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Application of Remote Sensing and GIS to Characterize Agricultural Drought Conditions in North Wollo Zone, Amhara Regional State, Ethiopia

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Abstract
Drought is the most complex but least understood of all natural hazards. Major food production in Ethiopia, especially in the Amhara Region, North Wollo Zone, is almost fully dependent on rain-fed agriculture and the area is often hit by periodic droughts. This drought causes serious economic, social, food security and environmental problems. In this study, the Standardized Precipitation Evaporation Index (SPEI) and Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI), were applied to characterize the agricultural drought conditions in North Wollo Zone from 2000 to 2015. Correlation analysis was performed between NDVI and SPEI, rainfall and NDVI, VCI and rainfall, NDVI and Crop Yield Anomaly and SPEI and Crop Yield Anomaly. SPEI values were interpolated to get the spatial pattern of meteorological based drought. Ground based crop yield data was used to evaluate the drought monitoring index. Finally, the combined drought severity map was generated by overlaying the agricultural and meteorological drought severity maps. The results showed that there was good correlation between rainfall and NDVI (r=0.71), VCI and Rainfall (r = 0.77), NDVI and SPEI (r=0.82) and NDVI and Crop Yield anomaly, (r=0.78) and SPEI and Crop Yield Anomaly (r=0.83). The drought severity was analyzed from 2000 to 2015 based on satellite and climate data. The two years 2005 and 2015 were considered as drought years and 2009 and 2013 were taken as slight-drought years. The extent of drought severity was increased by increasing time scale. The combined risk map showed that approximately 5, 19.5, 33 and 42. 5% of the study area has faced by slight, moderate, severe and very severe risk, respectively. Drought from socio-economic aspect has not been studied. Besides, delineating areas under drought risk relevancy of risk assessment can be made more meaningful when the human population as well as livestock population under risk will be assessed. Therefore, it is recommended to include the socio-economic data to better understand the vulnerability factors.
Keywords: Agricultural drought, Meteorological drought, SPOT, NDVI and SPEI.

INTRODUCTION

Climate change is one of the characteristics of natural atmospheric circulation. The effect of fluctuations in the atmospheric elements such as rainfall and temperature is achieved and environmental phenomena of drought and climate change are integral parts (McKee and Doesken et al., 1997). Major drought events have been reported in the USA, the Horn of Africa, Australia, and Southern Europe over the past few decades. Drought is a natural hazard that results from a deficiency of precipitation and water availability from expected or normal amounts, usually extended over a season or longer period of time (Mishra and Singh, 2010). Rainfed farming is the main form of crop production in Ethiopia; like for many of neighboring regions in Africa. However, it is highly variable in most parts of the country both in terms of length of the rainy season and amount of rainfall (Messay, 2006). Due to rainfall variability, frequent drought has been occurring in various parts of Ethiopia, which affect the crop production, food market prices and ultimately, the cost of living (NMSA, 1996).There are a number of indicators for drought monitoring and assessment. Every indicator has its successes and limitations in drought detection. Meteorological drought indicators assimilate information on rainfall, stored soil moisture or water supply but they do not express much local spatial detail. On the other hand, the derived drought indicators calculated from satellite-derived surface parameters have been widely used to study droughts. Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) are some of the extensively used vegetation indices. Currently, in Ethiopia use of intensive drought assessment tool is not common, which integrates climate, water and spatial variability of soil and land use properties as well as crop growth and root development. Due to this, it is not possible to fully characterize agricultural drought magnitude, spatial extent and potential impacts. Major food production in Ethiopia, especially in the Amhara Region, in North Wollo Zone, is almost fully dependent on rainfed agriculture and the area is often hit by periodic droughts. According to Ethiopian Government Disaster Risk Management and Food Security Sector of the Ministry of Agriculture (DRMFSS, 2012) report; the dry land semi-arid parts of North Wollo Zone, drought and crop failures have been common and rainfed agriculture is yet to provide minimum food requirement for rapidly growing population. Currently, in Ethiopia use of intensive or technology based drought assessment tool is not common, which integrates climate, water and spatial variability of soil and land use properties as well as crop growth and root development. Due to this, it is not possible to fully characterize agricultural drought magnitude, spatial extent and potential impacts. Therefore, this research was conducted seasonal wise using time series climate data (rainfall and mean temperature) and Remote Sensing Image, or data from satellite sensors with the objectives of characterization of the agricultural drought conditions using different drought indices.

MATERIALS AND METHODS

Description of the Study Area

This study was conducted in North Wollo Zone, Amhara National Regional State of Ethiopia. The North Wollo Administrative Zone is one of the eleven Zones of the Amhara National Regional State. Geographically, the Zone is located between 11^{o}N to 12^{o}N latitude and 39^{o}E to 40^o E longitudes and has an estimated area of 1,275,514.35 hectares, which covers about 20 percent of the region. The altitude of the Zone varies from 913 to 4187 masl. It has four agro-ecological zones, namely, lowland (*Kolla*) 500 to 1500 masl 38 percent, Mid-altitude (*Woina-Dega*) 1500 to 2300 masl , Highland (*Dega*) 2300 to 3200 masl , and *Wurch*>3200 by covering 38, 34, 21 and 7% of the Zone, resptively (NMSA,1996).

Data Sources and Collection Methods

In order to accomplish this study the following primary and secondary data have been collected. Remote sensing data: SPOT vegetation historical 10 day syntheses (S10) archive is freely available through SPOT Vegetation Program meat distribution server (http://free.vtvito.be/).

SPOT vegetation NDVI data can be obtained for the whole continent of Africa (38°N to 35°S. 26°w to 60°E) in a geographic projection, with a spatial resolution of 0.00892857 degree (i.e. approximately 1 km) for agricultural drought monitoring. The size of image was 9633 x 8177 pixels. SPOT and PROBA-V vegetation satellite images have been used for this study to generate the NDVI and VCI value to characterize Agricultural drought condition in the study area. These data is freely available through the website of the Vegetation Programme via the free S10 distribution server http://free.vtvito.be/. However, the 2014 and 2015 image was downloaded from Copernicus Global Land Service (http://land.copernicus.eu/global http://land.copernicus.eu/global). Meteorological data and monthly climate data of the study area such as minimum and maximum temperature and rainfall data were collected from Ethiopian national meteorological services agency (NMSA) for the study area. GPS points were collected from the study area of weather station site to interpolate SPEI value. Crop yield data (2000 to 2015) were collected from the Central Statistics Agency (CSA) of Ethiopia (Addis Ababa) for validation purpose of drought monitoring index.

Methods of Data Processing and Analysis

The RAW data of NDVI value range is 3 to 255; it is not given in standard range. Then, it has been rescaled it in to normal NDVI range (-1 to +1). To convert the RAW NDVI values in to normal NDVI: **Actual NDVI= Coefficient a*DN plus coefficient b:**

NDVI = Coefficient a*DN + b: Where; Coefficient a = 0.004, Coefficient b = −0.1 Then, actual NDVI was calculated from the raw data as (Raw data pixel value * 0.004) − 0.1 using Raster map algebra in ArcGIS. In addition to this, The PROVA-V vegetation data was rescaled to obtained the standard range of NDVI value (-1 to +1). The Raw digital NDVI value ranges is similar with that of SPOT vegetation data but its offset value is different. Therefore, the rescaling value is expressed as: **Actual NDVI= (DN/ Coefficient a) − coefficient b:** Where; coefficient a = 250 and Coefficient b = −0.08 Therefore, Actual NDVI= (Raster/250) −0.08.

NDVI Anomaly: NDVI can be used as an index to assess vegetation condition through analysis of NDVI anomaly (Murali et al., 2008).

NDVI Anomaly i= [(NDVI max i - Mean NDVI max)/ (Mean NDVI max)]*100

Where, NDVI max i=Maximum NDVI in the growing season in ith year and Mean NDVI max=long term mean maximum NDVI in the growing season during the period of study.

Vegetation Condition Index (VCI) :

Although the NDVI has been extensively used in the past for vegetation monitoring, it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. Vegetation condition index was first suggested by Kogan (1995). It is used to estimate the climate impact on vegetation.

VCI= (NDVI$_J$ - NDVI min)/ (NDVImax - NDVI min) *100

Where, NDVImax and NDVI min is calculated from long-term recorded for a particular year and j is the index of the specific year.

Standardized Precipitation and Evapotranspiration Index (SPEI):

To compute the values of SPEI, Computer software have been used. The software is automatically calculates the SPEI value over a wide range of time scales. It is freely available in the web repository of the Spanish National Research Council (available online at http://digital.csic.es/handle/10261/10002). It is new drought monitoring index, recently proposed by Vicente-Serrano et al. (2010). This software can be calculates the SPEI values by using the observed climate variables data to detect historical drought. The software can be run for 3, 6, 12, 24 and 48 month time scales. For this study 3 month time scale climate data (rainfall and mean temperature) have been used. In order to get spatial pattern of drought condition in the study area, interpolation of SPEI value was done with Inverse distance weighted (IDW) method using ArcGIS software from 2000-2015 time period in the main crop growing season. 16 years starting from 2000 to 2015 Yield anomaly has been calculated in the same way as the computation of NDVI anomaly for validation purpose. In order to show spatial patterns and severity of drought, drought and wet years were selected based on their respective drought Severity levels from each drought index. Finally, the combined agricultural drought severity map was generated by overlying the agricultural and meteorological drought severity maps. Different software packages were used to perform the data processing and analysis. The software packages include ERDAS IMAGIN 2014, ArcGIS 10.3, SAS 9.3, SPEI and Microsoft Excel for arrangement of data.

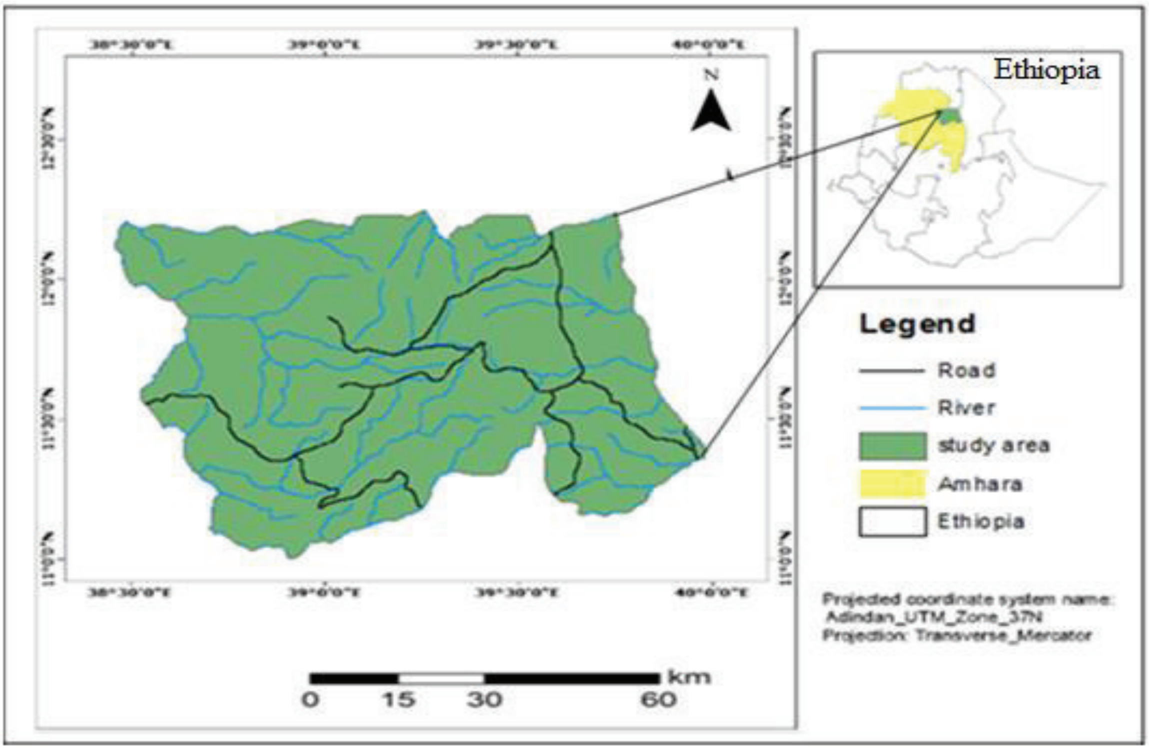

Figure 1: Location map of the study area

Table 1. **Drought severity classification**

	Drought severity classes			
Drought Indices	Slight/no Drought	Moderate Drought	Severe Drought	Very severe drought
NDVI anomaly	0 to – 10	-11 to - 25	-26 to – 50	below - 50
SPEI	$1 < SPEI \leq 1.5$	$-1 < SPEI \leq 1$	$-1.5 < SPEI \leq -1$	$-2 < SPEI \leq -1.5$
VCI	51 to 60	36 to 50	21 to 35	0 to 20

RESULTS AND DISCUSSION

Relationship between Seasonal Rainfall and NDVI

Seasonal Rainfall and NDVI analysis result showed that there was good correlation (r=0.71) between rainfall and NDVI (Fig. 2). During the sixteen years (2000 to 2015), there was considerable year to year variation in precipitation and NDVI. It revealed that, there was increasing trend both in rainfall and NDVI. Also they have better association that indicating with in16 year's data, 51 % percent of NDVI variability can be explained by seasonal rainfall (R^2 value 0.514). The result of this study lines with the findings of Aynamba and Tucker (2005), Beyene (2007) and Gizachew and Suryabhagavan (2014) who have reported the strong correlation between NDVI and seasonal rainfall.

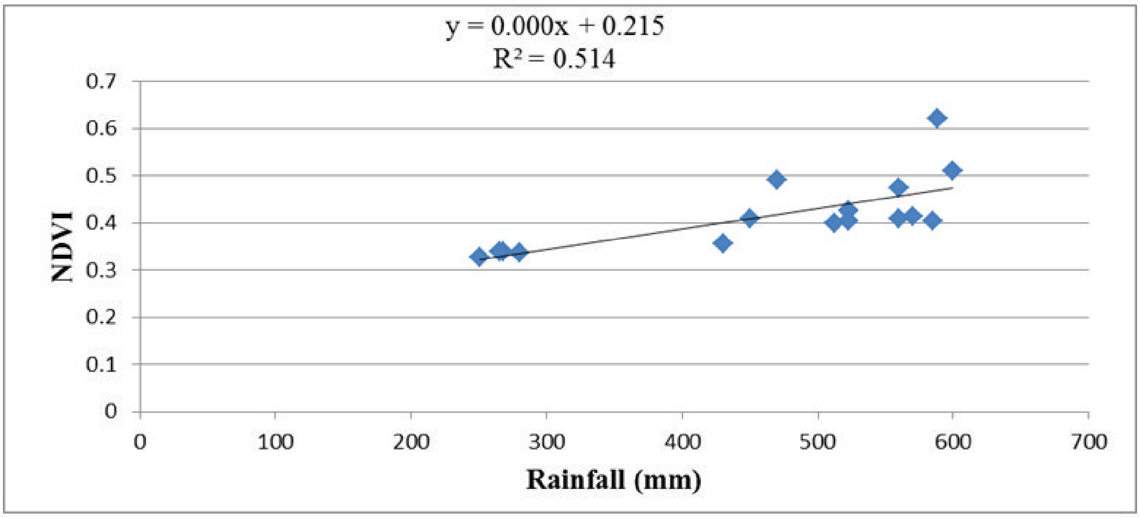

Figure 2: Relationship between Seasonal Rainfall and NDVI

Normalized Difference Vegetation Index Anomaly and Agricultural Drought

The NDVI is useful indicator as a measure of agricultural drought when compared to normal plant health. NDVI anomaly is one of agricultural drought index that shows the drought severity level. Based on this drought monitoring index result, 2005 and 2015 years were considered as a drought years during the main cropping season and the level of drought severity ranges from very severe to slight drought in both 2005 and 2015 drought years. However, the extent of moderate and slightly drought covered small pocket. The majority of the study area was suffering by very severe and severe agricultural drought (Fig. 3).The extent of drought severity was increased by increasing the time scale during the two year. Regarding the wet years, it can be observed from the map depicted in (Fig. 3) 2009 and 2013 years were taken as slight and non drought years.

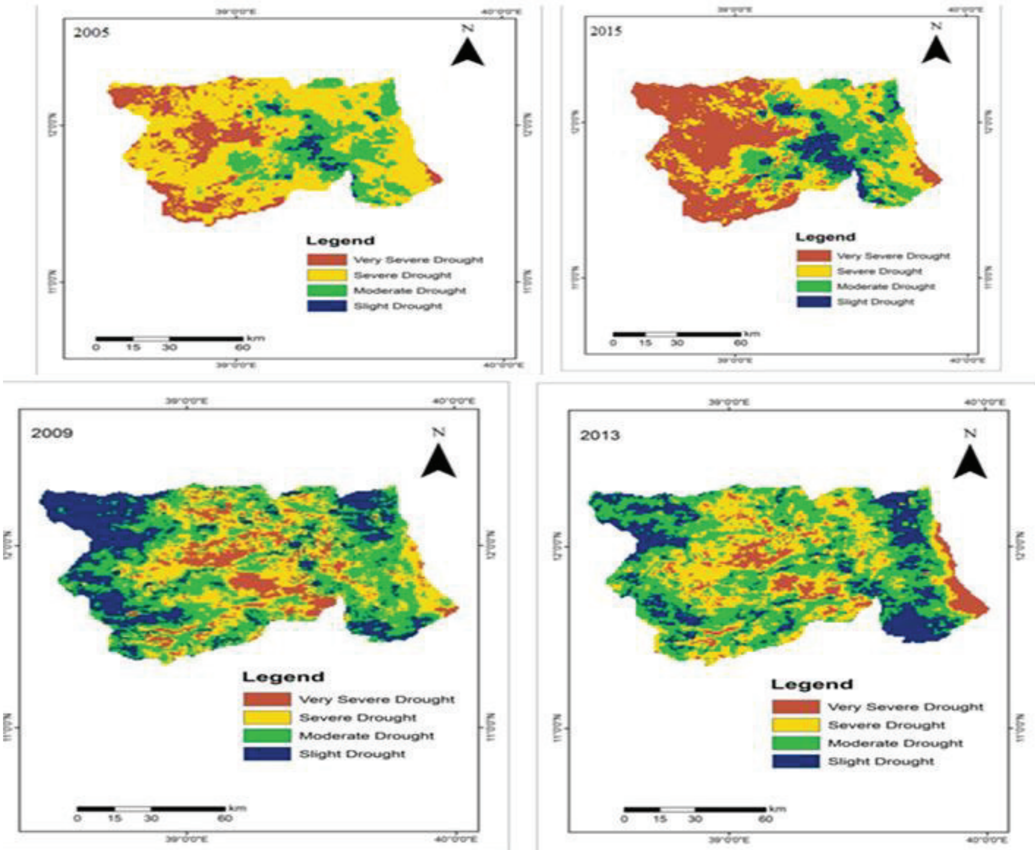

Figure 3: NDVI Anomaly for drought years (2015 and 2005) and wet years (2009 and 2013)

Relationship between NDVI Anomaly and Crop Yield Anomaly

Correlation analysis between NDVI and crop yield anomaly was conducted in order to evaluate how the crop yield changes with relation to NDVI for rainfed cropping systems. There was positive relation(r=0.78) between

NDVI and crop yield Anomaly (Fig. 4). This result confirmed that 62 % of crop yield Anomaly variability can be explained by NDVI Anomaly. The highest yield reduction occurred in 2005 and 2015 due to agricultural drought event (Fig. 4). The result of this study lines with the findings of Beyene (2007), who have reported the good correlation between NDVI and crop yield anomaly.

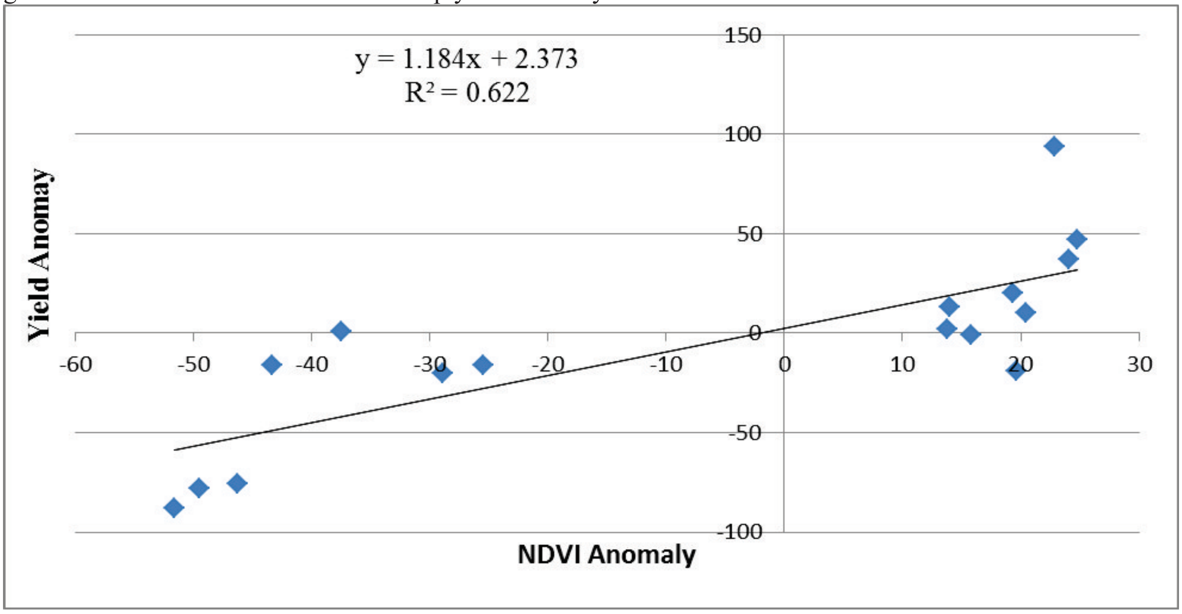

Figure 4: Relationship between NDVI and Yield Anomaly

Relationship between NDVI Anomaly and SPEI

Simple correlation analysis was conducted to evaluate the relationship between NDVI Anomaly and SPEI. The result obtained from the correlation analysis of the two parameters indicates there was positive strong correlation(r=0.82) between them (Fig. 5), which is in lines with findings of Vicente-Serrano et al. (2012) who reported that the strong correlation between the SPEI and NDVI Anomaly. In this study, R^2 value 0.67 percent indicates that 67 % of NDVI variability can be explained by SPEI. Wang et al. (2001) concluded that NDVI Anomaly was more strongly related to climate variables (precipitation and temperature).

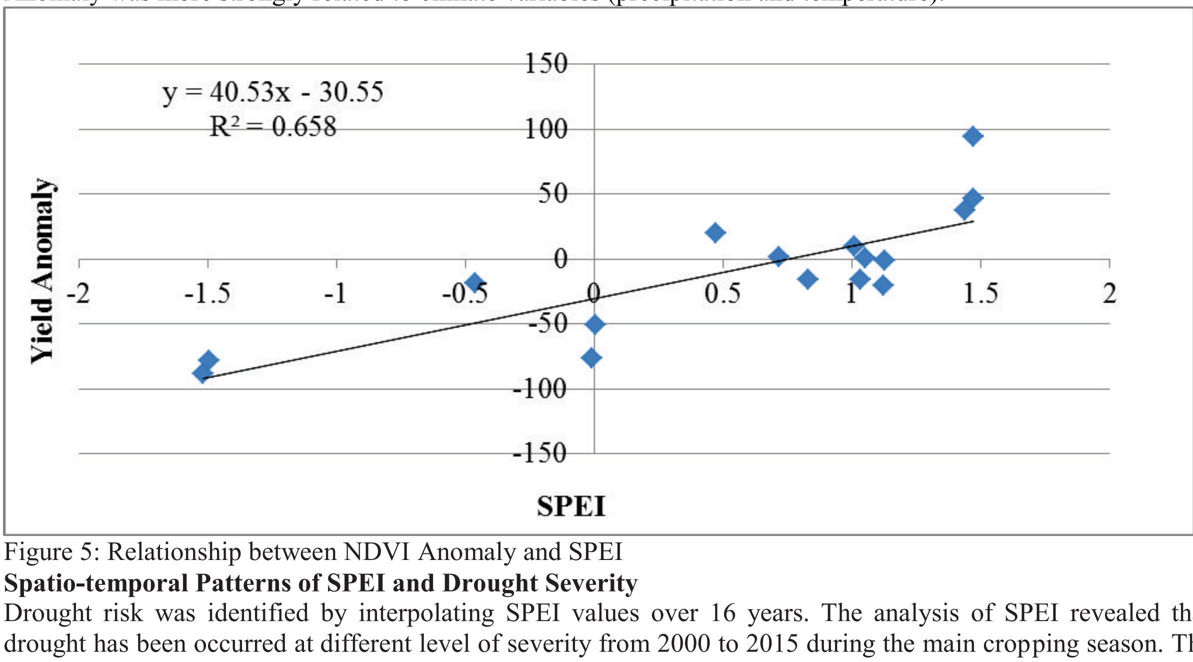

Figure 5: Relationship between NDVI Anomaly and SPEI

Spatio-temporal Patterns of SPEI and Drought Severity

Drought risk was identified by interpolating SPEI values over 16 years. The analysis of SPEI revealed that drought has been occurred at different level of severity from 2000 to 2015 during the main cropping season. The result showed that the drought years of 2005 and 2015 (Fig. 6) and normal years of 2009 and 2013 (Fig. 7). It can be seen that during the drought years of 2005 and 2015 the SPEI values was very low in the study area. This indicates low rainfall distribution and high temperature during the main crop growing season. Spatio-temporal drought severity map showed that Western and Eastern parts of the study area are vulnerable to both very severe and severe drought event while the central part of the study area was less vulnerable to the drought event. The highest SPEI value was observed in the year of 2009 and 2013 and the range of drought severity was from slight drought to no drought. This might be occurred due to the influence of the optimum distribution of rainfall and temperature.

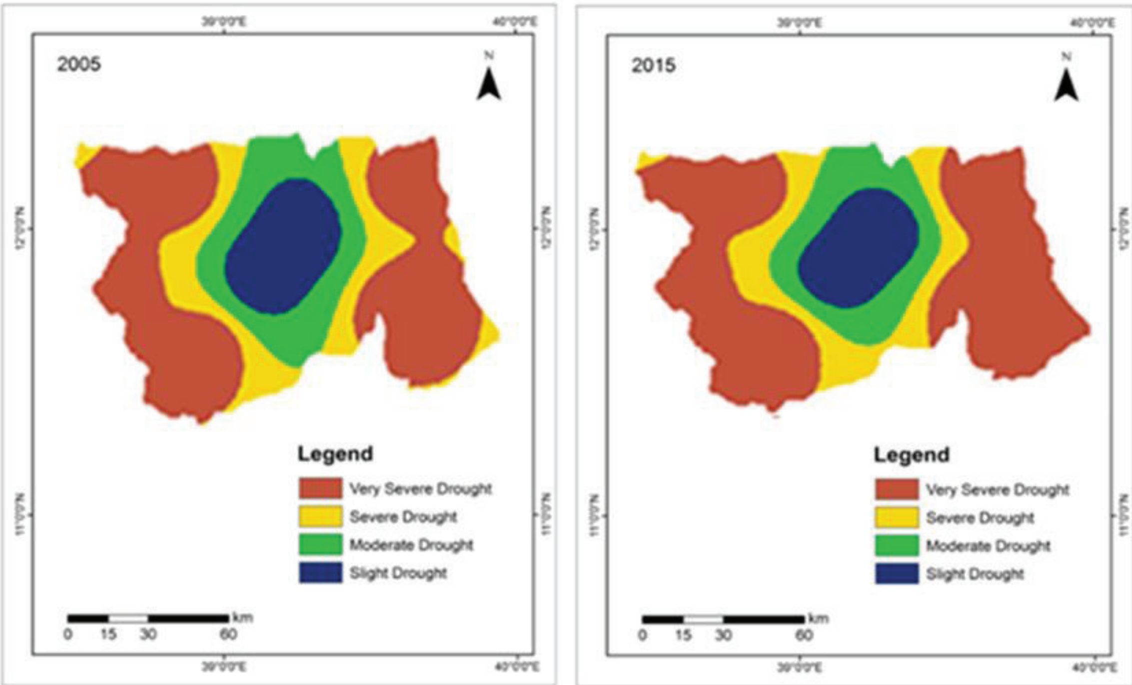

Figure 6: SPEI for drought years (2015 and 2005)

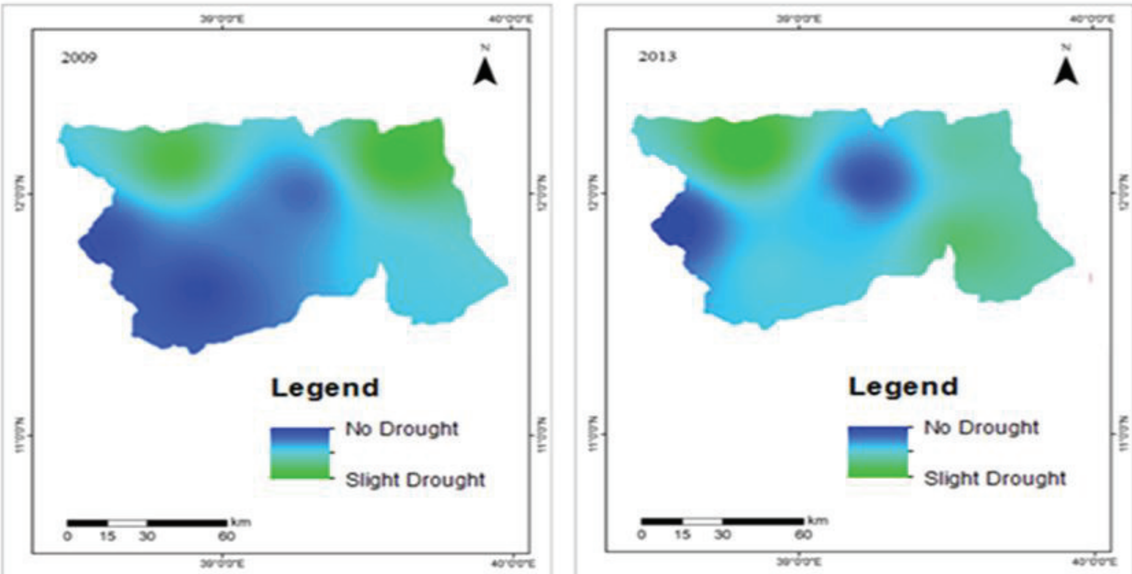

Figure 7: SPEI for wet years (2009 and 2013)

Standard Precipitation and evapotranspiration Index (SPEI) and yield anomaly

Agriculture is one of the most important sectors that humans rely on and can be significantly affected by droughts. Due to the fact that crop production is a function of rainfall, crop failure is most often associated with moisture deficit or agricultural drought. The correlation analysis result has showed that when SPEI is positive, yield anomaly also turns positive revealing a good positive correlation (r=0.83). Since SPEI is an index that represents water deficit or excess, positive SPEI represents that water has been available to plants so that yield become above normal condition (Fig. 8), Whereas, negative SPEI is reflected on crop production through yield reduction. Similarly, Taotao et al., (2016) reported the strong correlation between Yield Anomaly and SPEI.

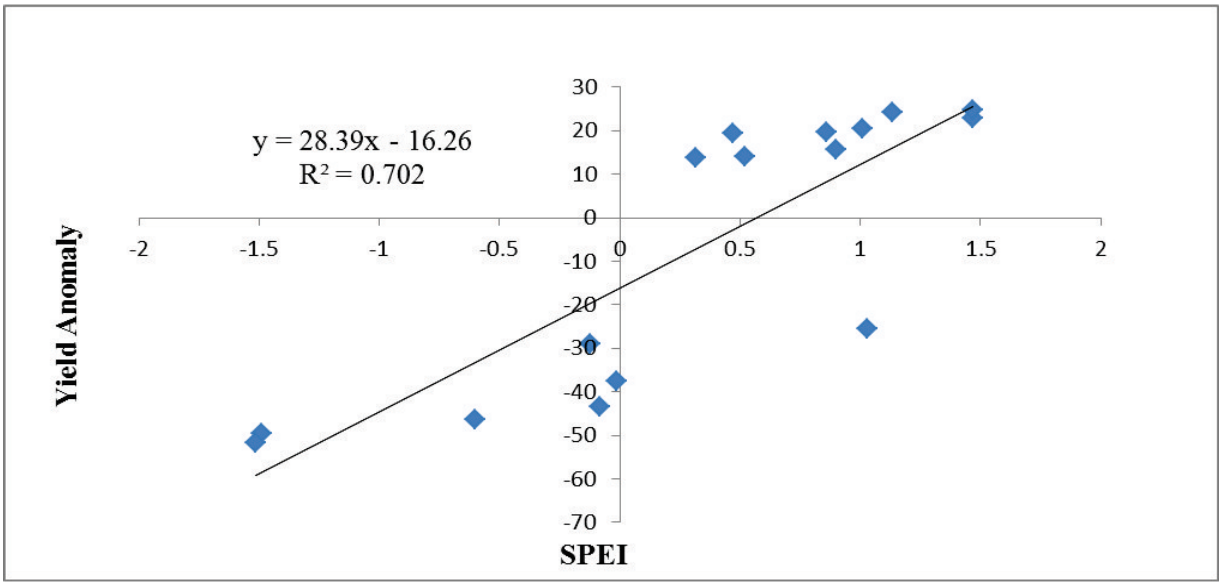

Figure 8: Relationship between SPEI and Yield Anomaly

Drought Monitoring through Vegetation Condition Index

In this study, the Vegetation Condition Index (VCI) has been computed for the year from 2000 to 2015 from Spot Vegetation NDVI and Prova-v vegetation data. The VCI value between 50% and 100% indicates optimal or above normal condition. It can be seen that the Vegetation Condition Index (VCI) values were below 50% in years 2005 and 2015 in the study area (Fig. 9). It revealed that the occurrence of very severe drought situation during main crop growing season in the study area. It might be due to deficiency of rainfall and temperature variability. Kogan (1997) illustrated that the VCI value of 35% can be identified as very severe drought condition, which is in line with this findings. The Vegetation Condition Index (VCI) result in 2009 and 2013 years showed that better vegetation condition during the main crop growing season (Fig 10). In these years also the vegetation Condition Index was above 50% in most of the study area. It indicates that the vegetation was not severely affected with water stress.

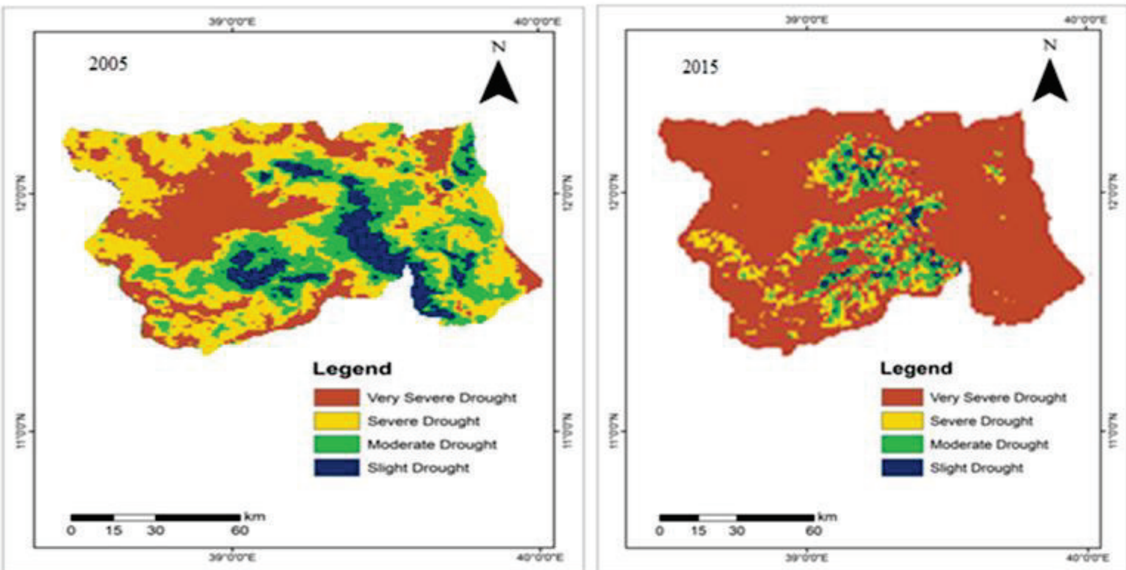

Figure 9: Spatial pattern of VCI for drought years 2005 and 2015

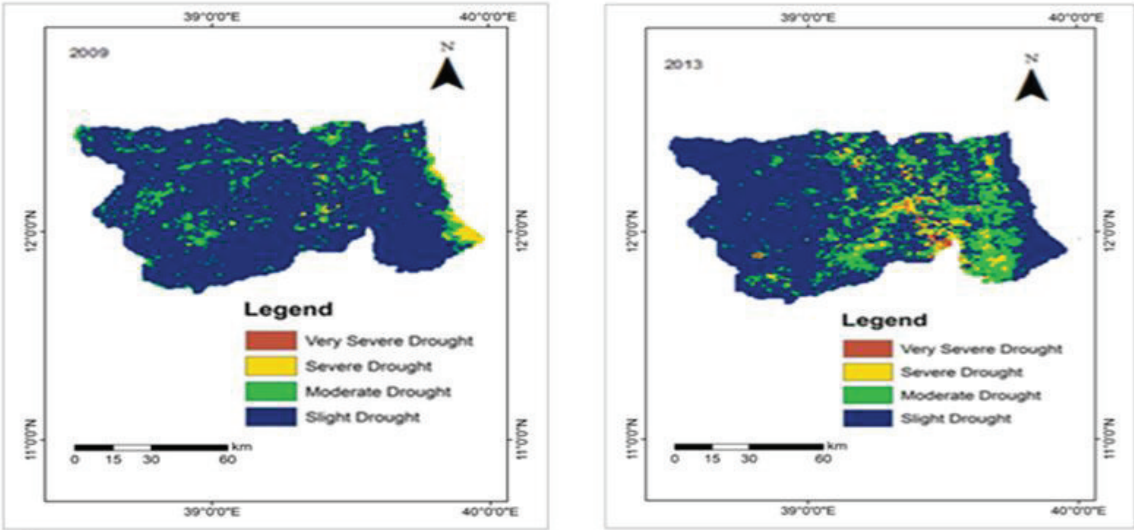

Figure 10: Spatial pattern of VCI for Wet years 2009 and 2013

Combined Drought Risk Map

The combined drought severity map was generated by overlying the agricultural and meteorological drought severity maps. The weight was given according to their degree of influence using pair-wise comparison. According to the combine drought map (Fig 11) very severe and severe drought primarily occurred in West, North West, South West, East, South east and North east parts of the study area while other study area experienced different type of drought. The area under severe to very severe drought conditions was 33.5% and 42%, respectively (Table 2) from the total study area, which indicated that almost 75% of the area was prone to drought. The moderate and slight drought succeeded to 19.5 % and 5 %, respectively.

The crop yield data analysis result showed that there was similar trend like different droughts monitoring indices analysis result. In addition to this, the informal interview with zonal agriculture expert's result showed that there was drought in the past 15-20 years. They explained that the fluctuation of rainfall and temperature are no unusual for them that it affect considerably human life, animals, crops as well as other natural resources.

Furthermore, information obtained from different published and unpublished sources confirms that every alternate year or after each 2 to 3 years cropping seasons, there was severe agricultural drought in study area, and consequently complete crop failure occurred in most of the study area. Similarly, Alemu (2011), who reported that years with climatic extreme events in the area were 1993, 1997/98, 2001/02 and 2004/05 and 2006 droughts have been occurred. Therefore, Drought mitigation and adaptation practices are unquestionable to meet food security. Adaptation is adjustment in natural or human systems in response to actual or expected drought effects, which moderates harm or exploits beneficial opportunities whereas mitigation of drought is a human intervention aimed at reducing the climate variability to improve livelihood of the community. The intervention might be irrigation based agriculture practices development, drought tolerated crop species adaptation and wisely resource conservation and utilization system. Rahel (2007) concluded that the fluctuation of rainy season, low rainfall of the small rainy season and late onset of the main rainy season can affect agricultural production and cropping system in East Amhara region, particular north Wollo zone, which is in lines with findings of our study.

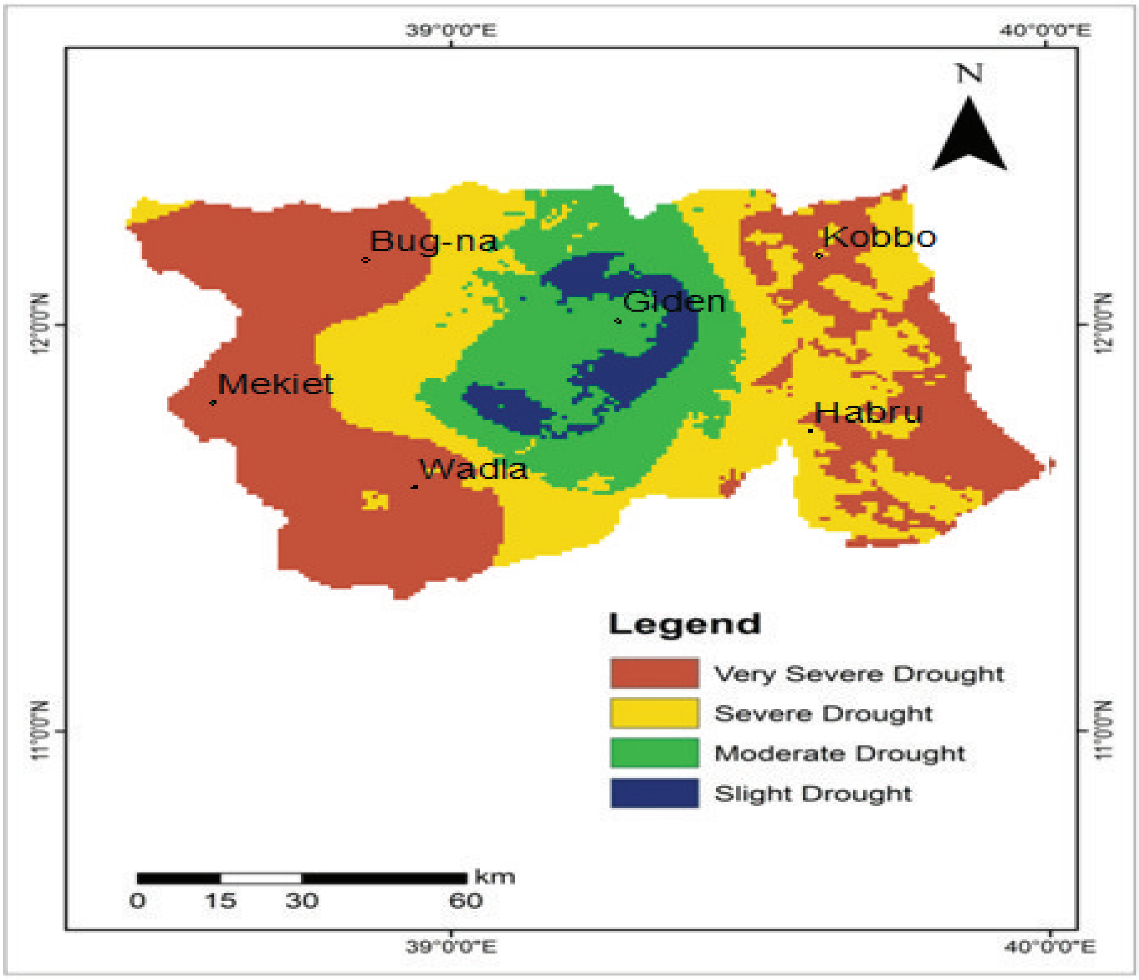

Figure 11: Combined drought risk map

Table 2: Area under Different Drought Conditions

No	Drought category	Area(ha)	Area (%)
1	Very severe drought	537758.65	42%
2	Severe drought	422794.83	33.5%
3	Moderate drought	249508.27	19.5%
4	Slight drought	65452.6	5%

Conclusion

Agricultural drought occurs when there is not enough soil moisture to meet the needs of crops at a particular time. Agriculture is the most vulnerable and sensitive sector that is seriously affected by the impacts of climate variability and climate change. Conventional methods of drought monitoring and early warning system using only station point data is time consuming and tedious. Similarly, the data are often incomplete and inconsistent. Also, there is scarcity of the research work on drought assessment in Ethiopia generally and north wollo zone particularly. Due to this there is a gap between the drought and pre awareness about it. Agricultural drought risk mapping can be constructive to guide decision making process in drought monitoring and to reduce the impact of drought on agricultural production and productivity, while identifying appropriate sites for specific adaptation and mitigation measures.

The observations of this study have suggested that the drought monitoring results showed that the drought severity on average was very high in North Wollo Zone. The two years 2005 and 2015 were considered as drought years and 2009 and 2013 were taken as slight-drought years. Final resultant risk map was obtained by integrating agriculture and meteorological drought risk maps, which indicate the areas, were facing a combined drought. By using time series climate data and satellite based drought monitoring system, the agricultural drought impact resulting from extreme temporal and spatial variability of rainfall and Temperature, and also lack of decision making process and strategic planning for drought monitoring and identifying appropriate site for specific adaptation and mitigation could be alleviated. It is important to establishment formal early warning information centers in the study area particularly for agricultural drought monitoring and coping strategies. The study could be more meaningful if effects of drought on human and livestock population would be assessed. Therefore, it is recommended to include the socio-economic data to better understand the vulnerable factors. Prioritization and implementation of site specific adaptation and/or mitigation projects should be made based on the drought severity levels of specific locations.

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