Tropical Ecology **55**(3): 349-363, 2014 ISSN 0564-3295

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Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia

GIZACHEW LEGESSE[1] & K.V. SURYABHAGAVAN[2*]

[1]*Agrometeorology Research Division, Melkassa Agricultural Research Center, Nazareth, Ethiopia*

[2]*School of Earth Sciences, Addis Ababa University, P.O. Box 1176, Addis Ababa, Ethiopia*

Abstract: In dry land semiarid areas of Ethiopia, including a large part of East Shewa zone, agricultural drought is common, and farmers inhabiting the area experience extreme temporal and spatial variability in rainfall during cropping seasons with frequent and longer dry spells. Therefore, spatio-temporal variation in agricultural drought pattern and severity was assessed using Water Requirement Satisfaction Index (WRSI), Standard Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI) anomaly. The results indicate that the cropping seasons of the years 2000 to 2005 experienced enhanced agricultural drought and reduction of grain yield with spatial difference in severity level. The year 2002 was the most severe among all the years, followed by the year 2000. Regarding strength of the indices, WRSI, SPI and NDVI anomaly explained 76 %, 64 % and 54 % of variability of the grain yield, respectively. Thus, WRSI can be a good indicator of agricultural drought. The obtained agricultural risk map indicates that East Shewa zone can be classified into slight, moderate and severe agricultural drought risk subzones covering 17.18 %, 41.32 % and 41.50 % of the total area, respectively. Hence, agricultural drought risk mapping can be used to guide decision making processes in drought monitoring, and to reduce the risk of drought on agricultural productivity.

Resumen: En las zonas secas semiáridas de Etiopía, incluyendo una gran parte de la zona de Shewa Oriental, la sequía agrícola es común, y los agricultores que habitan en el área experimentanuna variabilidad extrema tanto temporal como espacial de la precipitación durante la temporada de cultivo, con períodos de sequía frecuentes y más largos. Por esta razón, se evaluó la variación espacio-temporal en el patrón y la severidad de la sequía agrícola utilizando el Índice de Satisfacción por Requerimiento de Agua (WRSI), el Índice Estándarde Precipitación (SPI) y la anomalía del Índice de Vegetación de Diferencia Normalizada (NDVI), siglas de los índices en inglés). Los resultados indican que las estaciones agrícolas de los años 2000 a 2005 experimentaron una mayor sequía agrícola y una reducción en el rendimiento de granos, con una diferencia espacial en el nivel de severidad. El año 2002 fue el más severo de todos los años, seguido por el año 2000. En cuanto a la fuerza de los índices, el WRSI, el SPI y la anomalía del NDVI explicaron 76 %, 64 % y 54 % de la variabilidad en el rendimiento de granos, respectivamente. Por lo tanto, el WRSI puede ser usado como un buen indicador de la sequía agrícola. El mapa de riesgos agrícolas obtenido indica que la zona de Shewa Oriental se puede clasificar en subzonas agrícolas con riesgos de sequía leve, moderado y severo, los cuales cubren 17.18 %, 41.32 % y 41.50 % de la superficie total, respectivamente. La cartografía de riesgos de sequía agrícola se puede utilizar para guiar procesos de toma de decisiones en el monitoreo de las sequías y para reducir el riesgo de sequía en la productividad agrícola.

Corresponding Author; e-mail: drsuryabhagavan@gmail.com

Resumo: Em áreas de terras semi-áridas secas da Etiópia, incluindo uma grande parte da zona leste de Shewa, a seca agrícola é comum, e os agricultores que aí habitam estão sujeitos a uma variabilidade temporal e espacial da precipitação durante a estação cultural com ciclos de seca frequentes e longos. Portanto, a variação espaço-temporal no padrão de seca agrícola e severidade foi avaliada através do Índice de Satisfação de Necessidade de Água (WRSI), Índice Standard de Precipitação (SPI) eo Índice da Diferença Normalizado de Vegetação (NDVI). Os resultados indicam que as safras dos anos 2000 a 2005 experimentaram maior seca agrícola e na redução do rendimento de grãos com uma diferença espacial no nível de gravidade. De entre todos os anos,o ano de 2002 foi o mais grave, seguido pelo ano de 2000. Quanto à força dos índices, mostrou-se que WRSI, SPI e NDVI explicaram 76 %, 64 % e 54 % da variabilidade da produção de grãos, respectivamente. Assim, WRSI pode ser um bom indicador de seca agrícola. O mapa de risco agrícola obtido indica que a zona leste de Shewa pode ser classificada em subzonas de risco de seca agrícolaleve, moderado e grave cobrindo 17.18 % , 41.32 % e 41.50 % da área total, respectivamente. Assim, o mapeamento de risco de seca agrícola pode ser usado para orientar processos de tomada de decisão no monitoramento da seca, e para reduzir o risco da seca na produtividade agrícola.

Key words: NDVI, Spatio-temporal variation, SPI, WRSI.

Introduction

Climate is a dynamic entity, affecting natural systems through the consequences of climate variability and climate change. Frequent drought is an important aspect of climate variability and climate change that humans have been experiencing in recent decades. According to Segele & Lamb (2005), Ethiopia has been ravaged by severe drought for many of the last 35 years, primarily due to the failure of its main rainy season (*kiremt*). Areas affected by drought are increasing in Ethiopia due to climate change, climate variability and other human induced factors (NMSA 1996; WMO 1986). Based on the causative factors, drought can be classified into meteorological, agricultural, hydrological and socioeconomic types. Agricultural drought produces a complex web of impacts that span many economic sectors. Agriculture is the primary economic sector affected by agricultural drought. Short term agricultural drought at critical growth stages has severe impacts on agriculture (Wu & Wilhite 2004). Agriculture remains by far the most important sector in Ethiopian economy. According to Sadoff (2006), 80 % of Ethiopia's population subsists on rain-fed agriculture, thus welfare and economic productivity are linked to variable rains. This dependency on rain-fed agriculture has made the country's economy extremely vulnerable to the effect of climate variability and climate change, usually manifested through rainfall variability and recurrent drought.

In dry land semiarid areas of Ethiopia covering a large part of East Shewa zone, agricultural drought and crop failures have been common, and rain-fed agriculture is yet to provide minimum food requirement for rapidly growing population. According to Reddy & Georgis (1993), dry land which covers about 46 % of the total arable land in Ethiopia, contributes less than 10 % of the total crop production in the country. It implies that rainfall is highly risky in terms of distribution, and the rate of evapo-transpiration is very high. Farmers inhabiting the area experience extreme temporal and spatial variability of rainfall in cropping seasons with frequent and longer dry spells that affect their agricultural productivity. The risks associated with agricultural drought are spatially variable; hence they require different adaptation strategies and options.

In order to adapt to the adverse impacts of drought, agricultural drought assessment and identification of risk zones, *inter alia*, have to be the primary tasks. Identification of agricultural drought risk zone is usually carried out on the basis of analysis of rainfall and evapo-transpiration data on longtime basis (Lemma 1996). This conventional method lacks identification of spatial variations (Jeyaseelan 2004). Further, collecting sufficient spatial and temporal data is very difficult, especially in areas with rugged topography and low accessibility. The use of satellite data, therefore, is of paramount importance.

The advent of satellite era has introduced an entirely new technology of satellite remote sensing and a whole range of its application for the benefit of mankind. The use of remotely sensed data from satellite platforms for drought assessment has recently become wide spread (Alemayehu 1999; Amare 2007; Beyene 2007; Chopra 2006; Kogan 2000; Murali *et al.* 2008; Nageswara *et al.* 2005; Obi Reddy *et al.* 2013; Thenkabail *et al.* 2004; Wani *et al.* 2010). The use of satellite data using advanced techniques such as remote sensing and Geographic Information System (GIS) can assist in the detection and mapping of agricultural drought prone areas. Agricultural drought risk mapping in turn helps in decision making process for drought monitoring and identifying appropriate site for specific adaptation and mitigation. Hence, agricultural drought risk zone map produced from this study can be useful on one hand for policy makers to prioritize their actions based on the risk level, and on the other, for researchers to generate agricultural technologies and information including selection of drought tolerant and adaptive crops, as well as generation of crop management and soil moisture conservation practices. Moreover, it may be helpful for development agents and Non-Governmental Organizations (NGO) to facilitate scaling up of best technologies with success stories from similar risk zones elsewhere.

Since agricultural activities in the dry land semi-arid areas of Ethiopia in general and study area, East Shewa zone, in particular, are influenced and controlled by seasonal rain, agricultural drought analysis was carried out season-wise using different drought indices with the objectives of assessing agricultural drought risk using remotely sensed image based vegetation, climate and crop performance indices; estimating agricultural yield reduction due to moisture deficit, and preparing agricultural drought risk zone map showing the severity of drought condition at various levels.

Materials and methods

Study area

The study was conducted in East Shewa zone, Oromia Regional State of Ethiopia. Geographically, it is situated from 38° 03′ to 40° 05′ E longitude and from 7° 04′ to 9° 10′ N latitude covering a total area of about 13766.5 km^2 (Fig. 1). The altitude of the study area ranges from 538 to 3101 m above sea level. East Shewa zone is characterized by semi-arid and sub-humid climate based on the moisture index classification of climate (Lemma 1996). Considering the long-term average seasonal (June - September) rainfall, the area receives 458 - 518 mm rain. Based on mean annual rainfall and temperature of the area, the major climatic classes of the zone are dry climate and tropical rainy climate. Dry climate includes the arid and semi-arid subdivision, while tropical rainy climate is characterized by tropical humid and sub-humid climate. Soil is an important medium for plant growth and development owing to its power of storing water and providing anchorage for root growth and acting as a reservoir for mineral nutrients. According to Food and Agricultural Organization (FAO) classification, Andosols, Vertisols, Rendzinas and Phaeozems, and Fluvisols are the dominant soil types found in East Shewa zone. As far as agricultural activity is concerned, land use pattern is an important factor that influences agricultural production and productivity. Land use/ land cover patterns of the study area include water bodies, shrub lands, bare land, forest, sand dunes, settlement, rain-fed and irrigated farms (Fig. 2). Among these, the rain-fed farm covers a large area.

Data acquisition and software

A time series of advanced, high resolution radiometer (AVHRR), Normalized Difference Vegetation Index (NDVI) and rainfall estimate (RFE) satellite data were used in this study. Both have 8 km by 8 km spatial resolution and were obtained in decadal (10 days) time step basis for the main rainy seasons (June - September) of the years 1996 to 2008. Crop production is very sensitive to agricultural drought. In order to find out the relationship between crop yield and the existing drought condition and thus validate satellite based drought events, average zonal grain yield data of the study area were collected from the Central Statistics Agency (CSA), Ethiopia. The remote sensing and GIS software used in this study were ERDAS Imagine 9.1, ArcGIS 9.2, IDRISI, LEAP, INSTAT and Google Earth.

Data processing

Satellite image processing

As the National Oceanic and Atmospheric Administration (NOAA) AVHRR NDVI satellite

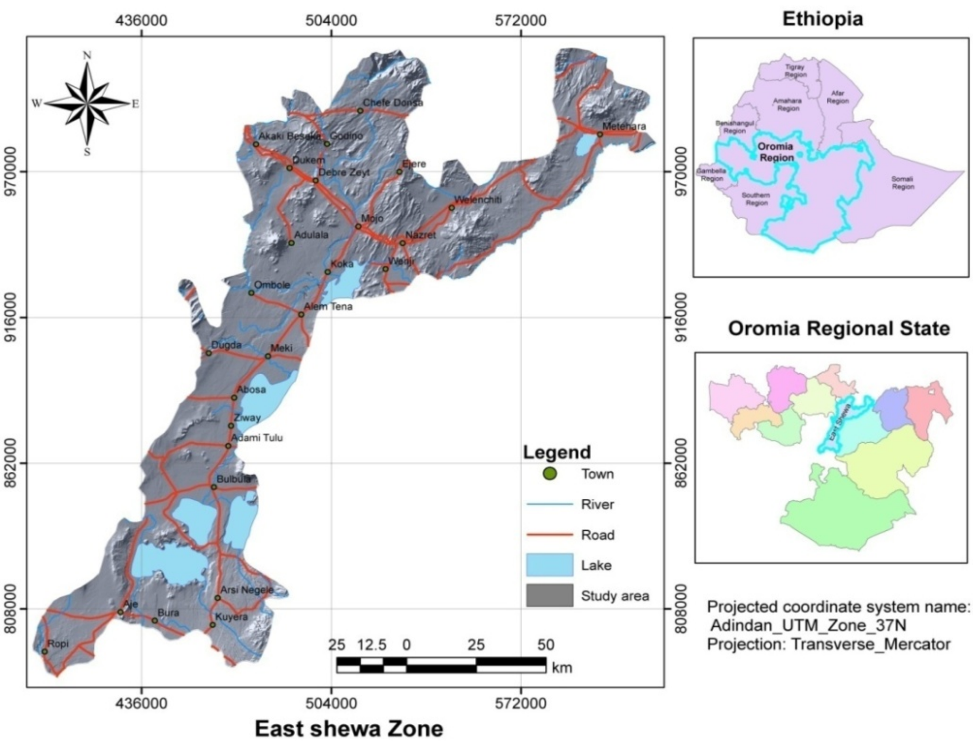

Fig. 1. Location map of the study area.

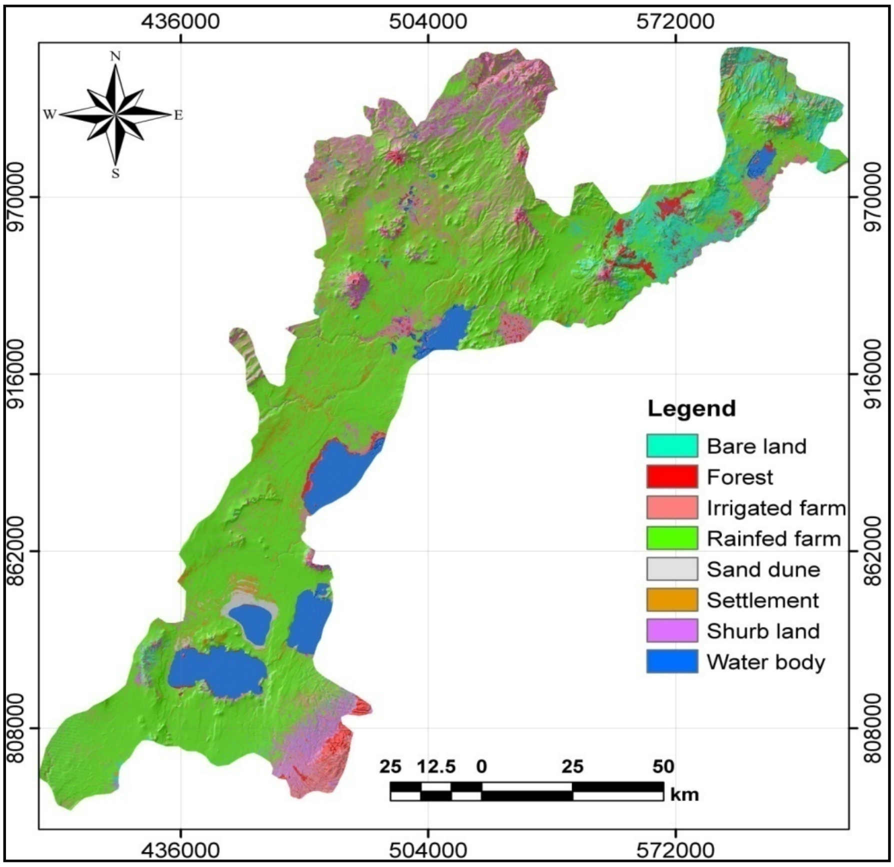

Fig. 2. Land use/land cover map of the study area.

Table 1. Drought severity classification.

Drought Indices	Drought severity classes				
	No drought	Slight drought	Moderate drought	Severe drought	Very severe drought
NDVI anomaly	Above 0	0 to -10	-10 to -25	-25 to -50	Below -50
SPI	Above 0	0 to -0.99	-1 to -1.49	-1.50 to -1.99	Below -2.0
WRSI	80 to 100	70 to 79	60 to 69	50 to 59	Below 50

images were radio metrically corrected, only geometric corrections were done. All images were imported in generic binary format in ERDAS Imagine software and information related to image dimensions and projection parameters were incorporated in the raw data. In order to transform the imported raw data into -1 to 1 range of NDVI, the formula (NDVI= raw data /250), which is provided with raw data by FEWS-NET was applied to each NDVI image. Thereafter, the study area was extracted for further analysis. Similar procedure except data conversion was applied to satellite RFE images so as to make the input RFE image for further analysis.

Analysis of agricultural drought using various drought indices

Spatio-temporal variation of seasonal agricultural drought patterns and agricultural drought severity were analysed seasonally using the following three drought indices:

NDVI anomaly: NDVI can be used as vegetative drought index to assess crop condition through analysis of NDVI anomaly (Murali *et al.* 2008). It has been calculated using NDVI values. Maximum NDVI and long-term mean maximum NDVI in the growing season (June to September) were computed in order to derive seasonal NDVI anomaly. NDVI anomaly percentage was then derived using the formula (equation (1) for each grid cell in the study area.

$$\text{NDVI anomaly index} = [(\text{NDVI}_{\max i} - \text{Mean NDVI}_{\max}) / (\text{Mean NDVI}_{\max})]\ 100 \qquad (1)$$

where, $\text{NDVI}_{\max i}$ = Maximum NDVI in the growing season in ith year and Mean $\text{NDVI}_{\max}$ = long-term mean maximum NDVI in the growing season. The resulting NDVI anomaly assigned to the respective grid cell was reclassified into five drought severity classes based on Table 1.

Standardized Precipitation Index (SPI): SPI is an index that was developed to quantify precipitation deficit at different time scales, and can also help assess drought severity. SPI was calculated using the following formula:

$$\text{Rainfall anomaly index} = (X_{ij} - X_{im}) / \sigma \qquad (2)$$

where, X_{ij}= is the seasonal precipitation and, X_{im} is its long-term seasonal mean and σ is its standard deviation. SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area, and reclassified based on drought severity classes (Table 1).

Crop specific index: Water requirement satisfaction index (WRSI) is an indicator of crop performance based on the availability of water to the crop during the growing season. The WRSI was generated by a crop water balance model using LEAP software. The most important input parameters of the model were satellite based RFE and spatially distributed potential evapo-transpiration images. Besides, the model uses relevant soil information from FAO digital soil map and topographical parameters derived from digital elevation model (DEM). WRSI was calculated as the ratio of seasonal actual evapo-transpiration (AET) to the seasonal crop water requirement (WR) (Equation 3).

$$\text{WRSI} = (\text{AET} / \text{WR})\ 100 \qquad (3)$$

where, WR was calculated from the Penman-Monteith reference crop evapotranspiration (ET_o) using the crop coefficient (K_c) to adjust for the growth stage of the crop: WR = $ET_o(K_c)$. AET represents the actual amount of water withdrawn from the soil water reservoir where shortfall relative to potential evapotranspiration (PET) was calculated by function that takes into account the amount of soil water in the reservoir. Soil water content was estimated through simple mass balance equation, where the total volume was defined by the water holding capacity (WHC) of the soil. WRSI was computed using LEAP software and imported into GIS environment. The WRSI result was then reclassified based on drought severity classes mentioned in Table 1 for each grid cell of the study area.

In order to show spatial patterns and severity of drought, two drought and wet years were selected and analysed from each index, and then reclassified based on their respective drought severity levels.

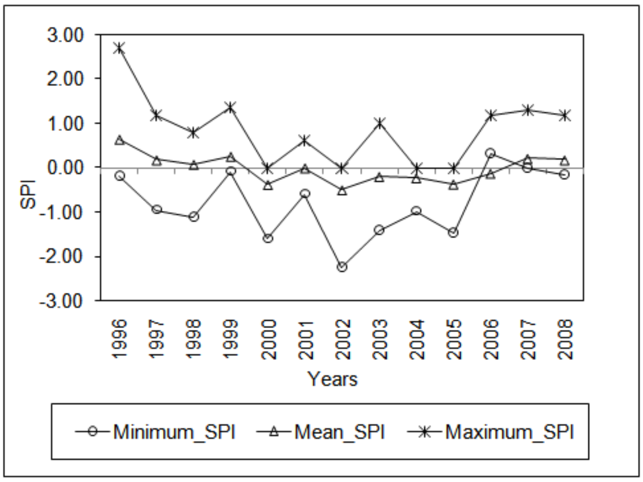

Fig. 3. Temporal pattern of seasonal (June-September) SPI (1996-2008).

Computation of yield reduction

The impact of agricultural drought on crop production can be largely expressed by yield reduction. In view of this, yield reduction due to water deficiency was computed using LEAP software. Yield reduction was calculated from water balance output combined with an empirical formula (Equation 4) developed by Doorenbosch & Kassam (Hoefsloot 2008).

$$100-((1-(1-A/B)\ K_y)\ 100) \quad (4)$$

where, A is the actual evapo-transpiration, B is the total water requirement without water stress. K_y is a crop dependent stress indicator determined by the authors. The major crops grown in the study area, maize, teff, wheat, sorghum, finger millet, haricot bean, chick pea, field pea, and lentil were considered in computing the aggregated yield reduction.

Regression analysis of grain yield with drought indices output

The relationship between average SPI, NDVI anomaly and WRSI value from each seasonal year with corresponding grain yield anomaly were analysed using INSTAT software to validate the derived indices output. In this regard, the average raster cell values of NDVI anomaly, SPI, and WRSI images were extracted using ERDAS Imagine software statistic information. Besides, information on agricultural drought hazard and its impacts on agricultural activities was collected from zonal and Woreda agricultural and rural development, and early warning and food security bureaus through questionnaire. It was also used for the evaluation of the result obtained from satellite images.

Agricultural drought risk map

Agricultural drought risk map of the study area was produced from the seasonal frequency maps derived from each of the drought indices. In order to compute the frequency of drought occurrence, drought class image from each index was reclassed into Boolean image based on their threshold value, and 13 binary images were generated for each drought index. These binary images were added to obtain the frequency map showing the frequency of drought occurrence at each pixel level.

According to Lemma (1996), the probability of drought occurrence in a given area can be classified into high, moderate and low drought probability zones when drought occurs in >50 %, 30-50 % and < 30 % of the years, respectively. Based on this criterion, the frequency maps of each drought class were reclassified into five classes on the basis of frequency of drought occurrence in study periods: 0-2 classified as no drought; 3-4 classified as slight drought; 5-6 classified as moderate drought; 7-10 classified as severe drought; 11-13 classified as very severe drought. Finally, maps from each drought index were weighted according to the percentage of influence using IDRISI software, and then combined using weighted overly analysis.

Results and discussion

Analysis of agricultural drought severity using different indices

Spatial and temporal patterns of SPI and drought severity

The analysis of SPI (Fig. 3) revealed that drought had occurred at different levels of severity during 2000 - 2005 cropping seasons. The droughts in 2000 and 2002 were very severe compared to other years as explained by the SPI values that range from -1.6 to 0 and -2.25 to 0, respectively. According to McKee *et al.* (1993), conditions of soil moisture react to precipitation anomalies in relatively short time period, and drought occurs when SPI is negative, and it vanishes when SPI is positive. Hence, the result indicates that during these years, there was rainfall deficit in the growing season and had the worst dry seasons.

Spatial patterns of SPI for drought years (2000 and 2002) and wet years (2007 and 2008) were

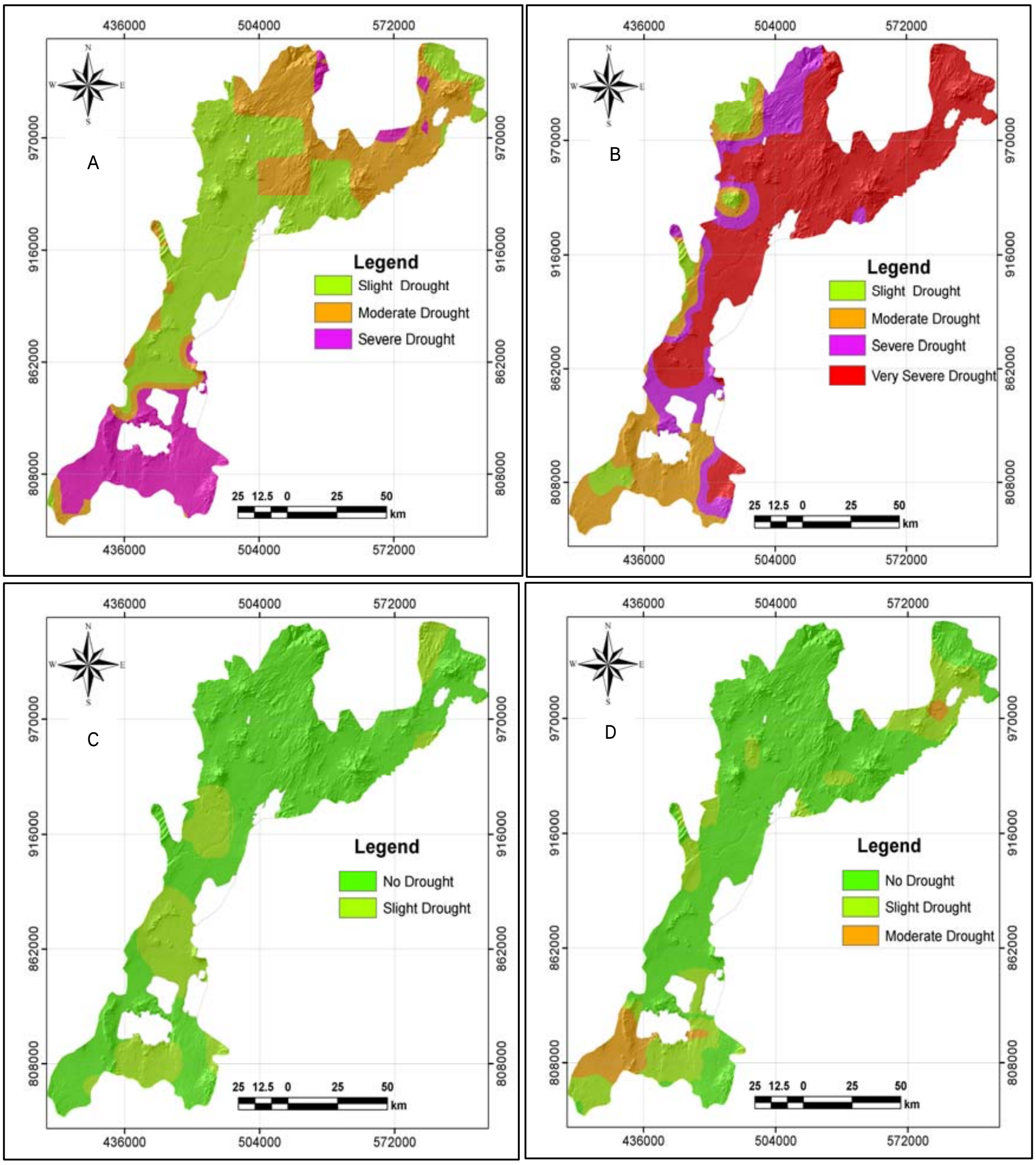

Fig. 4. Spatial pattern of drought severity for drought years 2000 (A) and 2002 (B) and wet years 2007 (C) and 2008 (D) expressed in SPI index.

analysed and reclassified to show spatial patterns of drought severity (Fig. 4A-D). The whole area was hit by drought from slight to severe levels of severity during 2000 cropping season (Fig. 4A) while in 2002 the range of severity was from slight to very severe drought levels (Fig. 4B). It indicates that in the year 2002, there was a very severe drought in wider extent that accounted for 5.17 % (711.5 km^2), 39.95 % (5500 km^2), 46.04 % (6338.5 km^2) and 8.84 % (1216.6 km^2) of the total area hit by slight, moderate, severe and very severe drought, respectively. In 2000, the level of severity reduced to severe only in some pockets of the southern part covering 0.65 % (89.2 km^2) of the total area while strike of moderate drought expanded to majority of the East Shewa zone, covering 75.69 % area (10420.1 km^2). During 2002, north eastern, eastern and central parts of the East Shewa zone were struck by severe and very severe drought.

As shown by the maps (Fig. 4C-D), the year 2007 and 2008 were wet years in East Shewa zone.

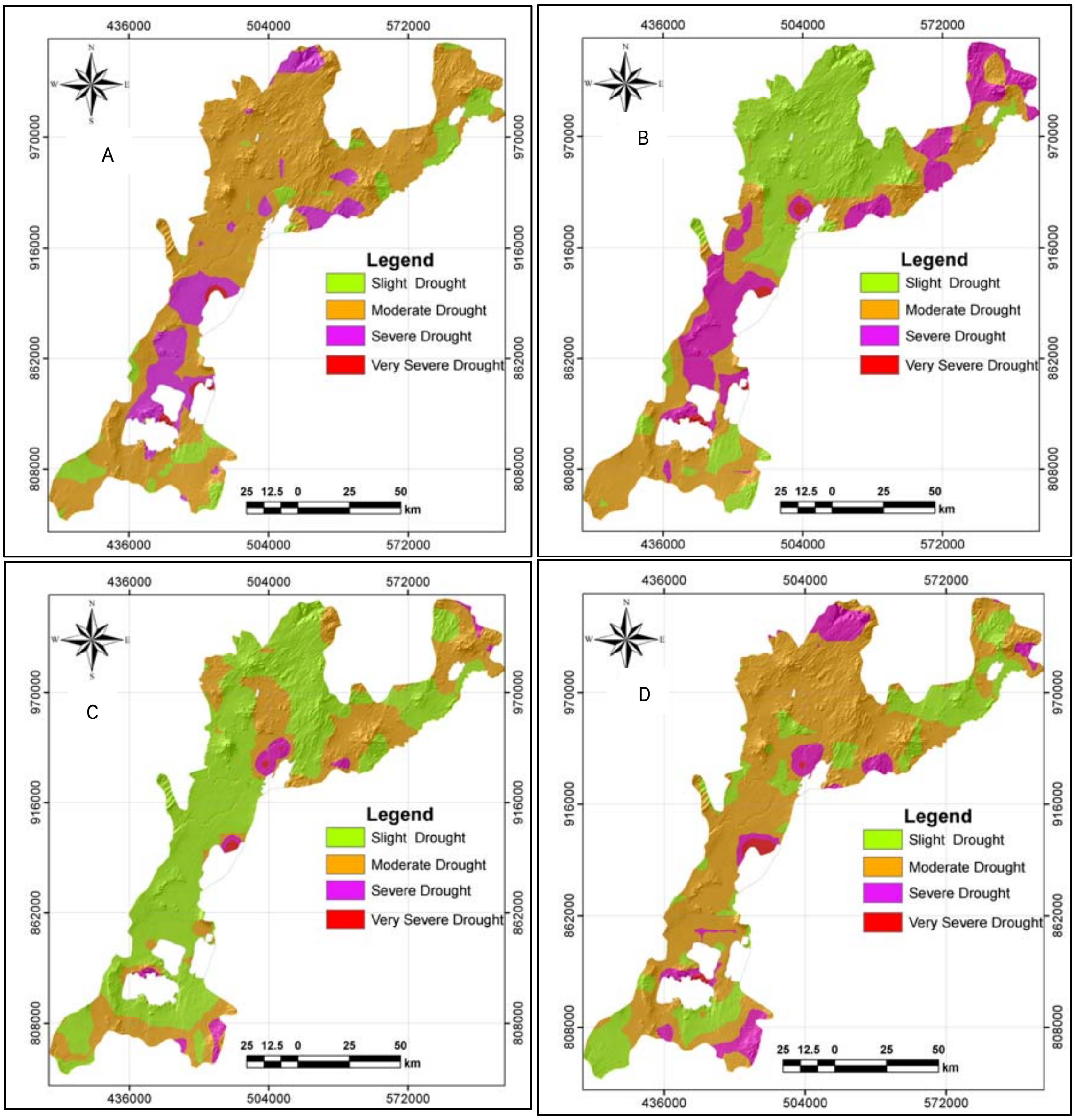

Fig. 5. Spatial pattern of agricultural drought severity for drought years 2000 (A) and 2002 (B) and wet years 2007 (C) and 2008 (D) expressed in NDVI anomaly index.

The range of severity was from no drought to slight drought. Although good seasonal rainfall helped almost the whole zone to avoid drought during 2008 cropping season, some small pockets covering 2 % (247.3 km^2) of the total area in the western part experienced slight drought. This could be due to low rainfall as well as occurrence of long dry spells.

Normalized Difference Vegetation Index (NDVI) anomaly and agricultural drought

The spatial patterns of agricultural drought events for drought and wet years are depicted in Fig. 5A-D. The level of drought severity ranged from slight to very severe in both 2000 and 2002 drought years (Fig. 5A-B). However, the extent of very severe drought covered small pocket areas that accounted for less than 4 % of the total area. The majority of the study area was struck by moderate and severe agricultural drought. During 2000 cropping season, the percentage area hit by agricultural drought was 10.15 % (1398.2 km^2), 71.28 % (9812.3 km^2), 16.53 % (2275.2 km^2) and 2.04 % (280.8 km^2) of the total area for slight, moderate, severe and very severe level, respectively, whereas the corresponding agricultural drought severity for 2002 cropping season was

40.38 % (5559.1 km^2), 34.43 % (4739.2 km^2), 22.63 % (3115.3 km^2) and 2.56 % (352.9 km^2) of the total area, respectively.

It can be observed from the map depicted in Fig. 5C-D that during the wet years, some very small areas were hit by severe and very severe agricultural droughts while majority of the area was under the influence of slight and moderate agricultural droughts. The percentage area of agricultural drought severity indicates that 64.32 % (8854.2 km^2), 30.90 % (4254.9 km^2), 4.18 % (575.3 km^2) and 0.60 % (82.1 km^2) of the total area was hit by slight, moderate, severe and very severe level of severity, respectively during 2007 cropping season, while the corresponding agricultural drought severity in 2008 cropping season was 22.41 % (3084.6 km^2), 64.69 % (8905.3 km^2), 11.07 % (1524.0 km^2) and 1.83 % (252.6 km^2), respectively.

Water Requirement Satisfaction Index (WRSI) based agricultural drought characterization

Low WRSI values indicating moisture deficit were revealed in large part of the study area during the drought years, 2000 and 2002 (Fig. 6A-B). During 2002 cropping season, very severe agricultural drought was prevalent in most part of East Shewa revealing that only less than 50 % of crop requirement was satisfied (Fig. 6B). Smith (1992) explained that seasonal WRSI value less than 50 % is regarded as a complete crop failure condition due to moisture deficit. Thus, the result has revealed that high yield loss was encountered in the area due to agricultural drought. Large area in north eastern, eastern and central part that accounts for 56.22 % (7739.6 km^2) of the total area was hit by very severe agricultural drought, whereas other parts of the area were struck by severe, moderate and slight agricultural drought i.e. 18.30 % (2519.2 km^2), 20.00 % (2751.6 km^2) and 5.48 % (756.1 km^2), respectively. As crop growing in most of the areas getting above 50 % of their crop requirement, the level of agricultural drought was less during 2000 cropping season as compared to 2002 cropping season. The percentage of the area was 45.52 % (6265.6 km^2), 29.71 % (4090.6 km^2) and 24.77 % (3410.3 km^2) for slight, moderate and severe agricultural drought severity levels, respectively.

Fig. 6C-D revealed that even though 2007 and 2008 cropping seasons were wet years, some small pocket areas were struck by agricultural drought, especially the southern part of the study area. During 2007 cropping season, only 23.76 % (3270.3 km^2) of the total area was hit by slight agricultural drought while 76.24 % (10496.2 km^2) was free from agricultural drought, whereas in 2008, besides slight agricultural drought covering 23.07 % (3175.3 km^2) of the total area, moderate agricultural drought was experienced in some small pockets accounting for 6.36 % (876.2 km^2). Generally, during those growing seasons, the water requirements of growing crops were satisfied above 80 % almost all over the study area indicating that most of the area was free from agricultural drought.

Characterization of yield reduction due to agricultural drought

Similar to drought indices output, the highest yield reduction occurred in 2000 and 2002 cropping seasons (Fig. 7A-B). In 2002 cropping season, nearly all areas were hit by agricultural drought, and agricultural yield reduction reached 80 %. During this season, eastern, north eastern and central parts of the East Shewa zone encountered 60-80 % yield reduction covering 26.52 % (3650.8 km^2) of the total area, while small areas in western and southern parts encountered 0 to 20 % yield reduction covering 12.64 % (1740.1 km^2) of the total area. From 20 to 60 % yield reduction was encountered in 60.84 % (8375.6 km^2) of the total area. In 2000 cropping season, the level of yield reduction was 40 % (Fig. 7A). Tesfaye & Walker (2004) explained that the reduction of crop performance and yield results from mismatches between water supply and demand. Thus, moisture deficit significantly influenced the growth and development of crops and the ultimate yields.

Spatial pattern of yield reduction for the wet years (2007 and 2008) is depicted in Fig. 7C-D. The level of yield reduction was very low (< 30 %) in most part, while small pocket areas around north eastern reached 3-6 % covering 0.23 % (31.7 km^2) of the total area in 2007 cropping season. In 2008 cropping season, 20-25 % yield reduction was observed in small pocket area covering 2.06 % (283.6 km^2) of the total area in the southern part of the zone, although the dominant part remained under low level of yield reduction. This may be attributed to mismatch of seasonal rainfall and crop requirement during the critical growth stage.

Evaluation of index based results of agricultural drought using grain yield and ground based information

Relationship between SPI and grain yield anomaly

Due to the fact that crop production is a function of rainfall, crop failure is most often

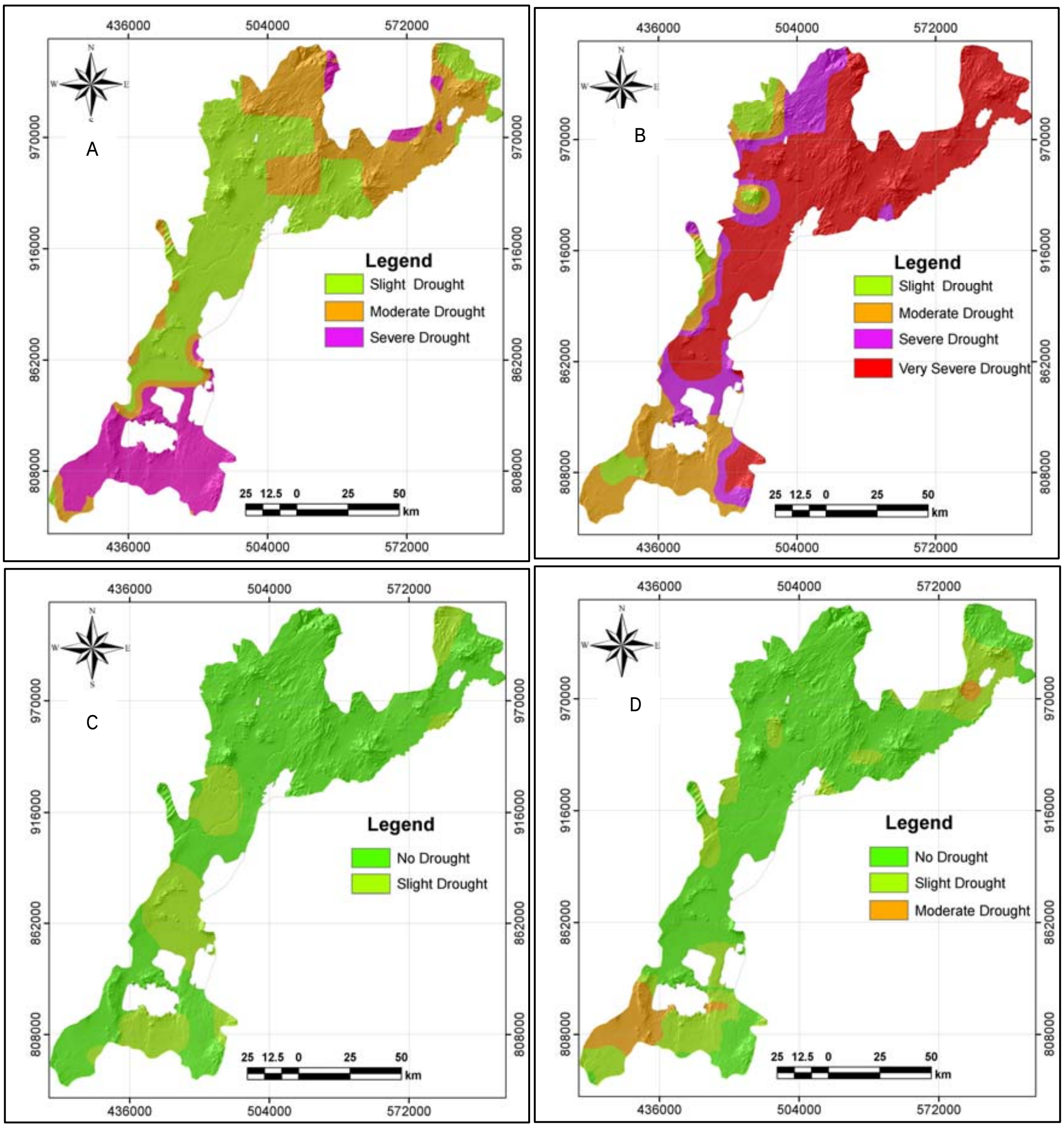

Fig. 6. Spatial pattern of agricultural drought severity for drought years 2000 (A) and 2002 (B) and wet years 2007 (C) and 2008 (D) expressed in WRSI index.

associated with moisture deficit or agricultural drought. Thus, a regression analysis between drought index and grain yield anomaly is indispensable for validation. In view of this, SPI and grain yield anomaly were regressed and the result showed that when SPI is positive, grain yield anomaly also turns positive revealing a good positive correlation (r = 0.8). The detailed result of regression analysis is presented in Appendix A. As SPI is an index that represents water deficit or excess, positive SPI represents that water has been available to plants so that grain yield was above normal condition, whereas, negative SPI or rainfall deficiency is reflected on crop production through yield reduction.

Relationship between NDVI anomaly and grain yield anomaly

The relationships between NDVI anomaly extracted only for cultivated area from land use/ land cover map of East Shewa zone and grain yield anomaly were analyzed. From scatter plot (Appendix B), it can be observed that the two variables have established good correlation (r = 0.74). This means that 54 % of yield variability can be explained by NDVI anomaly. The result revealed that the relationship established between the two

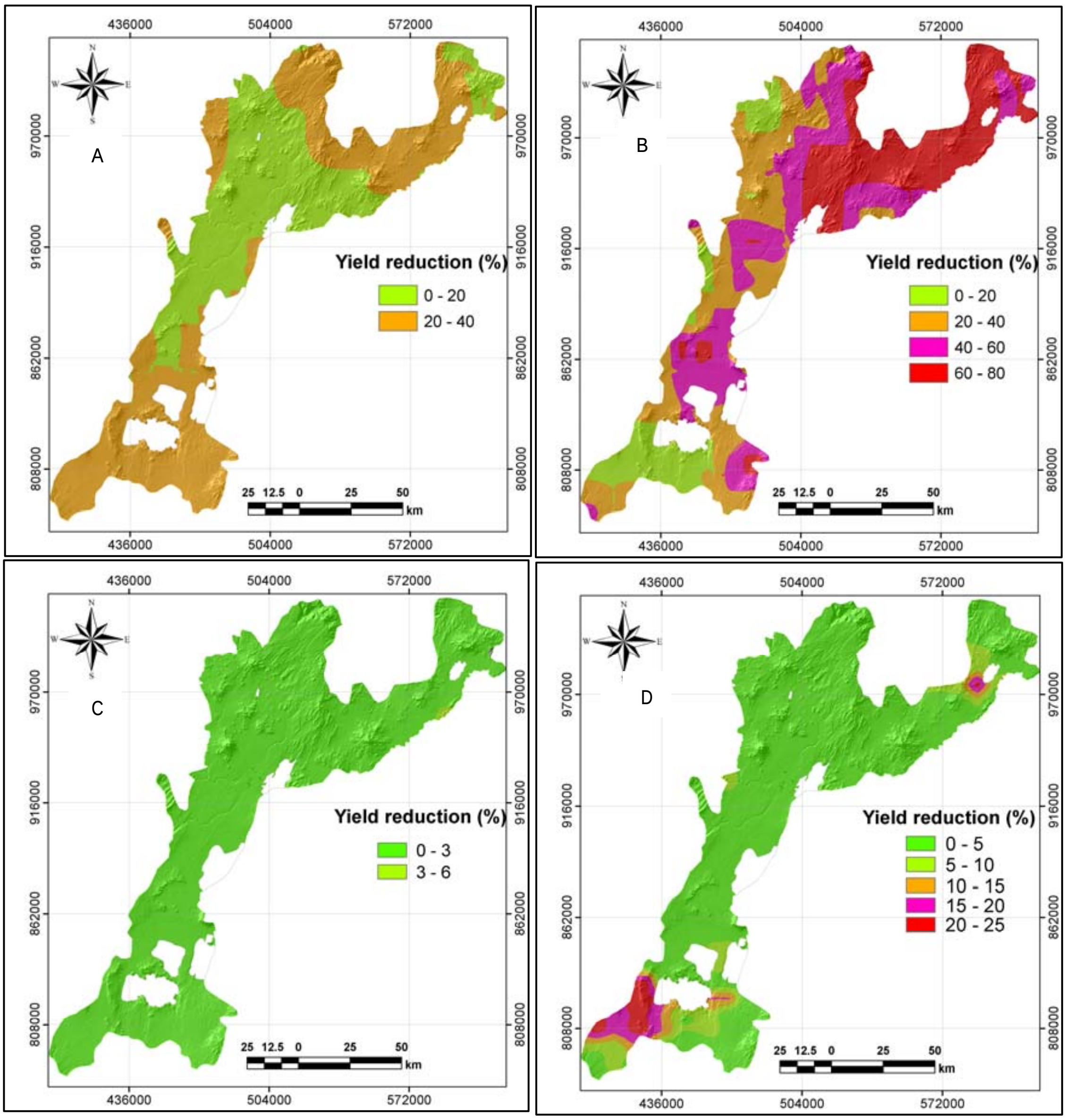

Fig. 7. Spatial pattern of yield reduction for drought years 2000 (A) and 2002 (B) and wet years 2007 (C) and 2008 (D) cropping seasons.

variables was positive; NDVI anomaly increased so did agricultural yield and vice-versa. Thus the strength of the index to explain the existence of agricultural drought through agricultural yield is relatively good.

Relationship between WRSI and grain yield anomaly

The relationship between satellite based WRSI and grain yield was analyzed using simple regression analysis. The relationship of average WRSI and grain yield is depicted in Appendix C and it can be shown that there is a good correlation between grain yield and WRSI (r = 0.87). Moreover, a linear best fit curve was plotted to see the strength of relationship between the dependant and independent variables. The result has shown that 76 % of grain yield variability can be explained by WRSI.

Relationship between number of affected population and estimated yield reduction

Agricultural drought having medium frequency of occurrence is a common phenomenon in East Shewa zone. According to Early Warning System (EWS) reports from national Disaster Prevention

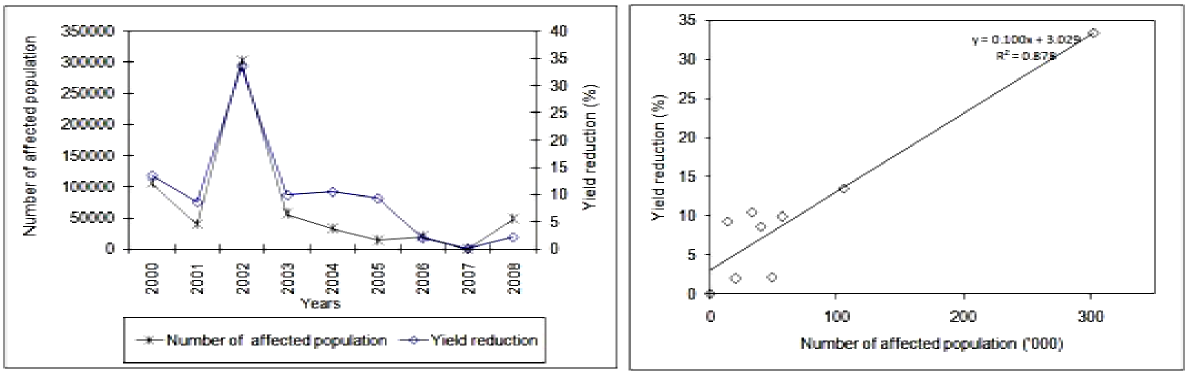

Fig. 8. Relationship between yield reduction and number of affected population.

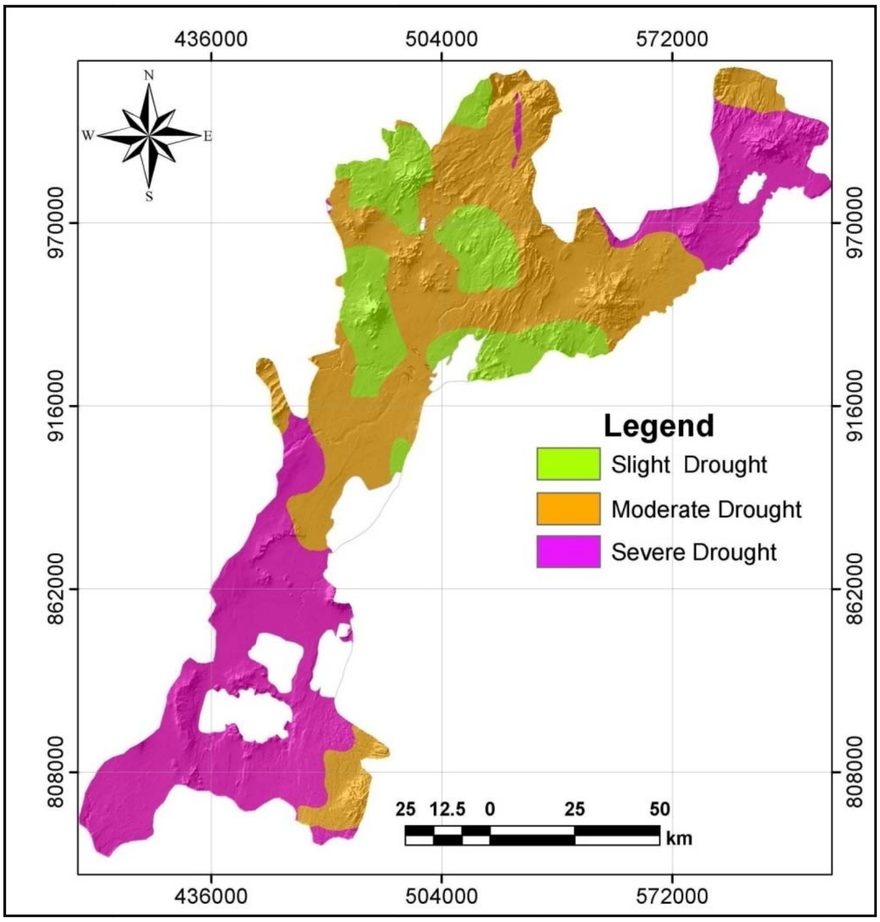

Fig. 9. Agricultural drought risk map.

and Preparedness Commission (DPPC), late onset and early cessation of the main rainy season, erratic distribution of rainfall and extended dry spells are the main weather related problems that cause agricultural drought. Furthermore, reports show that even though there was agricultural drought from the year 2000 through 2005 cropping seasons, the 2002 cropping season was the worst season that resulted in substantial yield reduction. As a result, the number of people affected by recurrent drought has increased significantly and the extents of food shortage and related problems have grown in East Shewa zone (Fig. 8). The size of affected population and the estimated yield reduction are highly correlated ($r^2 = 0.8$). Furthermore, information obtained from East Shewa zone agricultural and rural development, and DPPC offices confirm that during the year 2000 and 2002 cropping seasons, there was severe agricultural drought in East Shewa zone, and consequently complete crop failure occurred in most of the area particularly, north eastern part of the area including Fentale, Bosset and part of Adama and southern part particularly Adamitulu woreda.

According to the information obtained from East Shewa zone agricultural and rural development offices, agricultural drought mostly occurred as a result of mismatch of rainfall with crop requirement. Moreover, agricultural experts perceive that the length of growing period had declined due to climate change and thus the production options of farmers were limited to short duration crop varieties. Irrigation practice has also been introduced as adaptation options in the area to strengthen the agricultural activities while reducing the impact of agricultural drought in the area. Besides, adverse weather condition as a result of rainfall variability, agricultural drought increases the potential for pest infestations and crop diseases like stem borer reducing the crop quality and yield. Increased pest infestation and occurrence of disease during the drought years also contributes to significant yield reduction in East Shewa zone, which could be captured by the yield reduction function.

Agricultural drought risk

According to the results derived from the integration of all drought frequency maps, East Shewa zone is classified into slight, moderate and severe agricultural risk zones (Fig. 9). Agricultural drought risk map depicted in Fig. 9 shows that the percentage area affected by slight, moderate and severe agricultural drought risk encompasses 17.18 % (2365.3 km^2), 41.32 % (5688.3 km^2) and 41.50 % (5712.9 km^2) of the total geographical area of East Shewa zone, respectively. The probability of occurrence of agricultural drought ranged from 15 to 30 % for slight severity level, from 30 to 46 % for moderate severity level and from 46 to 76 % for severe severity level. Thus, the western and most of central part of East Shewa zone is categorized into slight and moderate drought probability zone while most of north eastern and southern part is categorized into severe drought probability zone.

Conclusions

Agriculture remains by far the most vulnerable and sensitive sector that is seriously affected by the impacts of climate variability and climate change, usually manifested through rainfall variability and recurrent droughts. Using satellite data as an input parameter for drought indices, spatiotemporal variation of seasonal agricultural drought patterns and severity can be detected and mapped with the help of advanced techniques of remote sensing and GIS. The obtained result is in agreement with the ground based surveyed information. Hence, agricultural drought assessment using satellite data is of paramount importance to assess the past and the present agricultural drought conditions, and generate baseline information that helps to monitor real time situation in the future for different adaptation options within relatively large geographical area and repetitive time scale coverage. The comparative performance of the indices explaining the existence of agricultural drought revealed that WRSI, SPI and NDVI anomaly expressed 76, 64 and 54 percent of variability of the grain yield, respectively. Thus, WRSI can be a good indicator for occurrence of agricultural drought. In this study WRSI expressed the real picture of agricultural drought followed by SPI and NDVI anomaly. Therefore, WRSI based agricultural drought assessment can better capture agricultural drought events. Agricultural drought risk can be viewed as a product of both exposure to the climate hazards and the vulnerability of farming or cropping practices to drought conditions. In view of this, agricultural risk zone map produced by integrating all drought frequency maps derived from all drought indices indicates that East Shewa zone can be classified into slight, moderate and severe agricultural drought risk zone, respectively. The agricultural drought risk mapping should be useful to guide decision making processes in drought monitoring and to reduce the impact of drought on agricultural production and productivity, while identifying appropriate sites for specific adaptation and mitigation.

Acknowledgements

The authors acknowledge the cooperation in providing all kinds of information by East Shewa zone agricultural and rural development offices, and East Shewa zone food security, disaster prevention and preparedness offices as well as their respective Woreda bureau. The authors are grateful to the Dean, and Head, College of Natural Sciences, School of Earth Sciences, Addis Ababa University, Addis Ababa, for constant encouragement and necessary support.

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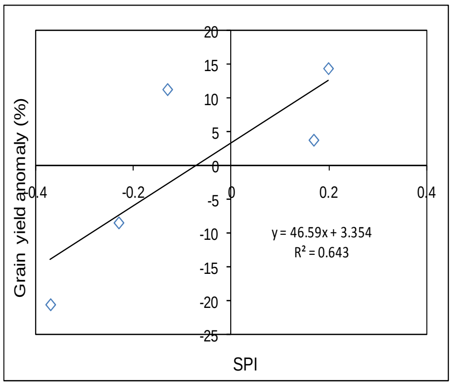
(Received on 13.12.2011 and accepted after revisions, on 14.05.2013)

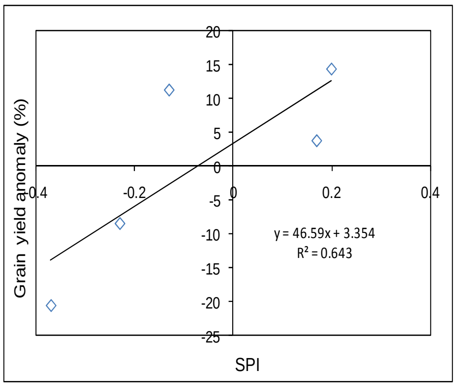
Appendices

Appendix A. Simple linear regression analysis between SPI and grain yield anomaly graph



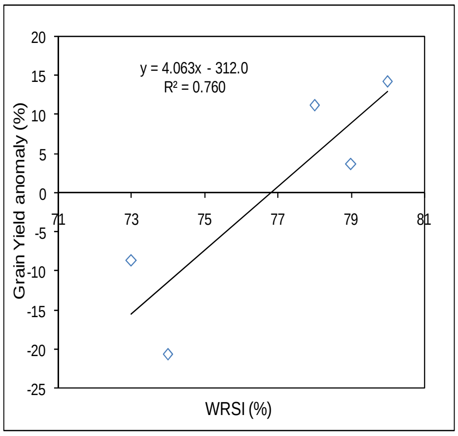
$R^2 = 0.643$, *P* value = 0.1023 is greater than 0.05 %, hence it is not significant.

Appendix B. Simple linear regression analysis between NDVI and grain yield anomaly graph



$R^2 = 0.541$, *P* value = 0.1563 is greater than 0.05 %, hence it is not significant

Appendix C. Simple linear regression analysis between WRSI and grain yield anomaly graph



$R^2 = 0.760$, *P* value = 0.0542 is greater than 0.05 %, hence it is not significant