Original Research Paper

Volume : 5 | Issue : 10 | October 2016 • ISSN No 2277 - 8179 | IF : 3.508 | IC Value : 69.48

Evaluation of Vegetation Indices for Agricultural Drought Monitoring in East Amhara, Ethiopia

Earth Science

KEYWORDS : Drought monitoring, Growing season, Remote sensing, SPI, Vegetation indices

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ABSTRACT

Remote sensing data and models for drought monitoring and early warnings must be validated and calibrated before they become operational to specific region and hydro-climatic conditions. The main objective of this research was to evaluate vegetation indices for agricultural drought monitoring. In order to achieve the objective of the study, a relationship between a 3 month Standardized Precipitation Index (SPI) and the respective growing season vegetation indices were first modeled using ordinary least square to vegetation conditions respond to rainfall variability. The coefficient of determination indicates the relationship was highest with Drought Severity Index (DSI) (R^2=0.85) while it was lowest with VCI (R^2=0.53). Relationships between four known MODIS vegetation indices products (NDVI, DSI, VCI an Eta) and crop yield were examined to compare the performances of vegetation indices for drought detection and monitoring. DSI was found to be the best to define agricultural drought phenomena among the four indices (R2=0.76). DSI is followed by VCI, NDVI and Eta. DSI was an efficient and reliable drought index among the four indices analysed. Consequently, drought vulnerable areas were identified and characterized. The results indicate that the study area can be classified into no stress, low stress and high stress agricultural drought risk sub-zones covering 34.94%, 43.18% and 21.88% of the total area, respectively. The present findings, would help to fill the gap by contributing evidences of effectiveness of vegetation indices in monitoring agricultural drought.

1. Introduction

Drought is a naturally occurring phenomenon, when precipitation is significantly below normal levels, causing serious hydrological imbalances adversely affecting farming production (UNCCD, 1999). Drought is the consequence of a natural reduction in the amount of precipitation received over extended period of time it may be usually a season, or more in length, although other climatic factors (such as high temperature, high winds, and low relative humidity) are often associated with it in many regions of the world and can significantly aggravate the severity of the event (Oliver, 2005). Agrarian developing countries are very much vulnerable to the impacts of drought. Frequent droughts experienced in the greater horn of Africa have negatively impacted the natural habitats, livelihoods of human and of animals, and the food production levels in the region. According to FAO (2011), the decline in food production associated with the drought conditions in this part of the world is one of the major factors responsible for the increased cost of food and malnutrition experienced by the inhabitants. Ethiopia is one of the most drought-prone countries in the Horn of Africa (Conway, 2000). In the mid 1980s, droughts in Ethiopia and Sudan caused more than a million deaths. Consequently, in order to reduce the negative impacts of drought, the Famine Early Warning System Network (FEWS NET) was founded in 1985 by the United States Agency for International Development (USAID) to improve the emergency response capabilities in Africa, including disseminating information and increasing food security (Brown et al., 2008).

In during the last three decades, a variety of remote sensing-based indices for agricultural drought monitoring and assessment has been developed. Various indices must be validated and calibrated to the specific region and hydro-climatic conditions to apply remote sensing data in drought monitoring (Gizachew and Suryabhagavan, 2014). This is due to the fact that drought indices were originally developed for specific regions and the inherent complex nature of drought (Hayes et al., 2000 and 2004). In 2009, the National Aeronautics and Space Administration (NASA, USA) has conducted need assessment to enhance remote sensing indices inputs to FEWS NET program and showed that the requirements vary according to specific ecological conditions and recommended to develop validation techniques and study their performance further (Ross et al.,2009). The objective of the present research was to test within the performance difference of vegetation indices could be evaluated for agricultural drought monitoring and compared by integrating geospatial techniques with statistical modeling.

2. Materials and Method

2.1 The study area

This study was conducted in East Amhara, north east Ethiopia. Geographically, it is located between 10°10′ N–13°15′ N latitude and 38° 30′E–40° 9′E longitude covering a total area of about 38339.36 km^2 (Figure 1). Topographically, the region is divided in to highlands in the west and lowlands in the east. The lowest areas are in the great Rift Valley of the Ethiopia, which is part of the East African rift system. Larger parts of East Amhara are characterized by rugged topography that consist very high mountains, deeply incised canyons and gorges, valleys and plateaus (FAO, 1984; Tefera et al., 1996). This area drains to four river basins, Abay (Blue Nile), Tekeze, Awash and Golina (Figure 1). Tekeze river joins the Blue Nile at Atbara in Sudan. Golina river sinks within the study area. Abay and Awash rivers drain the south western and the south eastern part of the study area, respectively. Tekeze drains the north western, while Golina drains the north eastern parts of the study area.

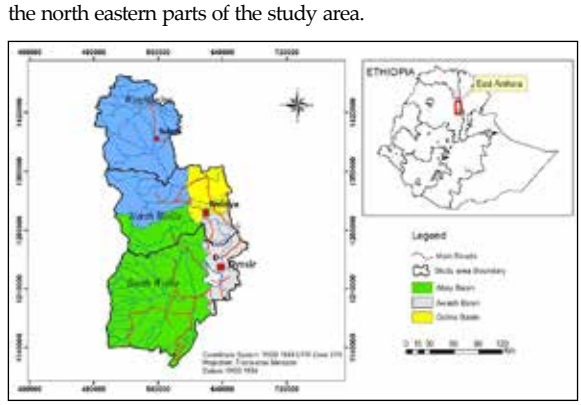

Figure 1: Location map of East Amhara

2.2. Data sources

2.2.1. MODIS vegetation indices data

The MODIS is the primary sensor for monitoring terrestrial ecosystems for the NASA Earth Observing System (EOS) program (Justice et al., 2002). The MODIS is more sensitive to changes in vegetation dynamics (Huete et al., 2002) and was found to be a more accurate and versatile tool to monitor global vegetation conditions. Expedited MODIS 5-day maximum-value composite NDVI images at 250 m spatial resolution were used to monitor vegetation condition. The real-time and historical NDVI products were composited in 10-day intervals (every 5 days are available at the following

2.2.2. Actual evapotranspiration anomaly (Eta)

The Eat product monitors actual vegetation water use in near-real time across rain fed and irrigated agriculture, natural vegetation, and wetlands. Using MODIS data (MODerate resolution Imaging Spectroradiometer), the product was currently operational to a 1-km resolution on 8-day and monthly basis (FEWSNET, 2015). Actual ET (ETa) was produced using the Operational Simplified Surface Energy Balance (SSEBop) model (Senay et al., 2013) for the period 2003 to 2012. The SSEBop setup was based on the Simplified Surface Energy Balance (SSEB) approach (Senay et al., 2007, 2011) with unique parameterization for operational applications.

2.2.3. Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data

The CHIRPS dataset developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara, is a blended product combining a pentadal precipitation climatology, Meteosat and Global Telecommunication System (GTS) data and the National Climatic Data Center (NCDC), atmospheric model rainfall fields from the NOAA Climate Forecast System version 2 (CFSv2) and *in situ* precipitation observations. Spanning 50°S–50°N (and all longitudes), starting in 1981 to near-present, CHIRPS incorporates gridded rainfall time series for trend analysis and seasonal drought monitoring.

Pentadal rainfall estimates created from satellite data based on cold cloud duration (CCD) based on regression models calibrated using Tropical Rainfall Measuring Mission (TRMM), are expressed as percent of normal and multiplied by the corresponding precipitation climatology. Next, stations were blended with this CHIRP data to produce CHIRPS. Quasi-global gridded products are available from 1981 to near-present at 0.05° spatial resolution (~5.3 km) and at pentadal, dekadal, and monthly temporal resolution. The data were downloaded from

2.2.4. Land-use/land-cover

A generalized land-use/land-cover map of east Amhara was prepared and used to extract cultivated areas of east Amhara. Landsat ETM+ was downloaded from global land cover facility website using the index, Landsat ETM+ sensor with Path 168, Row 052, Path 168, Row 053, and Path 169, Row 051, Path 169, Row 052 and Path 169, Row 053.

2.2.5. Crop yield data

Crop yield data and cultivated land areas for the years 2003 to 2012 except 2009 were collected from Central Statistical Agency and from Amhara Agricultural Development Bureau. The data were used for the validation of vegetation indices.

2.3. Methods of data preprocessing and analysis

2.3.1. Processing of MODIS vegetation indices

NDVI is the ratio of reflected infrared to red wave length and is an excellent measure of vegetation health. Healthy plants have a high NDVI value because of their high reflectance of infrared light, and relatively low reflectance of red light. The expression for calculating NDVI is given as follows:

$$NDVI = \frac{NIR-R}{NIR+R} \qquad (1)$$

Where: NIR and R are near infrared and red part of optical Spectrum, respectively. NDVI ranges from –1 to +1. Values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating healthy vegetation.

DSI is defined as NDVI deviation from its long-term mean.

$$DEV_{ndvi} = NDVI - NDVI_{mean} \qquad (2)$$

Where: *NDVI* is the NDVI value for month *i* and *NDVI* is the long-term mean NDVI for the same month.

VCI were used for the comparison of a temporal vegetation index image with previous seasons. The approach locates the value of each vegetation index pixel in the historical range of all preceding images. *VCI* should be read as a percentage in relation to a historic high.

$$VCI = \frac{(NDVI_J - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \times 100 \qquad (3)$$

Where, is the current seasonal NDVI value;

$NDVI_{max}$ and $NDVI_{min}$ are calculated from the long term record for that month and J is the index of the current month.

The first step in processing was extracting of all raster NDVI data for the period 2003–2012 with the shape file of the study area using Extract by Mask tool set of ArcGIS 10.2. As performance of the crop during the growing season was one of the indicators of agricultural drought, NDVI time series of the main growing season between 1st October 2003 and 31st October 2012 (6 composites per month, had 30 layers per year, except for 2009 were considered. The process was performed for all images using ArcGIS 10.2 software. The 10-day composites were sequentially composited to generate 6-pentadal (month), Seasonal (growing season) of time series for the period 2003–2012 using Geographic Coordinate system with spheroid WGS84. MODIS NDVI data has a spatial resolution of 250m and temporal resolution of six pentadal composite (10day updated every five days) for each month. The MODIS NDVI data were stretched (mapped) linearly between 0, to 200 when obtained from USGS database (FEWS NET, 2013). In order to transform raw data into NDVI data, the following formula were computed using the Map Algebra tool of ArcGIS10.2.

NDVI = (DN-100)/100. Where DN is the raw raster

To determine the average values of monthly and seasonal composites of NDVI values, Float (Math) and Cell Statistics toolset of ArcGIS 10.2 were applied. After computation of major cell statistics (mean, minimum, maximum and range). Drought Severity (Deviation) Index and Vegetation Condition Index for the period 2003–2012 were computed by creating models in Model Builder application of ArcGIS 10.2.

Volume : 5 | Issue : 10 | October 2016 • ISSN No 2277 - 8179 | IF : 3.508 | IC Value : 69.48

2.3.2. Processing of actual evapotranspiration anomaly (Eta)

The first step was extracting of all the raster Eta data for the period 2003–2012 with the shape file of the study area. As the performance of the crop during the growing season is one of the indicators of agricultural drought, in this study Eta time series of the main growing season between 1st October 2003 and 31st October 2012 (6 composites per a month, 30 layers per year, except for 2009 were considered. The 10-day composites were cumulated /composited to generate 3-dekadal (month), Seasonal (growing season) of time series for the period 2003-2012 using Albers equal area conic Projection with spheroid (Clarke, 1866). Then, to determine the average values of monthly and seasonal composites of Eta values, Float and Cell Statistics toolset of ArcGIS 10.2 were applied.

2.3.3. Processing of standardized precipitation index (SPI)
Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) were used to compute SPI. GeoCLIM v1 and Early Warning Explorer are newly available softwares to analyze time series remotely sensed rainfall data. They were developed by USGS/FEWSNET scientists. These softwares allow extracting SPI values at administrative regional/zonal level. The study considered the average kiremt (1st June-31st August) SPI values to explain the main growing season vegetation indices. A 3-month SPI provides a comparison of the precipitation over a specific 3-month period with the precipitation totals from the same 3-month period for all the years included in the historical record. Accordingly, the 3-month SPI values of the kiremt for the study periods were computed.

2.3.4. Land-use/land-cover classification
Digital image of Landsat ETM+ sensor with Path 168, Row 052, Path 168, Row 053, and Path 169, Row 051, Path 169, Row 052 and Path 169, Row 053 (with a map projection of UTM_ Zone 37N, spheroid and datum WGS84) acquired in 23/09/2010 were stacked and mosaicked. ERDAS Imagine ®10. Accuracy Assessment tool were used to conduct an accuracy assessment. ERDAS Imagine uses a square window to select the reference pixels. Among the three different types of distribution parameters simple random were used to evaluate the accuracy assessment of the land cover/land-cover classes. Then, error matrix for each classification has been created and then overall accuracy and Kappa coefficient was computed and evaluated. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification.

2.4. Evaluation of selected drought indices
As it was mentioned in the problem statement existing vegetation indices were developed mostly for use in specific regions, and therefore may not be directly applicable to other regions due to inherent complexity of drought phenomena and different hydro-climatic conditions. Therefore, an evaluation of these indices was carried out to investigate the most appropriate indices for agricultural drought monitoring. Performance evaluation was carried out using ordinary least square model.

2.4.1. Standardardized precipitation index (SPI) and vegetation indices
The interaction of precipitation and vegetation are highly connected. n a rain-fed based cropping system, seasonal rainfall variability is inevitably reflected by vegetation density. In order to analyze the impact of rainfall deficiency on drought, SPI is important to quantify the precipitation deficit. Therefore, a 3 month SPI and the respective growing season vegetation indices were modeled using ordinary least square analysis.

2.4.2. Vegetation indices and crop yield
Vegetation indices and crop yield data were modeled using ordinary least square analysis. OLS models were developed to identify which of the drought indices (NDVI, DSI, VCI, as well as the Eta anomaly) explain agricultural drought in the respective growing season. The main season yield accounts for 90–95% of the annual crop production of Ethiopia (FEWSNET, 2009). The yield data observed in this season was crucial for characterizing the food security status of Ethiopia. In this study, the dependent variables were yearly crop yield data while pixel values as independent variables for the period 2003–2012. The relationship between the spectral properties of crops and their biomass/yield were recognized since the very first spectrometric field experiments. The use of spectral data was studied extensively by using satellite imagery after the launch of the first civil earth observation satellite (Landsat-1) in 1972 (Degefu, 1987; Kogan and Sulvian, 1993). In this research only cereal yield statistics was considered. The flow chart of research method is shown in Figure 2.



Figure 2: Flowchart of the methods followed in this study.

3. Results and Discussion
3.1. The relationship between SPI and vegetation indices
Agricultural drought is a manifestation of meteorological drought. Typically, rainfall is an important meteorological parameter which influences the type of vegetation in a region. The SPI has been defined as a key indicator of meteorological drought by the World Meteorological Organization (WMO, 2006). The advantage of the SPI approach is that it can be used more beneficially than rainfall in spatial analysis for drought. This is because of the possibility of comparing different stations in different climatic regions (or climatic sub-regions) regardless of the fact that they may have different normal rainfalls. This because in SPI, the rainfall is already normalized and compares the current rainfall with the average. Therefore the rainfall of two areas with different rainfall characteristics can be compared in terms of how badly they are experiencing drought conditions since the comparison is in terms of their normal rainfall. The relationship between SPI and vegetation indices were computed for the period 2003–2012. Figures 3–6 show the relationship between 3-month SPI and vegetation indices of the main growing season.

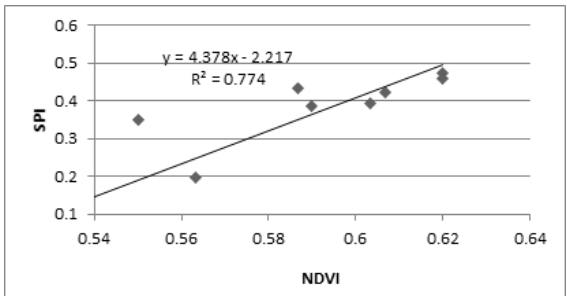

Figure 3: Relationship between SPI and Seasonal NDVI

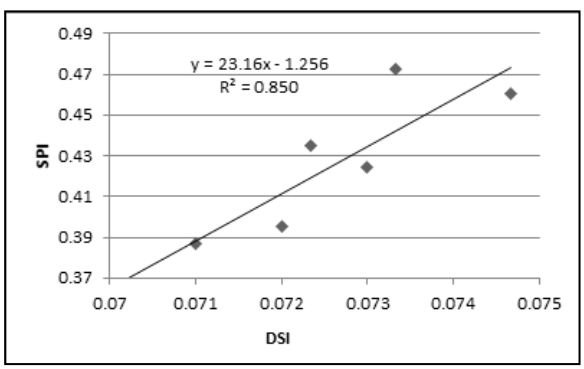

Figure 4: Relationship between SPI and Seasonal DSI

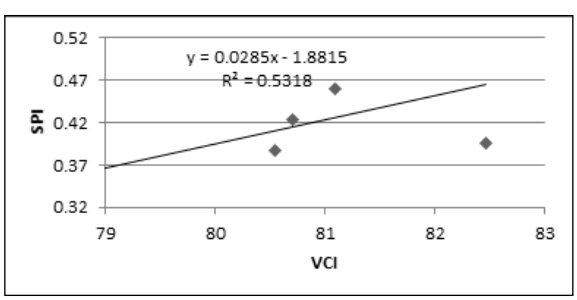

Figure 5: Relationship between SPI and Seasonal VCI

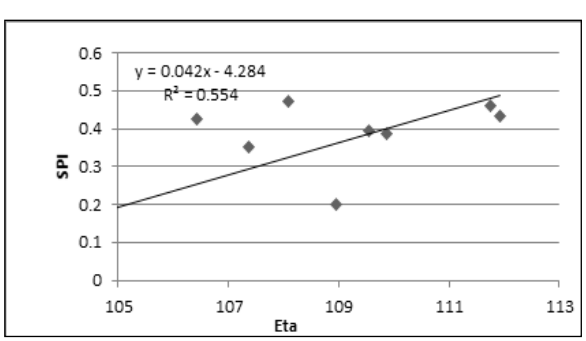

Figure 6: Relationship between SPI and Seasonal Eta Anomaly

There was a significant relationship between SPI and the indices. The highest relationship was with DSI while the lowest was with VCI. Rainfall was one of the climatic variables that largely determine the occurrence of drought. The severity of drought was considered to be a function of rainfall. In many research studies, the relationship between rainfall and satellite based vegetation indices have been analyzed in order to see the pattern between them (Pavel et al., 2006).

3.2. The relationship between vegetation indices and crop yield

The relationship between growing season vegetation indices and crop yield for the periods 2003–2012 was computed using ordinary least square model. The regression relationship between vegetation values and crop yield was illustrated in Figures 7–10. As depicted in the illustrations, there exists significant relationship between vegetation indices and crop yield. There is a variation in the performance among the indices. The correlation between crop yield and DSI was the highest while it was the lowest with Eta. Results also show VCI slightly outperform NDVI.

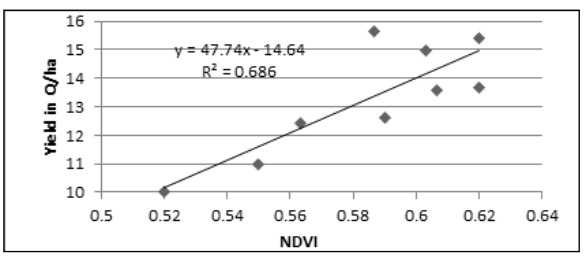

Figure 7: Relationship between Seasonal NDVI and crop yield

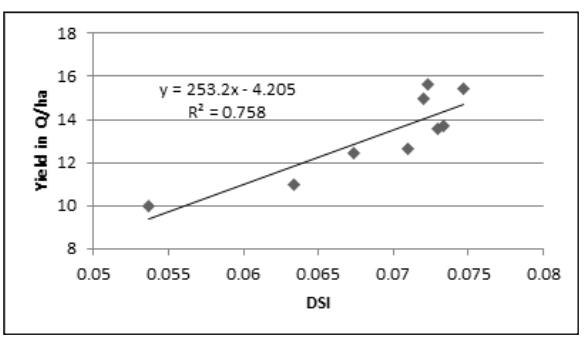

Figure 8: Relationship between Seasonal DSI and crop yield

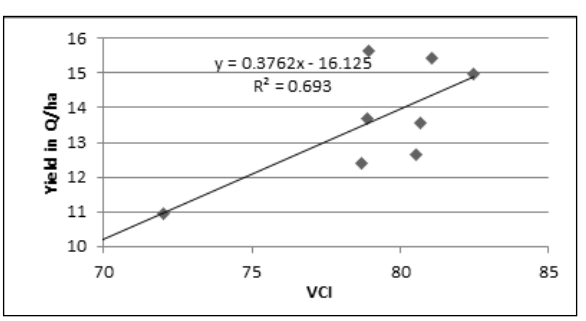

Figure 9: Relationship between Seasonal VCI and crop yield

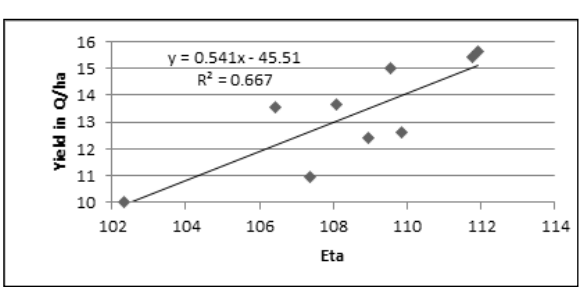

Figure 10: Relationship between Seasonal Eta and crop yield

Volume : 5 | Issue : 10 | October 2016 • ISSN No 2277 - 8179 | IF : 3.508 | IC Value : 69.48

3.3. The influence of rainfall on vegetation indices

As precipitation is the primary cause of drought development, vegetative drought is a manifestation of meteorological drought. In order to see the impact of rainfall deficiency on vegetation density in the study area SPI were used to quantify the precipitation deficit for periods 2003–2012. The coefficient of determination indicates the relationship was highest with DSI and lowest with VCI.

3.4. Comparison among vegetation indices

The coefficient of determination (r^2), which is a measure of the strength of linear dependence between two variables, is calculated between four drought indices and crop yield. The OLS analysis of the vegetation indices with crop yield is summarized in Table 1. It is revealed that DSI has the highest r^2 values among the four indices, and hence, DSI has more capability to monitor agriculture drought. DSI is followed by VCI and NDVI, which are slightly higher than that of the Eta. The performance of NDVI is almost as good as VCI. The overall results suggest that DSI is an efficient and reliable drought index among the four indices. Therefore, for operational applications DSI is recommended for agricultural drought monitoring and early warning.

Table 1: Performance comparison among vegetation indices using R^2

Variables	Performance Evaluation using R^2			
	NDVI	DSI	VCI	Eta
SPI	0.77	0.85	0.53	0.55
Crop yield	0.69	0.76	0.69	0.66

3.5. Identification of drought vulnerable areas

Drought primarily occurred in the north, north east and south parts of the study area region. The drought severity condition is categorized as high stress for values below 0, low stress between 0.1 and 0.25 and no stress for values above 0.25. Accordingly, more than 65% of the study area is vulnerable to agricultural drought. A comparison was carried out to differentiate which of the administrative areas are more vulnerable to agricultural drought. As shown in Table 2 and Figure 11, Waghimira Administrative Zone has the highest proportion of drought vulnerable areas, followed by North Wollo and South Wollo, respectively.

Table 2: Area coverage of drought severity classes per administrative zones

Administrative Zones	Areas of drought Severity Classes in km^2			Total Area in km^2
	High Stress	Low Stress	No Stress	
North Wollo	1938.43	6109.85	4124.06	12172.34
South Wollo	3254.78	6898.28	6893.66	17046.72
Waghimira	3194.13	3547.04	2379.13	9120.30
Total Area	8387.34	16555.17	13396.85	38339.36

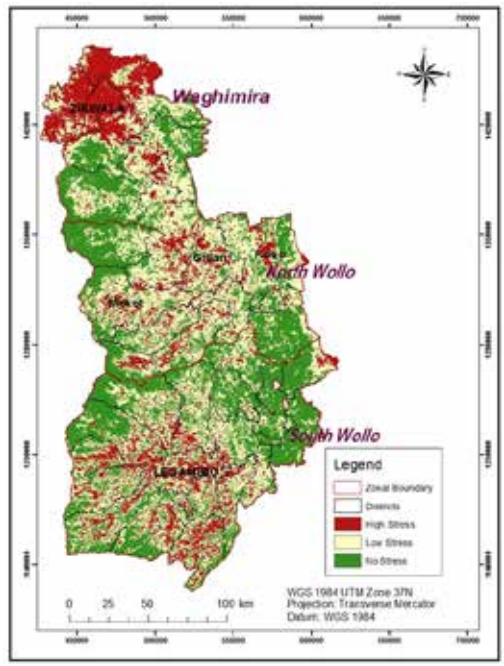

Figure 11: Map of drought vulnerable areas

A study by Henericksen (1986, as cited in Gadisso, 2007) indicated that NDVI was highly sensitive to extended rainfall anomaly. Simple linear regression analysis between dekadal rainfall and NDVI were carried out for different lag time periods so as to better understand the influence of rainfall on vegetation growth and development. Consequently, significant relationship was observed between 1–3 month time lag in the vegetation response to rainfall, would be expected between vegetation indices such as NDVI and rainfall. In this study, the relationships between SPI and vegetation indices were used to see the performance of vegetation indices in drought monitoring. The overall result suggests that there is causal relationship between the variables. However, the main criticism of the SPI is that its calculation is based only on precipitation data. The index does not consider other variables that can influence drought severity, as SPI relies on the following two assumptions: i) the variability of precipitation is much higher than that of other variables, such as temperature and potential evapotranspiration (PET); and ii) stationary (i.e. they have no temporal trend). The importance of variables other than precipitation is negligible in this framework, and droughts are assumed to be mainly controlled by the temporal variability of precipitation. The correlation between NDVI anomaly and grain yield were used to conduct agricultural drought risk assessment (Chopra, 2006; Gadisso, 2007). Moreover, the correlation between grain yield and NDVI is important to quantify the impact of drought on the crop production. Kumar (1997) also suggested that NDVI can be used for the assessment of weather impact on vegetation, and evaluation of vegetation health and productivity. Significant correlation has been observed between vegetation indices and agricultural production yield to the present study. This case study conforms to the view of Kogan (2000) that agricultural drought could be monitored using vegetation indices.

Conclusion

The general consistence of the numeric values results of vegetation indices with SPI and agricultural statistics proved the applicability the method. This has been

achieved by combining remote sensing and GIS techniques with statistical modeling. The general consistence of the numeric values results of vegetation indices with SPI and agricultural statistics proved the applicability the method. Thus, the research presented here would fill the research gap by contributing evidences of effectiveness of vegetation indices in monitoring agricultural drought. Results of the present study can also be used as inputs for drought risk-management efforts in East Amhara and for the development of drought monitoring system.

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