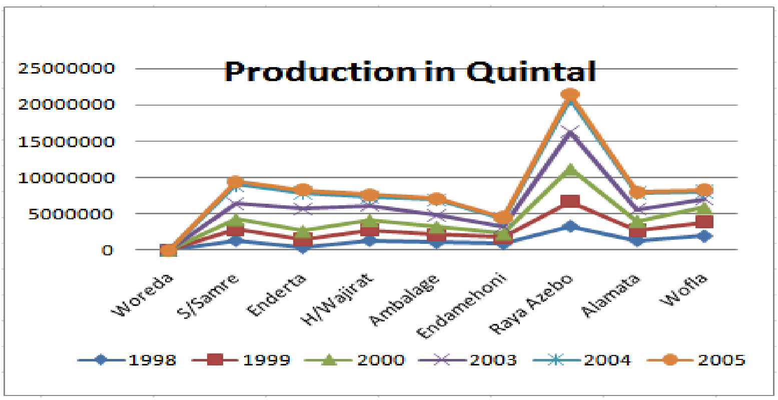
Appendix

Appendix A: Population Number of the Study Area by Woreda

Woreda	Urban + Rural			Urban			Rural		
	Both sexe	Male	Female	Both sex	Male	Female	Both sex	Male	Female
Raya Azebo	136,039	67,774	68,265	16,055	7,626	8,429	119,984	60,148	59,836
Endamehone	84,726	42,048	42,678	2,985	1,278	1,707	81,741	40,770	40,971
S/samre	124,499	61,954	62,545	9185	4290	4895	115,314	57,664	57,650
Wofla	142803	69446	73357	15,850	7,135	8,715	126,953	62,311	64,642
H/wajirat	152,219	75,262	76,957	11928	5627	6301	140,291	69,635	70,656
Enderta							114,277	57,472	56,805
Alage	107,954	52,840	55,114	7,565	3,668	3,897	100,389	49,172	51,217
Alamata	118,557	58,591	59,966	37,761	18,264	19,497	80,796	40,327	40,469
Maychew				23,484	11,057	12,427			
Total	**866,797**	**427,915**	**438,882**	**124,813**	**58,945**	**65,868**	**879,745**	**437,499**	**442,246**



Production In Quintal (1998_2005)

Number of beneficiaries for each year.

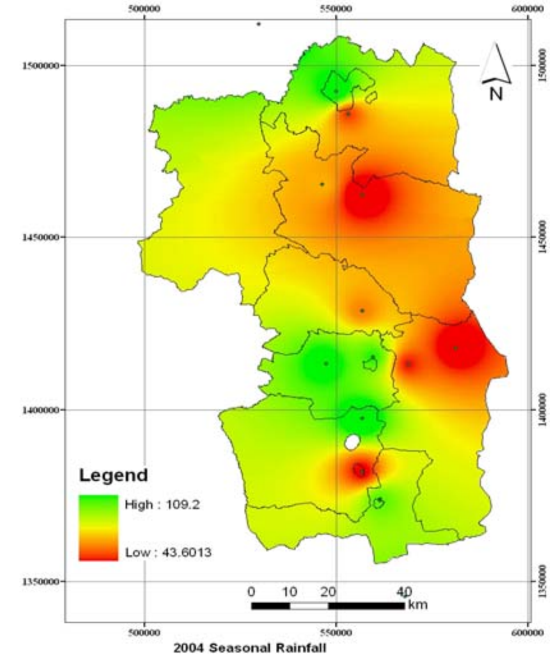
Woreda	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Alaje	4000	5500	20500	1613	7358	22400	18840	33600	40000	79700
S/ Seharti	6050	14800	57000	5035	12700	41800	32300	73300	23200	50700
H/Wajirat	6967	32400	60000	3227	9820	40000	34900	92650	57800	90264
Enderta	16900	91900	49800	2017	12750	55000	42500	98000	18267	64000
Alamata	0	5200	53500	13608	8298	16600	23000	51300	39000	61700
Raya Azebo	4000	0	63400	16051	15012	24200	21000	88800	51700	104926
Ofla	13350	12400	56200	13610	13540	49600	48260	55900	31400	22000
Endamehoni	16000	5100	30000	1590	7260	24500	25000	40100	26100	64000

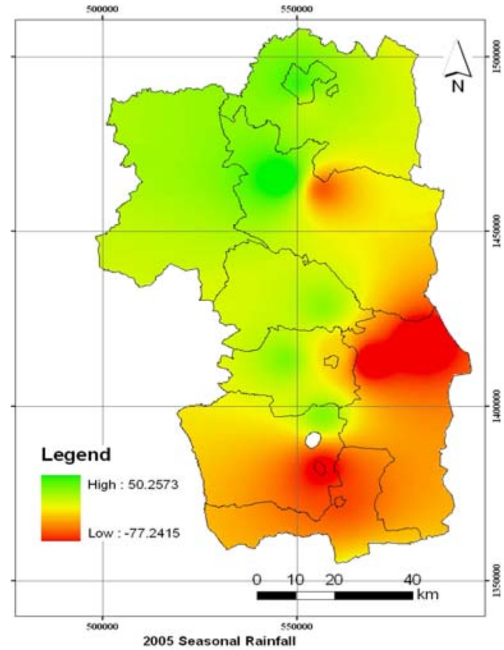
(Source: Early Warning System Net (EWS NT)

Table: Number of beneficiaries

Description	1998	1999	2000	2001	2002	2003	2004	2005
Number of beneficiaries	604311	906856	783294	1018896	1037600	2033677	1107000	690026
%	89.52	75.5	74.18	107.59	109.3	111	100	100
Distributed Food in Qt.	557629	876298	697368.5	983380.2	492240.87	1963407.73	1328400	1189287.5

(Source: Regional food security office, 2008





Seasonal Rainfall (1998_1999)