

Drought Risk Assessment using Remote Sensing and GIS: The Case of Southern Zone, Tigray Region, Ethiopia

Birhanu Gedif
Director for Geospatial Data and Technology Center, Lecturer at college of agriculture and Environmental Sciences, Department of Natural Resources Management, Bahir Dar University
Email:birhanu 1968@gmail.com

Legesse Hadish
Legesse Hadish, GIS expert, Central Statistical Agency, Ethiopia.
Email:legese. yons@gmail.com

Solomon Addisu
PhD Research Scholar at Andhra University, College of Science and Technology,Environmental Sciences Department, India
E mail: soladd2000@yahoo.com

K.V.Suryabhagavan
Assistant Professor, Department of Earth Sciences, Addis Ababa University,
E mail, suryanarayana_nv@yahoo.com

Abstract
This study used satellite sensor data which are consistently available, cost effective and can be used to detect the onset of drought, its duration and magnitude. Moreover, an effort has been made to derive drought risk areas facing agricultural as well as meteorological drought using eight-year time series rainfall data and dekadal satellite SPOT NDVI (Normalized Difference Vegetation Index). A deviation of the current NDVI with the long-term mean NDVI, and the Vegetation Condition Index (VCI) derived from the SPOT were used in this study for drought detection and monitoring. The results revealed 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 that Enderta, HintaloWajirat, Eastern part of Raya Azebo and southern part of Alamata distric that more susceptible to drought. Moreover, it has been indicated that the two remote-sensing indices used, DEV_{NDVI}, and VCI are complementary and were found to be sensitive indicators of drought conditions. SPOT NDVI at 1km by 1km resolution, which incorporates the long-term NDVI, is also found to be one of the best data for drought risk assessment.
Keywords: Drought, Normalized Difference Vegetation Index, Vegetation Condition Index, Risk assessment

Introduction

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.

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 rainfall dependent, drought should be given with due attention in achieving food security for all.

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 failureand has raised serious food security concerns for the region.

At country level in Ethiopia, "Meher" (summer rain that occur from June-September) season is mostly used to be 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. Data collection is done mostly by those who do not have training on the importance and technique of early warning. The post-harvest assessment, used to be compiled mostly by district agricultural experts is not reliable for targeting drought risk areas and then food insecure areas. 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 District level, which most of the time misleads decision makiers.

(Sharp 1997, cited in Devereuex, 2004) stated that in Ethiopia poor targeting system for food aid becomes a significant determinant of food insecurity. Since the major cause for food insecurity is drought, the area in which drought is series should be identified to utilize the minimum resources that the country has.

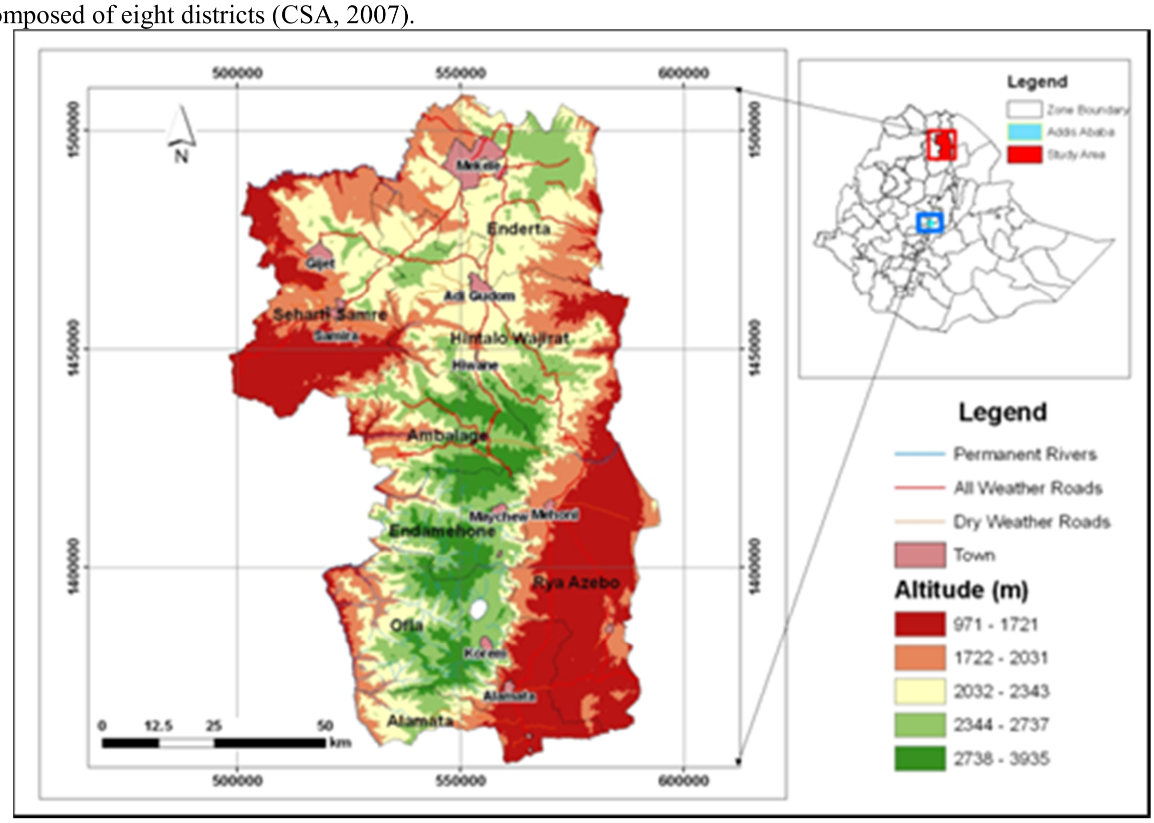
To minimize the problem related to area targeting, it is better to use satellite images which are consistently available, cost-effective and can be useful to detect the onset of drought, its duration and magnitude. As timely information on the extent and severity of drought the assessment system can limit impacts of drought-related losses. The near real time assessment through effective monitoring using SPOT NDVI images and satellite Rainfall data plays significant role in mitigating its adverse impacts.

The general objective of this research is to delineate drought risk areas using Remote Sensing and GIS techniques in south Tigray administration zone. The specific objectives include, to prepare NDVI deviation map from normal year to drought year, to calculate the percentage of drought affected area by drought risk level and to show the effectiveness of satellite derived drought indices as an indicator for drought risk assessment and to identify the most draught vulnerable area.

Methodology

Description of the study area

Southern administration zone is located in Tigray National Regional State, Ethiopia and it is located 660 km north of the capital Addis Ababa. It is geographically located 12^{o} 15'and 13^{o} 41' north latitude and 38^{o} 59'and 39^{o} 54'east longitude, constituting an area of 9,446 km^{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 (Figure 1). The study area has a total population of 1,006,504 of which the rural population consists of 880,717. The zone is composed of eight districts (CSA, 2007).



Methods

Data were collected from different sources to achieve the indicated objectives. All were analyzed and interpreted in the ERDAS 9.1, ArcGIS 10.2 and IDRISI environment. SPOT-4 and rainfall dekadal data were aggregated in to monthly basis for seasonal agricultural drought map generation. Rainfall data (mean seasonal), were utilized

for meteorological drought map generation. Finally the drought layers were overlaid for generating Drought severity risk map.
NDVI were calculated from two bands, the near-infrared (NIR) and RED wavelengths, using the following algorithm:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

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).

The raw Normalized Difference Vegetation Index (NDVI) data were 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

NDVI by itself does not reflect the severity and level of drought, since it does have some lagging period after the amount of rainfall reduced to some extent. The severity of drought can be better defined by NDVI deviation (DEV_{NDVI}).. This DEV_{NDVI} is calculated as the difference between the NDVI for the current month and a long term mean for this month (IWMI, 2006).

$$DEV_{NDVI} = NDVIi - NDVI\ mean,\ i$$

Vegetation Condition Index (VCI) used to be measured in percent provid an assessment of spatial characteristic of drought, as well as its duration and severity and is 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 and allows for 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.

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

The MaNDVI 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:

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

Where, MaNDVIi and MiNDVIi represents maximum and minimum Normalized Difference Vegetation Index of year *i*, $NDVIi_{13}$ represents the first 10-day NDVI composites image of May (which is the 13^{th} dekad from the beginning of the sensor in 1998), $NDVIi_{27}$ is the third 10-day NDVI composite data of September. 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 percent. 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.

For the purpose of delineating agricultural drought, seasonal VCI were 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

2. <50% to 35%, moderate drought;
3. <35 to 20% severe drought;
4. <20% to 0% very severe drought

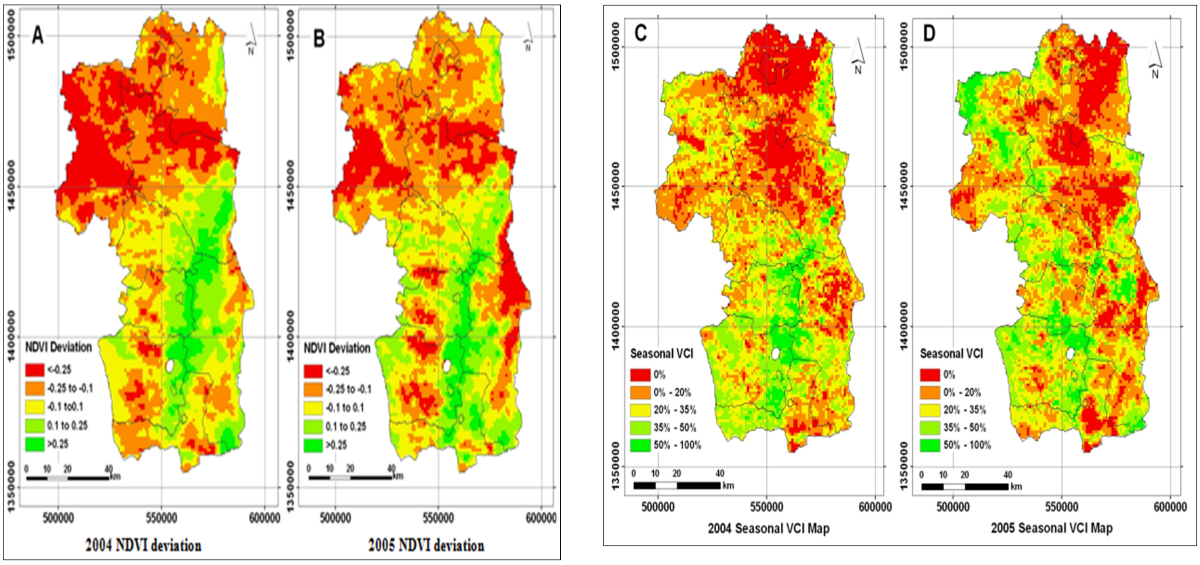


Figure 1: VCI (above) and NDVI deviation (below) maps for selected seasons

Results and Discussion

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 2 using Seharti Samre, Enderta and HintaloWajirat district as example. The DEV_{NDVI} above zero values indicate the normal condition of the vegetation. When an index deviates below the value zero for a period of a few successive months, it points to 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 Hintalo Wajirat Districts, 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.

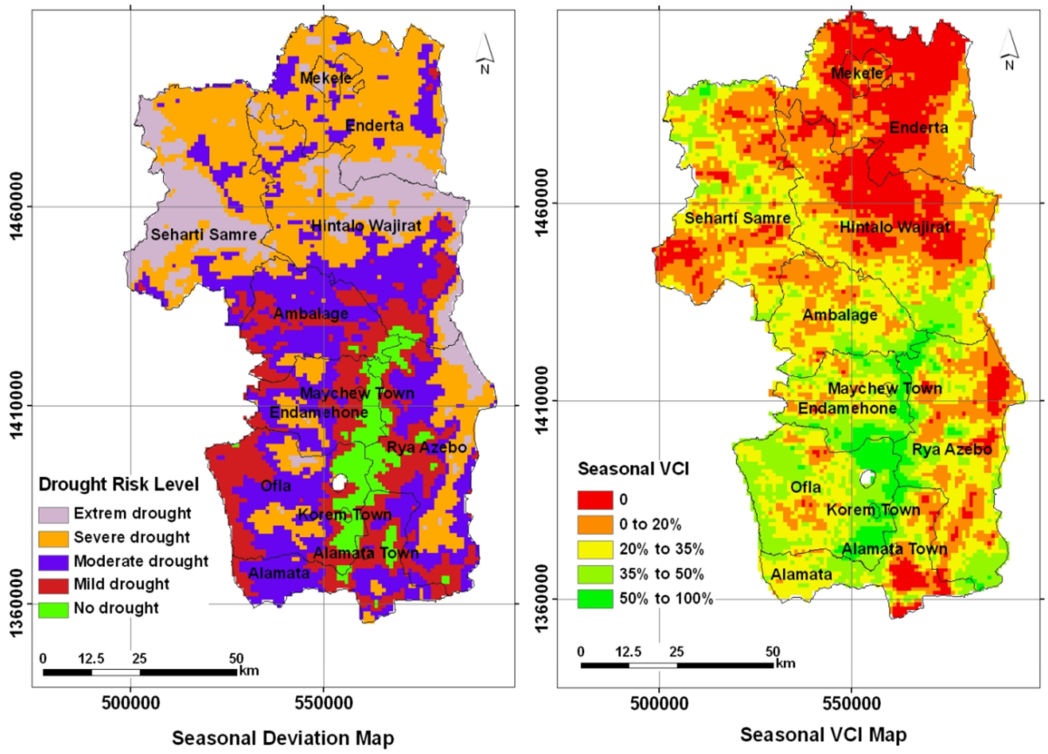


Figure 2: Drought map generated from seasonal NDVI deviation and Vegetation condition *Index* (VCI)

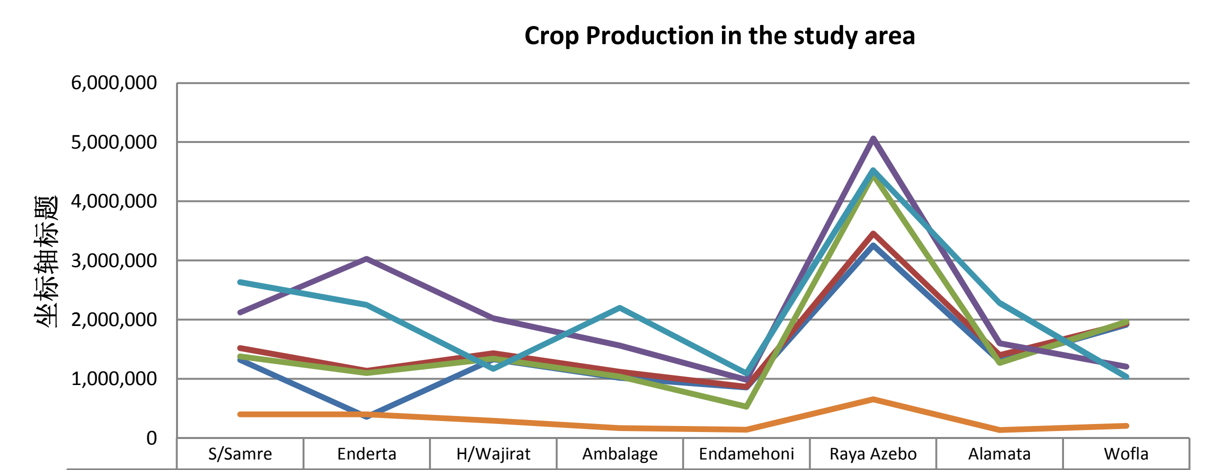
Table 1.Number of drought affected Districts

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

Table 2: Number of drought affected Districts

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

Even though there are data inconsistencies, the result can be validated by the yearly crop production of each District in the following selected years in which data are available.



	S/Samre	Enderta	H/Wajirat	Ambalage	Endamehoni	Raya Azebo	Alamata	Wofla
1998	1,321,746	361,735	1,332,250	1,020,712	857,585	3,257,161	1,305,568	1,916,851
1999	1,521,746	1,136,275	1,432,379	1,120,313	869,534	3,457,161	1,405,068	1,935,432
2000	1,378,178	1,099,627	1,342,757	1,037,557	532,560	4,452,192	1,271,189	1,963,181
2003	2,120,586	3,028,977	2,023,365	1,565,317	985,755	5,061,466	1,603,056	1,207,171
2004	2,632,411	2,250,489	1,168,960	2,204,146	1,096,837	4,528,575	2,284,487	1,033,207
2005	404,648	401,136	295,326	172,462	141,871	655,851	135,254	209,311

Figure 3: Production in Quintals (1998_2005)

The total crop production in 2005 was the lowest of the 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 HintaloWajirat districts were highly affected by drought conditions in the given eight years.

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 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 Figure 3 there was failure of seasonal rain in 2000 compared with that of the other years in almost all Districts 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 Districts. The failure of seasonal rain indicated high probability of drought occurrence in years 2000, 2002 and 2004. In general; Ofla, Endamehoni, AmbaAlage and HintaloWajiratDistricts very close to highland had relatively better rains for all study years.

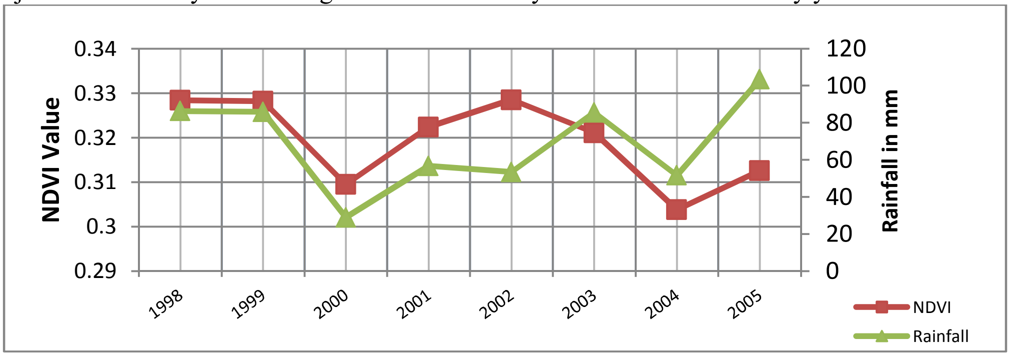


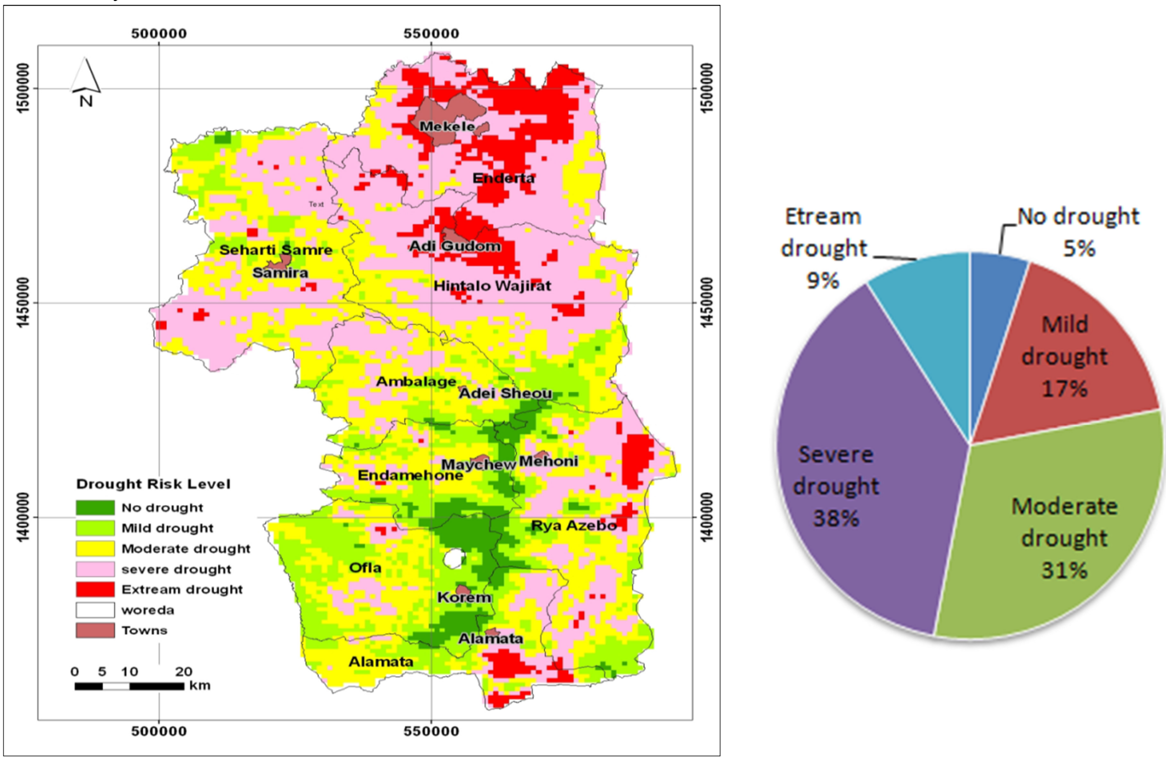
Figure 4: Average Seasonal NDVI and Rainfall relationship

Figure 4 relates the seasonal rainfall situation with NDVI value. According to Fig.4, 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.

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 uses historical vegetation index data derived from NSPOT satellite series and provides spatial information on drought risk area depending on the trend in vegetation development 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 in 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.

The researchers 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" District of the study area.



Figur: 5 Drought Risk Map (left) and percent in severity (right)

Conclusions

The temporal and spatial characteristics of drought can be detected, tracked and mapped from satellite data. Based on the findings from this study, drought condition scenario can be constructed from the deviation of Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI) and Satellite Rainfalls.

The eight years' seasonal pattern of rainfall and NDVI (1998- 2005) indicate that the northern, western and eastern parts of the study areas have low rainfall distribution during farming season as well as has low NDVI values. 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 correlations. SPOT4 NDVI images were 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 the percentage of the NDVI change were calculated. The moderate drought risk category accounted for 31.85% of the land (3009km2). 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 amount in both seasons (belg and meher) of the years. Thus, NDVI could be used as an indicator to assess drought risks. 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 457km2 (9.4% of Enderta and HintaloWajirat). The larger proportion of the drought risk (Enderta, Hintalo Wajirat, SehartiSamre, Raya Azebo and Alamata Districts) were moderate drought risk level which accounted for 3009km2 (31.45%) and Enderta, HintaloWajirat, Raya Azebo and AlamataDistricts were severe drought risk areas accounted 1568km2 (17%).

In the it is found that Enderta and Hintalo Wajirat Districts 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. There is also strong correlation has been observed between NDVI and agricultural production yield. 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. Thus, the satellite derived drought-indices with support rom ground data, can sufficiently identify and characterize the onset and severity of drought condition Therefore, it is essential to quantify the magnitude of drought severity into various degrees of drought severity classes.

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