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Integrated approach to estimate agricultural drought severity using satellite sensor for drought adaptation and mitigation at highland and lowland in northeastern Ethiopia

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IDI using RSP, M. Tizazu et al. Volume 1; 1-25

Abstract

Agriculture is the backbone of Ethiopia and it is the most vulnerable and sensitive sector that is frequently affected by drought due to spatial and temporal variability of rainfall. Correspondingly, including the study area in the northeastern parts of the country, suffered by drought due to failure in crop production because of rainfall fluctuation. Integrating various weather-based indices derived from the Earth observing (EO)-sensors can help capture drought in order to assist planning in the agricultural sector. Both the study areas, *Dessie and Bati* districts are contrasting agro-ecological zones which selected in northeastern Ethiopia. Multiple indices derived from earth observing sensors are a method used to estimate agricultural drought severity and frequency to assist agricultural drought adaptation and mitigation strategy. The most significant indices, such as SPEI, SPI NDVI, and LST are used as an integrated drought indicator (IDI) from EO-sensors products (LST, NDVI, ENACT and CHIRPS). The result shows that ENACT and CHIRPS satellite estimates rainfall have a better correlation with ground rainfall observations which are 0.98 and 0.90 respectively. The correlation coefficients between IDI with SPEI are 0.85 and 0.76 in Lowland (*Bati*) and Highland (*Dessie*) district respectively. On the other hand, correlations IDI with VHI have 0.79 and 0.71 at *Bati*, and *Dessie_Zuria district* respectively. Furthermore, crop production with IDI shows a good correlation coefficient in *Bati* and *Dessie-Zuria* district, which are 0.72 and 0.56 respectively. Results show that a most part of the study area was affected by different levels of drought severity during 2002, 2011, and 2015. During those years, 97 %, 95 %, and 100 %, of the area were affected by drought respectively. Specifically, during 2015 more than 77 % of the areas were shaken by severe drought. Based on field survey and drought indicators, the frequency of drought was observed at least one drought year during three successive years while the probability of extreme drought occurred at five percent in the study area. Based on field survey, the main adaptation and mitigation strategy was by using water harvesting, short period cropping and supporting by Safety-Net program in the community of the study area. Upcoming will be solved by implement permanently constrictive project. Such as, constructing irrigation canals in drought-affecting areas, either river diverts

or excavate of underground water, while water harvest during the rainy season, on the other hand improving crop production by using fertilizers, selective seeds, facilitate afforestation, soil and water conservation.

Keywords: GIS, Integrated Drought Index, LST, NDVI, Remote sensing, R_ program, SPI

1. Introduction

Ethiopia's economy is dependent on rain-fed agriculture, which is frequently affect by drought and causing significant impacts on agricultural productions and economic losses, particularly in the north and northeastern part of the country (Mohammed *et al*., 2017). In order to mitigate and address the impact of drought various researches are conducted based on weather-indices (Legesse, 2010; Viste *et al*., 2012; Mohammed *et al*., 2017; Demisse *et al*, 2018) . However, most researches in Ethiopia related to drought analysis based on the use of single weather-index. Hence, integrating various weather-based indices to capture drought is important in order to assist planning in agricultural sector (WMO & GWP, 2016).

Various indices utilized to estimate drought in Ethiopia. Mastawesha *et al*., (2014) assessed drought events in Amahara region using different satellite products through utilizing PET, NDVI, rainfall (estimated from satellite and ground gauge station) as single drought indicator in order to compared indicators individually. Studies by Little *et al*, (2006) and African student center (2000) were using socioeconomic indicator to assess the impacts and severity of drought in South Wollo, though these lacks climate related parameters as indicators. Mohamed et al., (2017) utilized SPI to assess drought in South Wollo zone. Even if there is easy to estimate and compare drought events by using single weather index like SPEI or SPI, particularly the area that have the same SPI value but different rainfall amounts to capture drought (Viste et al., 2012; WMO et al., 2016). Additionally, Legesse & Suryabhagavan, (2010) documented agricultural drought assessment in East Shewa zone using SPI, NDVI and WRSI to estimate crop yield in detail using indicators. Furthermore, Gidey et al, (2018) and Demisse et al., (2018) documented to characteristic of agricultural drought in using SPI, NDVI, LST and oceanic indices, and verified with ground based rainfall data even if didn't come together with combined indicators using three parameters.

Generally, to monitor vegetation stress and Agricultural drought occurrence, the reliable remotely sensed tool that integrated a combination of drought-related parameters can help in better estimation of agricultural drought events (Kogan, 1994; Karnieli et al., 2009; NASA, 2016; WMO et al., 2016). In Europe, developed CDI in order to capturing drought severity utilized SPI and soil moisture (SM) anomaly, and vegetation production indicates watch, warning and alert respectively (Horion et al., 2012). Also Bijaber et al., (2018) developed model in Morocco utilized SPI, NDVI, LST and SM by weighting in to single drought indicators. Moreover, developed based on remote sensing agricultural drought indicators using SPI, NDVI, LST and SM integrated into the result of single indicator to capture effective drought mitigation and prevention plan over all Ethiopia (Bayissa et al., 2018). Therefore, integrated drought indicator (IDI) is an alternative drought indicator as opposed to single drought indicator and to develop effective early warning system and agricultural drought mitigation plan, and preventing action (Kogan, 1994; WMO, 2016; Bayissa et al., 2018; Bijaber et al., 2018).

Furthermore, several researcher used remote sensing products as impute parameters like CHIRPS, MOD13Q1 and MOD11A2 used to drive agricultural drought assessment, to determine onset and cessation of drought episode and seasonal crop production forecast (Mekuria, 2012; Kouadio et al., 2014;

Tuck & Scharlemann, 2014; Bayissa, 2018; Demisse et al., 2018; Gidey et al., 2018; Yang & Huntingford, 2018).

The frequent impacts of drought in the study area are documented different researchers. Based on Little et al., (2004) documented that frequently events an insufficient *Belig* and *Meher* harvesting, during 1998 and 1999 did happen a 90-percent of crop production failed, while needed of humanitarian about 785,864 people in South Wollo and 124,870 people in Oromia zones (DPPC, 2000). In addition, FEWSNET Ethiopia, (2016) conducted a drought analysis using historical rainfall data and crop estimation model and result indicates that the study area experienced strong drought during 2015. The objective of this study is to assess and estimate agricultural drought severity and frequency in selected districts during the main rainy season using an integrated approach from satellite and ground-based data in order to adopt a best mitigation strategy from socioeconomic survey.

2. Materials and methods

2.1 Description of the study area

The study area is including Dessie Zuria, Tehuldere, and Kalu district in south Wollo zone and Bati district in Oromia special zone of Amhara regional state, those are located in the northeastern part of Ethiopia. Geographically the study area is situated 10.85° to 11.49°N and 39.30° to 40.20° E and covers an area of 3,747-km^2 and altitude ranging from 925 m to 3,829 masl (Figure 1). The slop of land feature is 14% covers steep slope, 29 % average slope, and 57 % also flat area. Most part of Dessie-Zuria district belongs to the Abay river basin and high land compared from the other district, while in the eastern part including Tehuldere, Kalu and Bati district are belongs to the Awash River basin. Kalu and Tehulder district in medium elevation, however, most part of the beautiful district associated with flat low land. Furthermore, the study area is located along the Eastern- escarpment of the country (Figure 1). As classification by per Hans, (1998) the study area has five agro-climatic zones such as: *Kur, Wurchi, Dega, Weyinadega* and *Kolla,* which covered an area of 1.2, 8.4, 21.7, 44.5 and 25.2 in percent respectively.

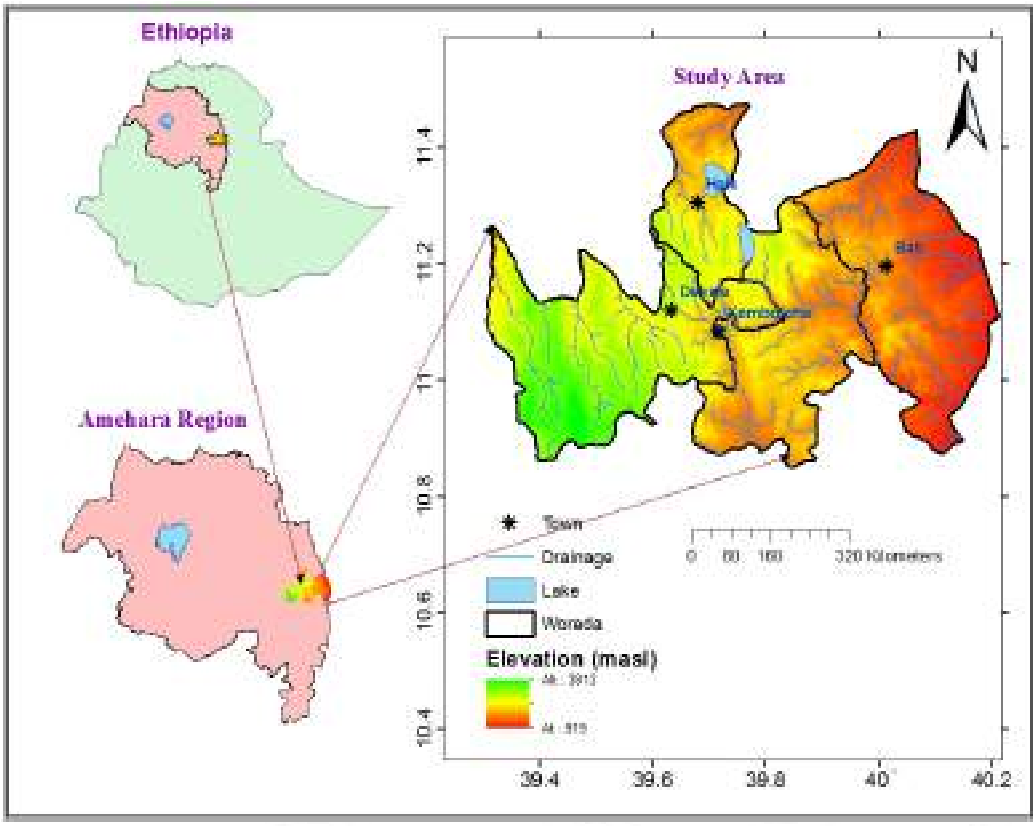


Figure 1 Location of the study area

According to FAO, soil classification from harmonized world soil database (HWSD), the soil types in the study area classified into four such as Leptosols, Combisole, Vertisols, and histosols. In terms of area coverage, Leptosols are the most dominate one distributed in all districts and Histosols and Vertisols accounts small portions of Kalu district. According to on Muhamed (2017) the mean annual mean temperature varies from 5°C in the western highlands to 22°C in the eastern lowlands. Whereas annual rainfall varies between 1,000 mm in the western part to 1,200 mm in the eastern part in South Wollo zone. On the other hand, Bati (lowland) district annual rainfall varies between 700 mm to 1000 mm also average minimum and maximum temperature is about 19°C and 34°C respectively. The main rain season of the area is (June-September) and a short rainy season i.e. March-May which provides low in amount. Seasonal rainfall contribution in the study is 10, 28 and 62 in percent during dry (*Bega)*, spring (*Belg*) and summer *(Kiremt)* respectively. Based on Gebeyehu et al., (2009) studied that, LULC of bare-land and farmland was increased, while grassland, bush-land and forest land were decreased from 1973 to 2000 in Dessie Zuria district.

According to CSA, (2007) those four districts have a total population of 638,904. Economic activity depends on agricultural production. There are different types of crop for agricultural activity but the main dominate cereal crops are Sorghum, Maize, Barley, *Teff*, and Wheat (CSA, 2015).

2.2 Data Acquisition and conceptual frame work

Ground station climatic data including maximum and minimum temperature, and rainfall obtained from national meteorology agency (NMA; Figure 2). Haik, Harbu, Guguftu, and Bati selected by considering different agro ecological zone of the study area and having long historical data to validate satellite products. Furthermore, ENACT data also collected from NMA, which have four km spatial resolution contained rainfall, maximum and minimum temperature. ENACT data is derived from satellite products with ground observing data from the time period 1981 to 2016 to compute standard precipitation and evapotranspiration index (SPEI). Additionally, Radiation data accessed from IRI data library based on latitude to compute SPEI. Furthermore, the current ten years socio economic data such as population of the study area and agricultural production collected from Central Statistics Agency (CSA; Figure 2) covered the period from 2008 to 2017. Further, socio-economic data in each district, from Kebeles selected considering the dominant AEZ of the district and the success and drought story. Socioeconomic data at the household level collected using a questionnaire by systematic sampling to capture the agricultural production from 2017 to 2018. Sample area was selected from four districts to survey eight Kebeles based on different agro-ecological zone.

MODIS data collected from the Terra satellite in order to derive NDVI and LST (MODIS; Figure 2). MOD13Q1 normalized difference vegetation index 16-day temporal resolution and 250m spatial resolution, while MOD11A2 LST in Terra 8-day temporal resolution and 1000m spatial resolution. Those are aggregated into monthly basis and MOD13Q1 resample into 1000m resolution. NDVI and LST obtained from Terra MODIS in NASA-USGS, its observation at 10:30AM. This data obtained from the path and row are allocating of 168 and 52 respectively downloaded in Lpdaac/usgs website (https://lpdaac.usgs.gov) starting from 2001 to 2018. Additionally, Climate Hazard Group Infrared Precipitation with station (CHIRPS) monthly-improved data is a spatial resolution of five kilometers within temporal resolution monthly based since 1981 to 2018, and resample in to 1000m resolution. CHIRPS used to compute the standard precipitation index and the historical climatic condition of the study area.

The conceptual framework of the study is to utilize ground and satellite based data to derive weather-based indices to capture drought (Figure 2).

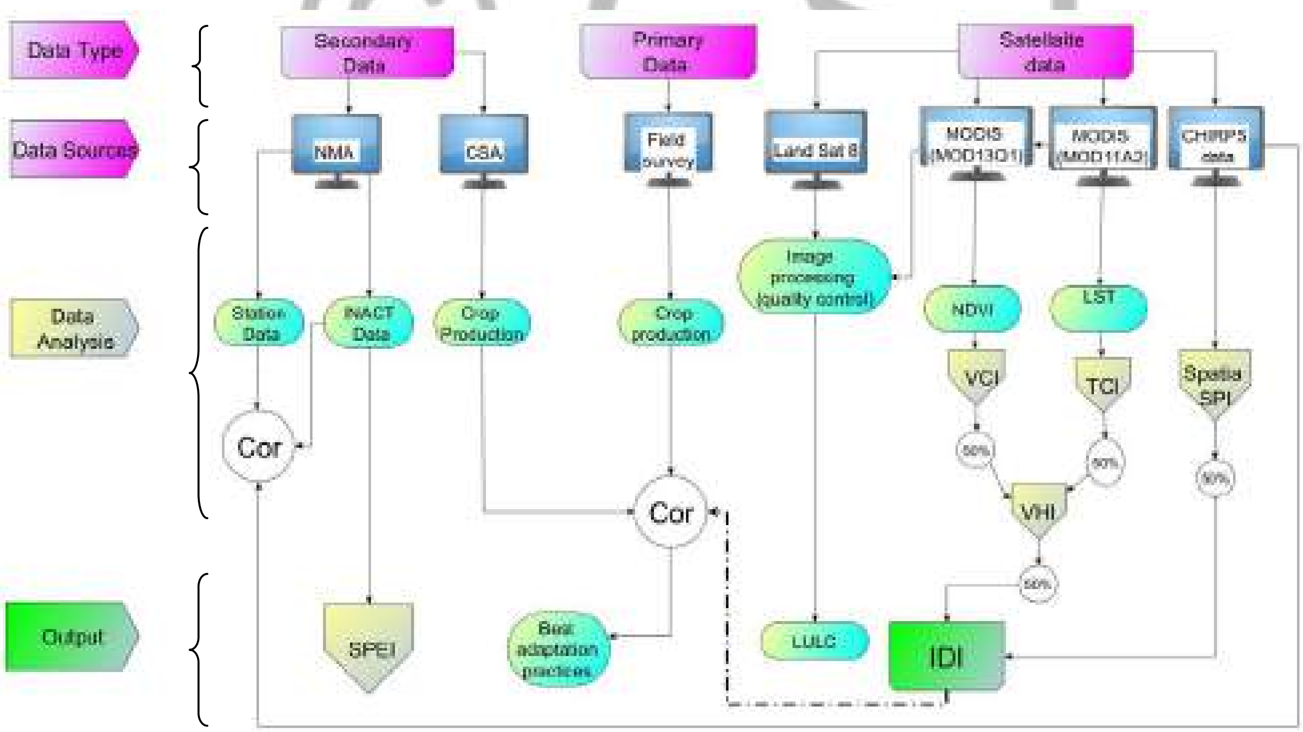


Figure 2 Work flow diagrams of the study

2.3 Methods

Standard precipitation index (SPI) is one of the main meteorological drought indicator in time series including monthly, seasonal and annual precipitation data set from CHIRPS for a continuous period. SPI formula developed by (Mckee et al., 1993).

$$SPI_{ij} = \frac{X_{ij} - M_{ij}}{\delta} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where i = month, j = years SPI_{ij} is the SPI of the i_{th} month at the j_{th} time scale, X_{ij} is rainfall total for the i_{th} month out of the j_{th} time scale, M_{ij} is the long term mean value of rainfall and δ is the long years of standard deviation associated with the i_{th} month at the j_{th} time scale. Before multiplying the indicator by weighting factor to obtain IDI, make those indicators changed into index in the scaled b/n zero and one by using the historical value of maximum and minimum value in order to categorize scale of drought severity index.

$$\text{PSPI} = \frac{(SPI_{i} - SPI_{min})}{(SPI_{max} - SPI_{min})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 9$$

Whereas PSPI percent of SPI condition, SPI_{mon} is SPI value of the month and SPI_{Min} minimum value of historical SPI and SPI_{max} is maximum value of historical SPI.

The most commonly used vegetation index is the normalized difference vegetation index (NDVI) are MOD13Q1, which is resulted from difference between the maximum reflectance in NIR spectral region and absorption of radiation in R. This data products are computed from atmospherically corrected surface reflectance and that have been masked for water, clouds, heavy aerosols, and cloud shadows by using MOD13Q1 user manual (Layers, 2014).

$$\text{NDVI} = \text{MOD13Q1} * 0.0001 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

from historical observations NDVI data was converted into the Vegetation Condition Index (VCI), which was applied effectively for drought monitoring and assessment of the vegetation condition (Kogan, 1996).

$$\text{VCI} = \frac{100\,(\text{NDV}_{i} - \text{NDV}_{min})}{(\text{NDV}_{max} - \text{NDV}_{min})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

Surface temperature also have effect on agricultural drought which provides useful information about vegetation condition (Kogan, 1995). The rising of temperature influences the vegetation condition by facilitating evapo-transpiration when the amount of rainfall is deficit.

$$LST = (\text{MOD11A2\_Day\_Time} * 0.02) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

$$TCI = \frac{100(LST_{max} - LST_{i})}{(LST_{max} - LST_{min})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

Where LST is land surface temperature of a month LST_{max}, and LST_{min} are, also the long year's maximum and minimum value of the month. In this study from Mod11A2 the day time land surface temperature conversion factor of the valued scientific number from 7500 to 65535 multiplied by 0.02 (Terra & Surface, 2000). TCI decreases with LST higher land surface temperatures indicate soil moisture deficiencies and therefore stress in the vegetation cover.

Vegetation Health Index (VHI) or (VCI–TCI) approximate derived from NDVI and BT values used to assess the incidence of agricultural droughts using the following equation:

$$\text{VHI} = \text{aVCI} + (1 - \text{a})\text{TCI} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 6$$

The relative contributions of each index has been usually assigned by a and (*1-a*) with the value define 0.5, considering an equal effect of both variables to get the combined index (Kogan, 1994). VHI develop from using VCI normalization approach with TCI based on brightness temperature (BT) values (Kogan, 1995; Karnieli et al., 2010; Gidey et al.,2018).

Standard precipitation and evapo-transpiration index (SPEI) are one of the modified of standard precipitation index and consider radiation and temperature which introduces evapo-transpiration data for identify the severity of agricultural drought by using precipitation and evapotranspiration. Which, given by,

$$\mathrm{SPEI} = \mathrm{P} - \mathrm{PET} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 7$$

PET given by different methods, but in this study use Hargreave formula that is

$$\mathrm{PET} = 0.0022 * \mathrm{Ra} * (\mathrm{T_{max}} - \mathrm{T_{min}})^{0.5} * (\mathrm{T_{mean}} + 17.8) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where PET is potential evapotranspiration, Ra is radiation, T_{max} is Maximum temperature and T_{min} is minimum temperature. The time scale used in this study for seasonal and annual base of time scales.

During the collection of socio-economic data to select sample Kebeles is considering by different agro-ecological zones, depend on potential of agricultural production and based on different type of crop to well represent of districts. Simple Kebeles are eight representative areas such as, Abaso kotu and Guguftu are in Dessie-zuria district; Abichu and Birki-Debeli are in Kalu district; Bededo and Seglen are in Tehuldere district; and Garore and Fura are in Bati district. To get the key information about Kebele, contact Kebele manager and extension agents also to select the household or respondent to interview. The sample method of the size of the respondent was computed by using the following statistical sampling formula, $n=N/(1+Ne^2)$ where n = sample size, N= number of population (heads of household) and e confidence interval.

The result of integrated approach drought indicators is weighted the result of SPI, NDVI and LST, which describe above to the estimation agricultural drought severity of the area. Such weighting factors are in percent, such as 50 for SPIC and 25 for each of VCI and TCI. This model is based on Bijaber et al., (2018) and Beyissa et al., (2018) studied in Morocco and Ethiopia the whole country respectively by using parameters SPI, NDVI, LST and ET. However, in this study have the factor of ET is included in land surface temperature. Therefore, the main result of the study ***integrated approach drought indicator*** generates using the following Equation (IDI).

$$\mathrm{IDI} = 50 * (\mathrm{PSPC}) + 25 * (\mathrm{VCI}) + 25 * (\mathrm{TCI}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 10$$

2.4 Data presentation and analysis

MOD13Q1 and MOD11A2 needs to convert them into a GeoTIFF image format in order to read by different analysis software by using MODIS re-projection tool (MRT), because both of the images is in the form of the Hierarchical Data Format (HDF). Furthermore, extract the image using folder extraction in ARC-GIS into the area of interest to obtain NDVI and LST. Therefore, based on MOD13Q1 and MOD11A2 user manuals remove an invalid scientific number out of the range in each grid pixel value using R-program script. The valid numbers are contained from the range -2000 to 10000 and 7500 to 65535 for NDVI and LST products respectively. Furthermore, using a conversion factor of both parameters processed to obtain VCI and TCI. Finally re-sample all the three images, which are NDVI, LST and CHIRPS data into the same resolution of 1000m, which have different resolution.

Gauge station's data consistency checked by using Tamet software in order to validation of satellite products. Moreover, the statistical fitness of ground rainfall data is best from CHIRPS and ENACT satellite product in the study area Table 1; by using the method Mean-error, RMSE, RMS, Efficiency score, Bias and correlation coefficient. Similary, T.Dinku, (2007; 2018) validated the whole Ethiopian rainfall by using those methods. After collecting of the data, such as CHIRPS and ENACT products check the fitness with ground gauge station in different agro-ecological zone in the study area. Table 1 is shows that satellite data fitness with station data in selected station, such as Bati in the lowland and Guguftu from highland in those selected districts. Satellite products CHIRPS and ENACT rainfall related with station rainfall in highland and lowland area significant association but ENACT shows best relation compared from CHIRPS using CC, EFF and RME statistical equation.

Maximum and minimum temperature also fit with ground station particularly in low land area. Similar studied documented that gauge station has been best fitness with satellite rainfall products ENACT, CHIRPS, TAMSAT and ARC2 respectively (Tufa Dinku et al., 2018). Therefore in this analysis CHIRPS is used to compute SPI that is why CHIRPS has better association with the rain gauge observations than TAMSAT and ARC 2 (Tufa Dinku et al., 2007) and continuous statistical assessments timely updated data available compare to ENACT. Also used ENACT rainfall and temperature used to compute standard precipitation evapo-transpiration index.

Table 1 Fitness of CHIRPS and ENACT monthly data with gauge station

Method of examining	**Bati**				**Guguftu**			
	CHIRPS	Enact			CHIRPS	Enact		
		RF	Min	Max		RF	Min.	Max
Number of pairs	322	310	308	308	290	280	253	253
Linear correlation coefficient (CC)	0.89	0.98	0.98	0.99	0.94	0.99	0.67	0.83
Mean error (ME)	-2.81	-12.58	0.38	0.37	-6.89	-20.15	1.40	1.78
Root-mean-square error (RMS %)	53.28	30	4.82	1.59	43.86	25.91	46.24	12.38
Efficiency (EFF)	0.79	0.93	0.95	0.97	0.90	0.96	-0.72	-3.27
Bias	0.96	0.83	1.03	1.01	0.94	0.82	1.36	1.12

3. Result and discussion

3.1 Spatio-temporal climatic condition of the study area

Mean maximum temperature in study area is supper in eastern low land, including most part of Bati district observed about 32^{o}C. But, it is decrease to 16^{o}C in the western highlands of the area in Dessie-Zuria district. Similarly mean minimum temperature from historical records change from the highest positive in low lands Bati district to become decrease negative value in around highlands of Dessie-Zuria district (figure 3 (B&C).

The amount of long year mean monthly temperature observed from April to July in all district become highest distribution in individual districts of the study area. Generally, temperature distribution is highest in the eastern lowland and lowest in the western highland. Conversely, rainfall distribution is the highest amount in the western highland area, whereas low in the eastern lowland. Therefore, in the low land area is not favorable condition for agricultural activity compared from the highland due to low rainfall amount and high temperature facilitates evapotranspiration. In general, living in eastern lowland is challenging due to high temperature and low amount of rainfall which difficult to get crop production only with rain-fed agricultural activity. The result of the analysis from figure 3 and 4 are similar to NMA map room historical climatic analysis at district level. While, surface temperature is decreasing and rainfall increasing from east to west (NMA, 2014; Dinku et al, 2017).

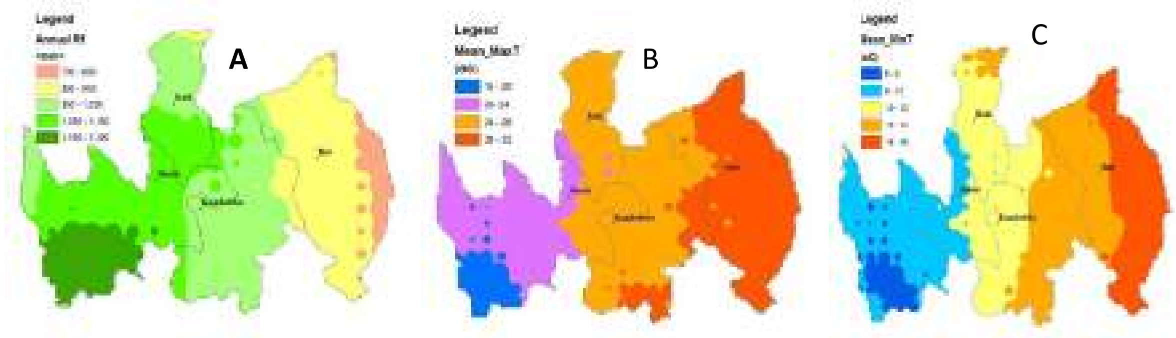


Figure 3 Maximum minimum temperatures and rainfall condition (A, B&C)

The spatial rainfall distribution in selected districts have highest in amount all part of Dessie-Zuria district (1000 to1300)mm. Whereas, in most parts of Bati district have lowest amount of rainfall (700 to 900)mm since 1981 to 2018 represent in figure 3 (A). In addition, Kalu and Tehuldere district get from 950-mm to 1150-mm in a year. Even if these districts have the same types of rainy season, the amount of rainfall variation increases from eastern low land to western highland of the area. Moreover, figure 4 is indicates that two rainy seasons near bimodal type of monthly rainfall distribution of the study area. According to Korecha & Barnston, (2007); Degefu & Bewket, (2016) seasonal classification performed summer (June to September), Dry (October to January) and spring (February to May) in Ethiopia. This summer season will contribute the highest amount of annual coverage of rainfall. The spatial distribution of mean monthly rainfalls was higher in Dessie district than in the other districts during summer season. Whereas Bati district gain the lowest amount, rainfall compared from the rest of all other districts. In summer season during July and August, provide pick rainfall in low land as well as high land of the area. The amount rainfall is around 200-mm per month in low land, whereas, in highland area obtain greater than 300 mm per month. While, similar amount of rainfall is obtaining through highland, middle and lowland during the month of March and April. The main crop-growing period start from middle of June to the end of September in high land as well as low land area (figure 4). The contribution of rainfall during the main rainy season is about 57, 70, 62 and 62 in percent on Bati, Dessie-Zuria, Kalu and Tehuldere districts respectively since June to September.

Based on field survey respondents reacted that, the rain-fed agricultural activity is mainly during the main rainy season. Beginning April to October in the study area is could long cropping period in highland area, while June to September for short cropping period especially in lowland area. Furthermore, during field survey most respondents understood that, only one rain feed agricultural activity. The second harvesting time is not confidential unless it supported by applying irrigation practice when the area is accessible for irrigation propose. Generally, the study areas have two rainy seasons not only Belg in midland and highland, but also summer season in the whole parts of the area. The results of monthly rainfall analysis similar results on the analysis of (Gebeyehu, 2009; S.ROSELL, 2015; Mohammed, 2018) in the study area.

Temporal distribution of annual areal average rainfall amount in district level observed that dry and wet situation could identify in the period of study (1981 to 2018). Wet situation observed in all districts during 1988, 1998, 1999, 2000, 2010, 2016 and 2017 were being observed. Furthermore, during 1984, 1990, 1991, 2002, 2008, 2009, 2011 and 2015 rainfall amount indicated below the lower standard deviation illustrate in Figure 5. Even if the amount of rainfall is different in temporal trend analyses all districts shows similar characteristics. The seasonal and annual time scales rainfall data is test using Mann Kendall trend analysis starting from 1981 to 2018. Generally, from the result of rainfall trend analysis in 1984, 2002, 2008/09, 2011 and 2015 dry years, this is lead to drought events in all districts. This time series analysis of dry and wet years in this study also similarly explained by (Mohamed, 2017; Korcha, 2013)

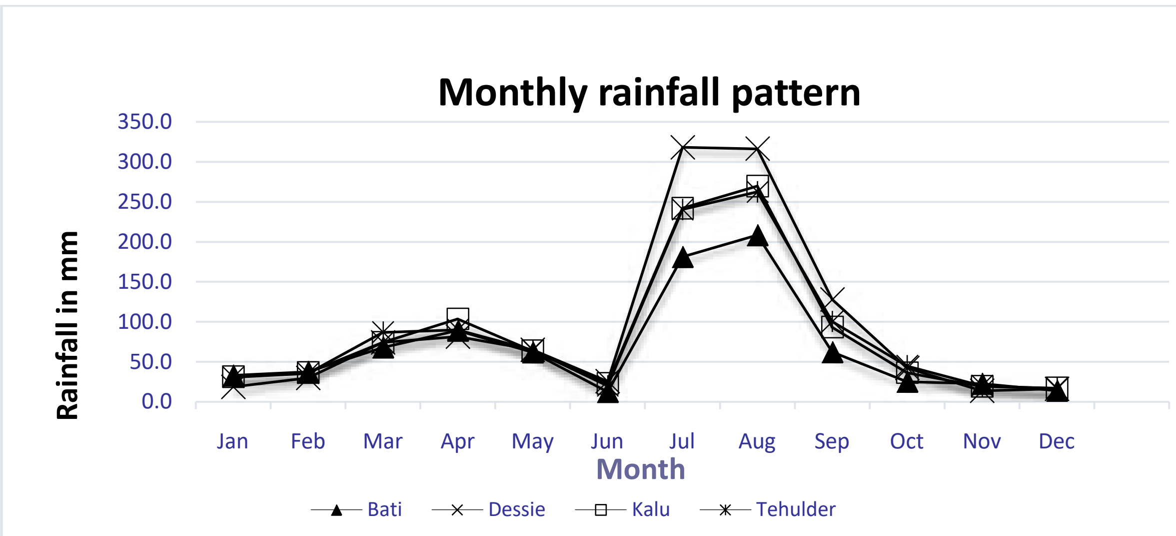


Figure 4 Monthly total rainfall distributions in four districts

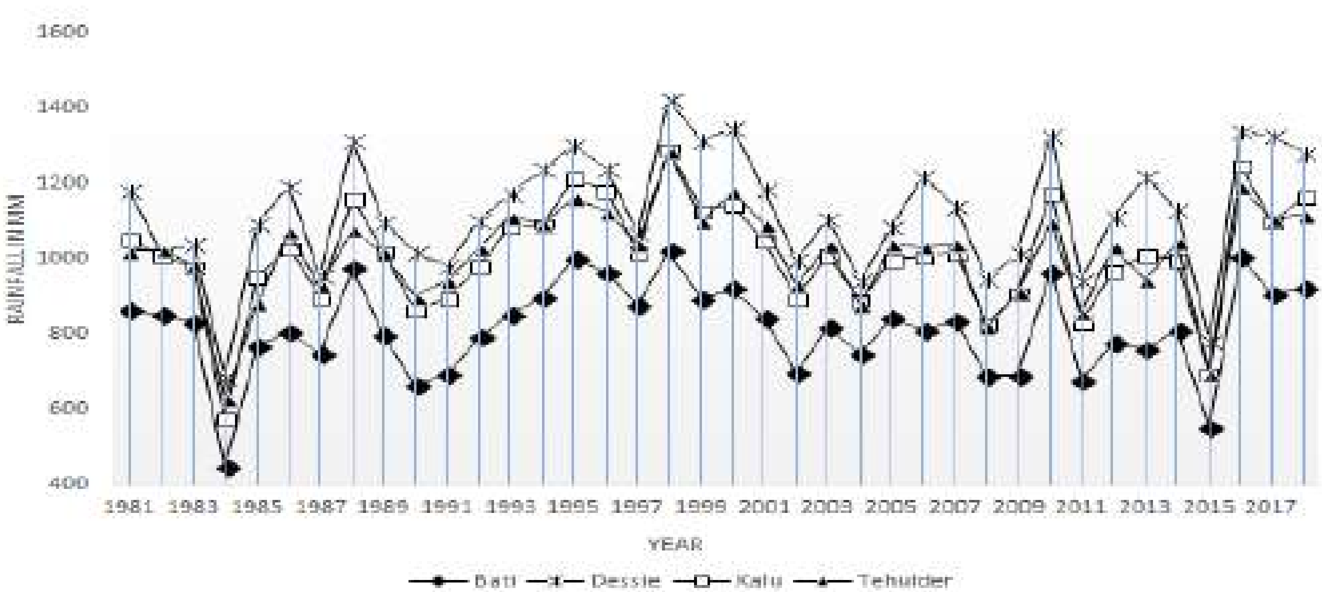


Figure 5 Rainfall time series data in four districts (1981_2018)

3.2 Role of remote sensing products to estimate agricultural drought

Standardized precipitation index (SPI) is one of drought indicators using precipitation, especially in the assessment of the meteorological drought and it leads to agricultural and hydrological drought. Figure 6 is indicated that results from monthly spatial analysis of SPI during the main rainy season (June, July, August and September) in selected drought years. It is indicate that drought years during 2008, 2011 and 2015 below zero value of SPI, while, in 2010 and 2016 the SPI value is greater than zero value during July and August in the study area. Even if the spatial difference in drought magnitude did not show clearly, it can identify the wet and dry condition of the area. Different area may have the same standard deviation and mean-division results the same SPI value. Limitation of SPI is show that the same drought severity in different field, which have different rainfall amount. The Similar to this result Viste et al., (2012) documented that, the practical implication of drought severity in different area has different rainfall variability and amount but it has the same SPI value.

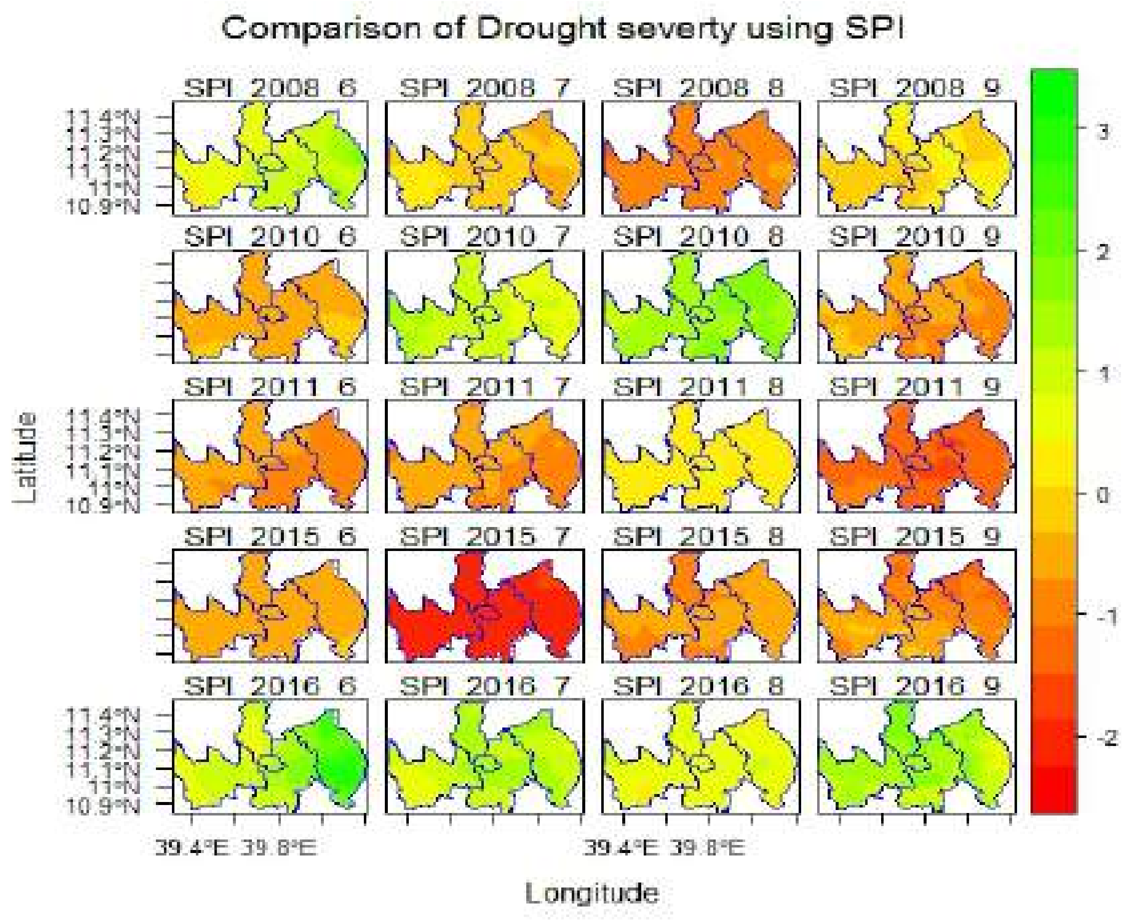


Figure 6 Temporal and spatial distribution drought indicator using SPI

The historical observations of NDVI data can assess the vegetation condition. It is changes into the Vegetation Condition Index (VCI) in order to monitor agricultural drought events. The result of VCI is clearly shows period of drought and wet conditions. Such as, 2008, 2011, 2015, drought and wet years in 2010 and 2016 compared from other years. The first two months (Jun and July) of 2008, July, and August in 2015 shows that vegetation stress in most part of the area which have drought years. Similarly, Legese, (2010) has similar results in Awash River basin vegetation condition calculated from the historical value of NDVI in the growing season to assess drought events. Only the result of VCI by itself not indicated agricultural drought but also needed additional parameters like temperature condition index and others parameters (Kogan, 1994; Bayissa et al., 2018; Bijaber et al., 2018). Land surface temperature of the area affects vegetation health due to the rising of temperature by facilitating evapotranspiration. Based on Kogen, (1994) equation, the result of TCI is becomes decrease when the temperature of the area increases at pixel-value. This TCI result shows that July 2008, June 2010 and August 2015 indicates that extremely high temperature relatively compare with others in the figures. In general, when the amount of rainfall is a shortage and vegetation condition stress, on the other hand high temperature facilitate the evapotranspiration and decrease soil moisture leads to agricultural drought phenomenon during growing period (figure 7).

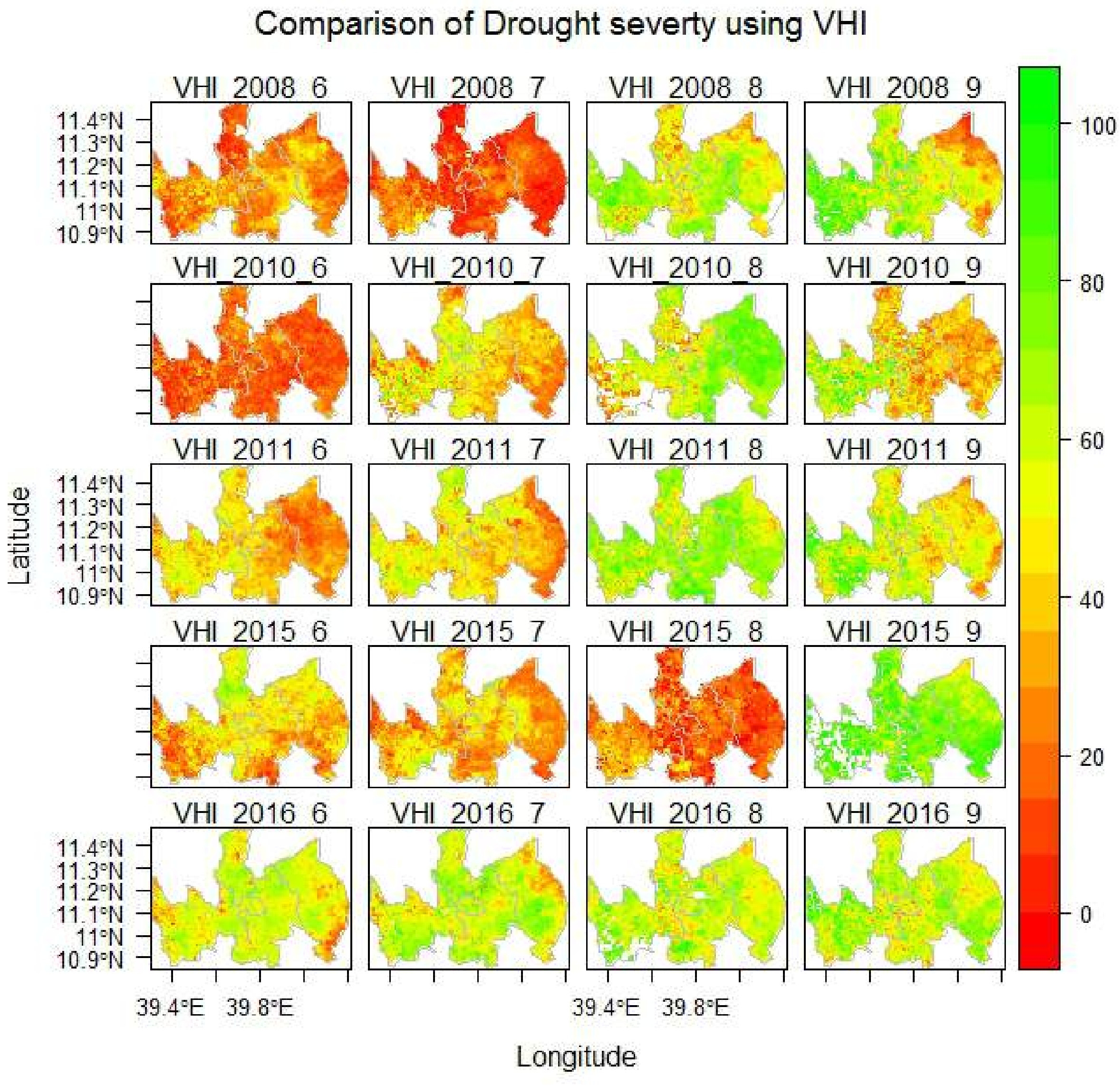


Figure 7 Temporal and spatial distribution VHI as drought indicator during summer season

3.3 Integrated drought indicator (IDI)

The result of weighted drought indicating parameters, which are standard precipitation index, normalized difference vegetation index and land surface temperature known as integrated drought indicator (IDI). It is the main outcome of drought indicators in the current study, while describe the result of monthly IDI starting from 2001 to 2018 during summer season. The recent articles Bijaber et al., (2018); Bayissa et al., (2018) and WMO, (2016) documented that integrated drought indicators derived from combination of various weather parameters, which is best to capture agricultural drought estimation. Figures 8 does shows below 50% of the index except three months such as September 2008, July 2009, and September 2015 through the figure. It means in the study area during 2002, 2004, 2008, 2009, 2011 and 2015 affected by drought at different levels of severity. The result of this study is similar to the concept of ENSO phenomena. ENSO condition during 2002, 2004, 2006-07, 2009 and 2015 are El Niño years which decrease rainfall in the study area and leads to results of agricultural drought. Supporting study similar to this result Korecha & Barnston, (2007) documented that statistical result is negative correlations which have between JJAS Drought years with El Nino in this study area. In addition to this Mohamed et al., (2017) documented that, droughts in Ethiopia occurred in 2002/03, 200/, 2008/09, 2011 and 2015/16 which corresponding with El Nino years. Generally, the result of Integrated Drought Indicator (IDI) is shows that similar with other scientific result.

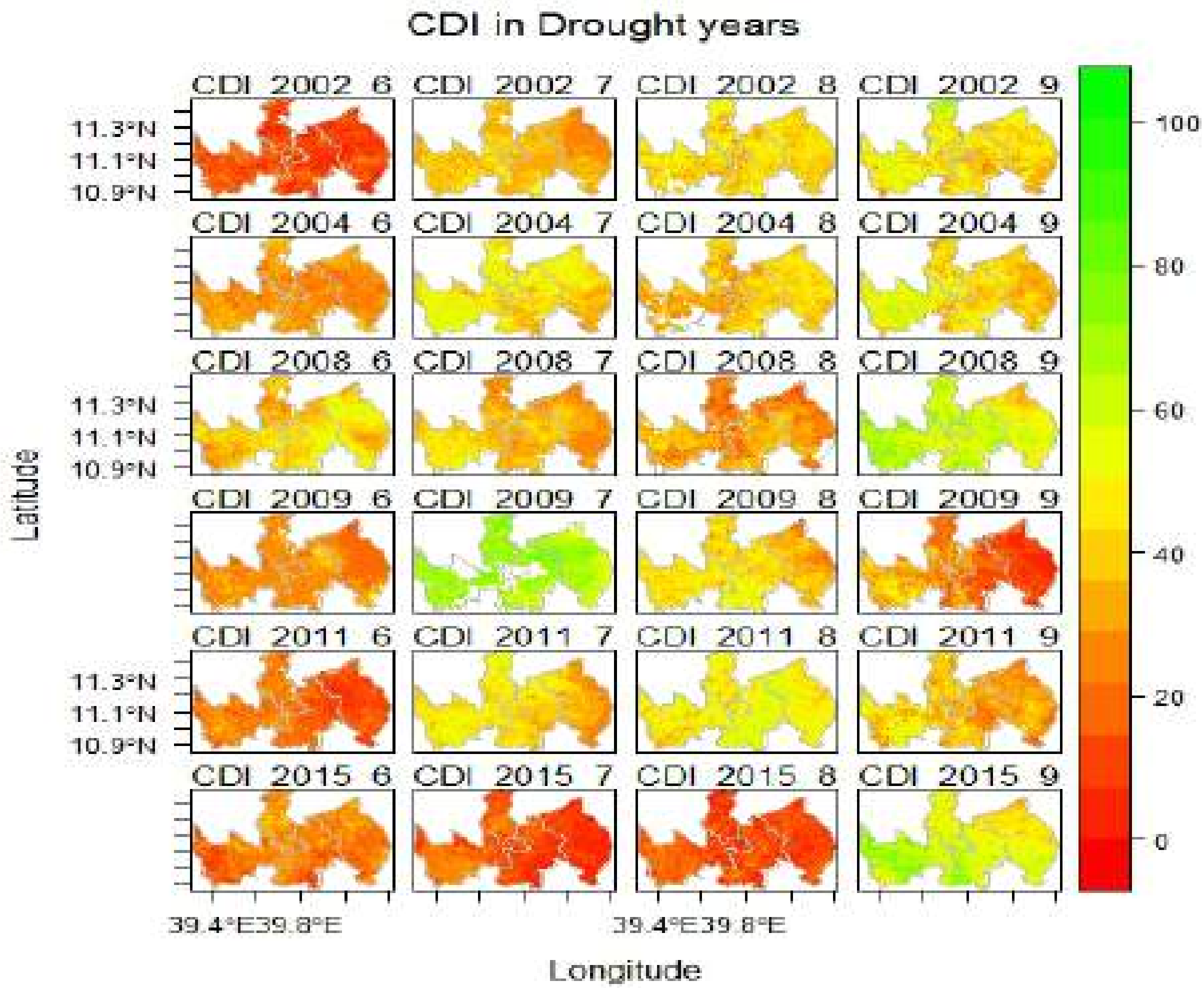


Figure 8 Comparison of drought years using IDI during the main rainy season

To identify strength and severity of drought need to scaled indices of the value by using 18 years monthly integrated drought results. The scale of this index classified into seven categories' from the result of the threshold value in IDI. The classification of this integrated drought indicator in takes into account the classification of Standard precipitation index (SPI) and the vegetation health Index (VHI) shown the tables 2. This figure is indicates that drought years by using time series spatial analysis from common legends, such as extreme drought (0 to 15), severe (15 to 30), moderate (30 to 45) and above 45 no drought.

Table 2 Scale of different drought Indicator

No	Scale VHI	Scale SPI	Scale CDI	Drought categories
1	<10	≤ -2	≤15	Extreme drought
2	10-20	-2 to -1.5	15 - 30	Severe drought
3	20-30	-1.5 to -1	30 - 45	Moderate drought
4	30-40	--------	----------	Meld drought
5	>40	-1 to 1	45 -55	Normal
6		1 to 1.5	55 - 70	Moderately wet
7		1.5 to 2	70- 90	Very wet
8		≥2	≥90	Extremely wet

In the figures most part of the study area covered the value less than or about 50% of drought magnitude. Such as, 2002, 2004, 2008, 2009, 2011 and 2015 are list of drought years from the result of IDI. Spatially, in 2002 and 2015 severe drought covers 18.4 and 76.6 percent respectively. On the other hand, during 2007, 2016 and 2018 the scale of IDI indicate greater than 50% of spatial coverage, which means wet years. Generally, in 2007, 2016 and 2018 are wet year, which are covered more than 78, 95 and 86 in percent, respectively represented wet conditions and normal on another portion of the area.

3.4 Comparison between IDI with other drought indicators

The spatial correlation coefficient and significant value of the monthly IDI with other climate related drought parameters in the study area show significant relation shows in figure 9 & 10. Such as, VHI and SPI have good associations with IDI in the major part of the study are based on correlation coefficient and significant of p-value. Numerically correlation confident is greater than 0.5 and significant value (P) less than 0.05 in most part of the study area. However, the relation between IDI with land surface temperature indicates that less than negative 0.05. Furthermore, the correlation between IDI with VHI is 0.71 and 0.79 in Dessie-Zuria and Bati district respectively. On the other hand, the relation between IDI with SPEI indicated that 0.86 in Bati and 0.76 in Dessie-Zuria district, in order to estimate agricultural drought phenomena from 2001 to 2016. Even if SPEI shows more relation compare with VHI, both indicators have good association with IDI to compute drought events by considering different agro ecological zone. Based on drought indices, a correlation coefficient of Bati district shows that better relation compared from Dessie-Zuria districts.

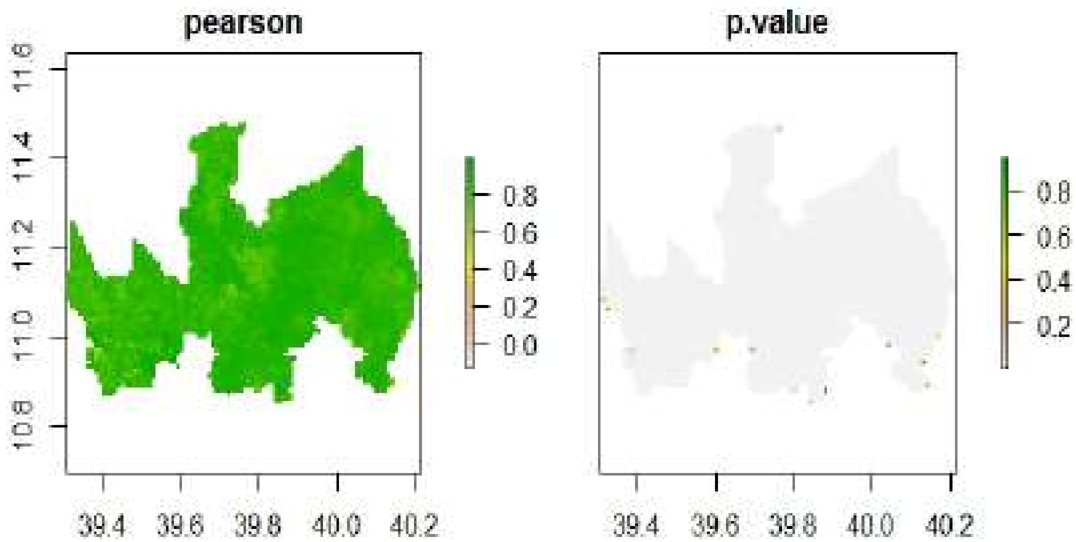
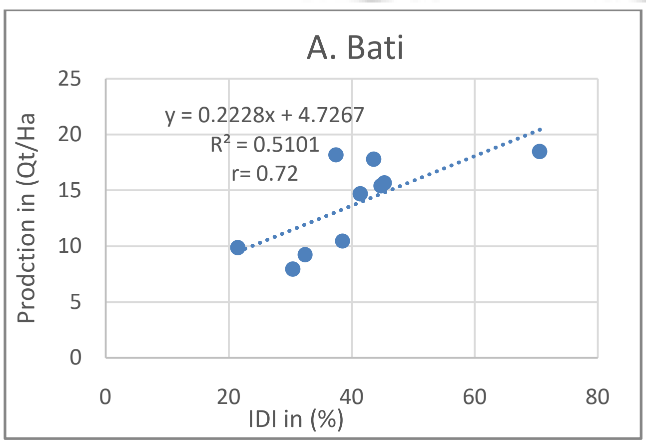


Figure 9 Association between IDI with SPI r and p value using the data (2001_2018)

On the other hand, the correlation coefficient of crop production per hectare with drought indicator shows that significant relation, but less compared from VHI and SPEI. Because crop production of the area does not only depend on weather related drought indices, but also depend on activity of society and environment bounders. Such as population size, land use land cover change, crop rotation in sampled area and using different types of technology to increase crop production like fertilizers, selective seeds and irrigation. Numerical correlation coefficient between crop productions with IDI is 0.72, and 0.56, in Bati and Dessie-Zuria, districts respectively (figure 10 A&B).



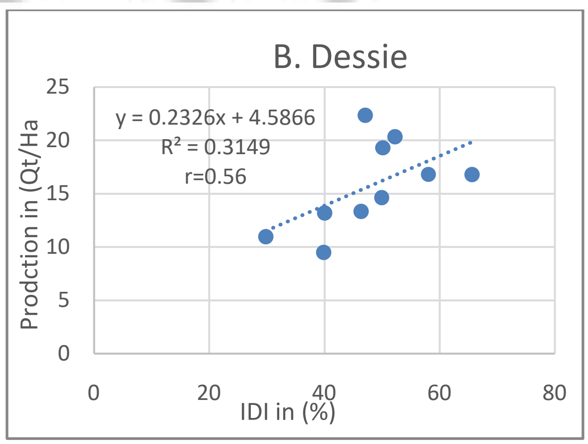


Figure 10 (A& B) Association between IDI with crop production in four districts using 10 years data

Figure 11 is shows that the shortage of production during 2008, 2009, 2011 and 2015, while in 2010, 2014, 2016 and 2017 shows better production in all districts. Furthermore, the result of crop production per hectare is corresponding with result of integrated drought indicator, during the drought year 2008, 2009, 2011 and 2015. This result of a bar graph is clearly corresponding to drought years, which is the average value in all districts in the study area (figure 10 & 11).

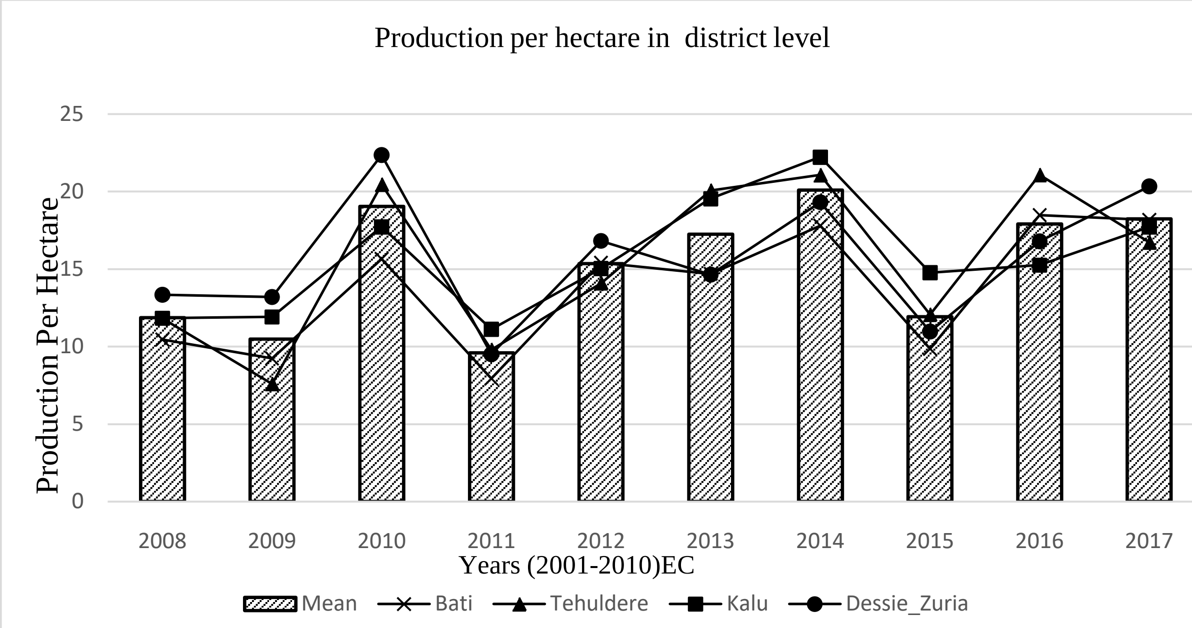


Figure 11 District level cereals crop production per hectare

The relation between NDVI with crop production data collected from field survey on selected sample Kebele in the study area during 2017 shows figure 12. This result indicated that when the biomass of the environment, increase crop production increase that shows a direct linear relationship except Guguftu and Garero Kebele. The relation between Production and NDVI value with R. square is 0.47 and correlation coefficient r is 0.68, it does show good association, but it is not best relation. During group discussion at Kebele level, the respondent did not respond theirs actual income or production. Even if they have good production, because they have considered humanitarian organization reduce any support from the organization.

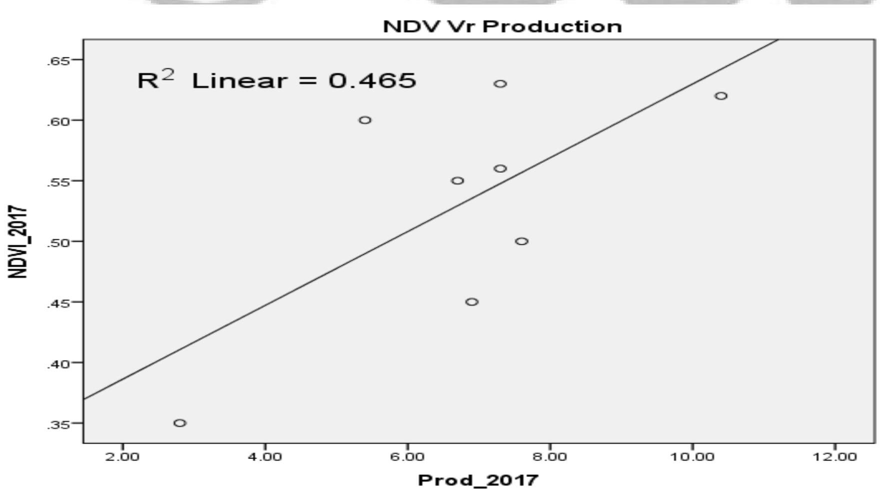


Figure 12 scatter plot between production per hectare and NDVI in selected sample station

3.5 Characteristic agricultural drought using SPEI

Standard precipitation and evaporation index (SPEI) is defined as the indices that indicate agricultural drought events by using historical weather and weather based parameters. Such events are intensity, frequency, severity and duration in a particular area. Figure 13 & 14 shows the result of standard precipitation and evaporation index derived from rainfall, temperature and radiation on heat map and chart. The result is based on 20 representative points on heat map, those points taken five sample areas from each district since 1981 to 2016. The result revealed that, during 1983/84, 1991/92, 2002/03, 2008/09, 2011 and 2015 are indicated a drought period in different magnitude of severity, while in 1988, 1998, 2000, 2010 and 2016 have shown wet and extreme wet years at all selective sample area. Besides, most severe drought years observed during 1983/84 and 2015at the whole area. In agreement with this results impact of drought during 2008, 2011, and 2015 in south Wollo explained by Viste *et al*., (2012) and Muhamed *et al*., (2017)

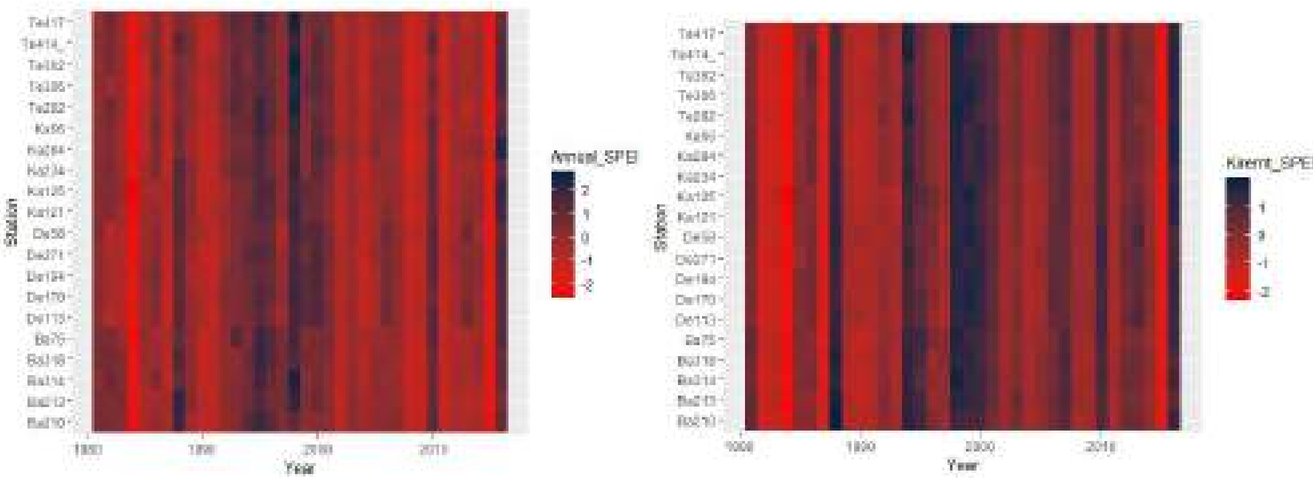


Figure 13 Annual and seasonal SPEI pattern at 20 selected area (1981_2016)

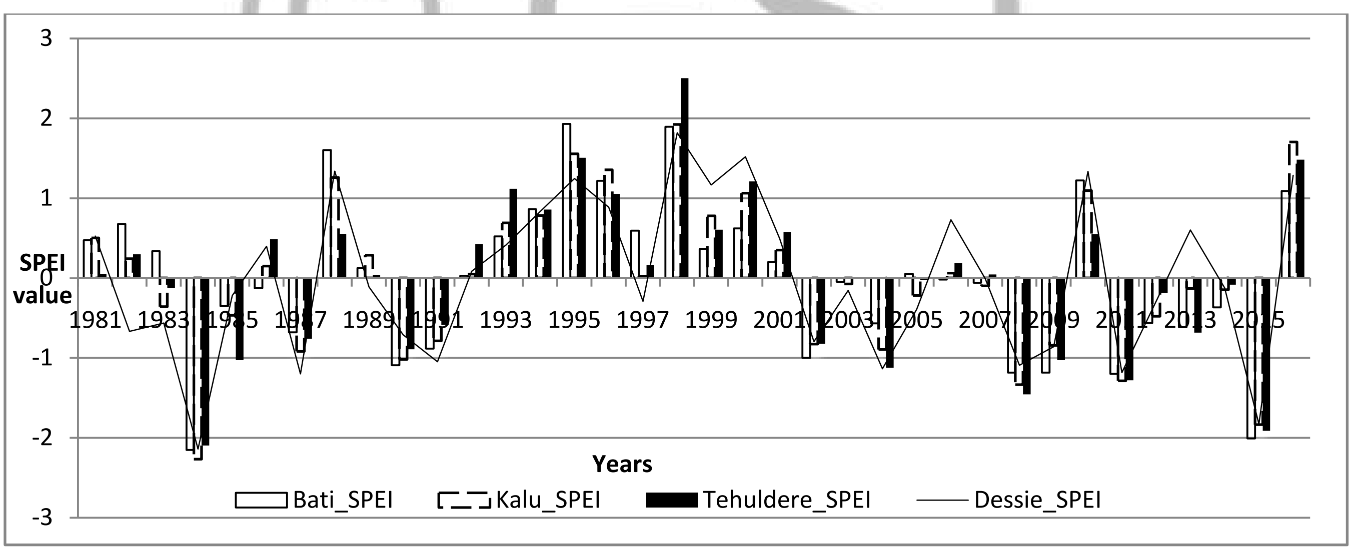


Figure 14 Time series distribution of annual SPEI pattern in district level

Figure 15 is shows that the magnitude and intensity of drought due to the deficit of rainfall and increasing of surface temperature in the representative point of the districts that corresponds to the cumulative sum of SPEI since 1981- 2016. The value of SPEI during 1984-85, 1987, 1991, 2004, 2008-09, 2011 and 2015 clearly shows drought events. Especially, in 1984 and 2015 indicated a strong drought year in magnitude and intensity relative to the other drought years listed on the figure.

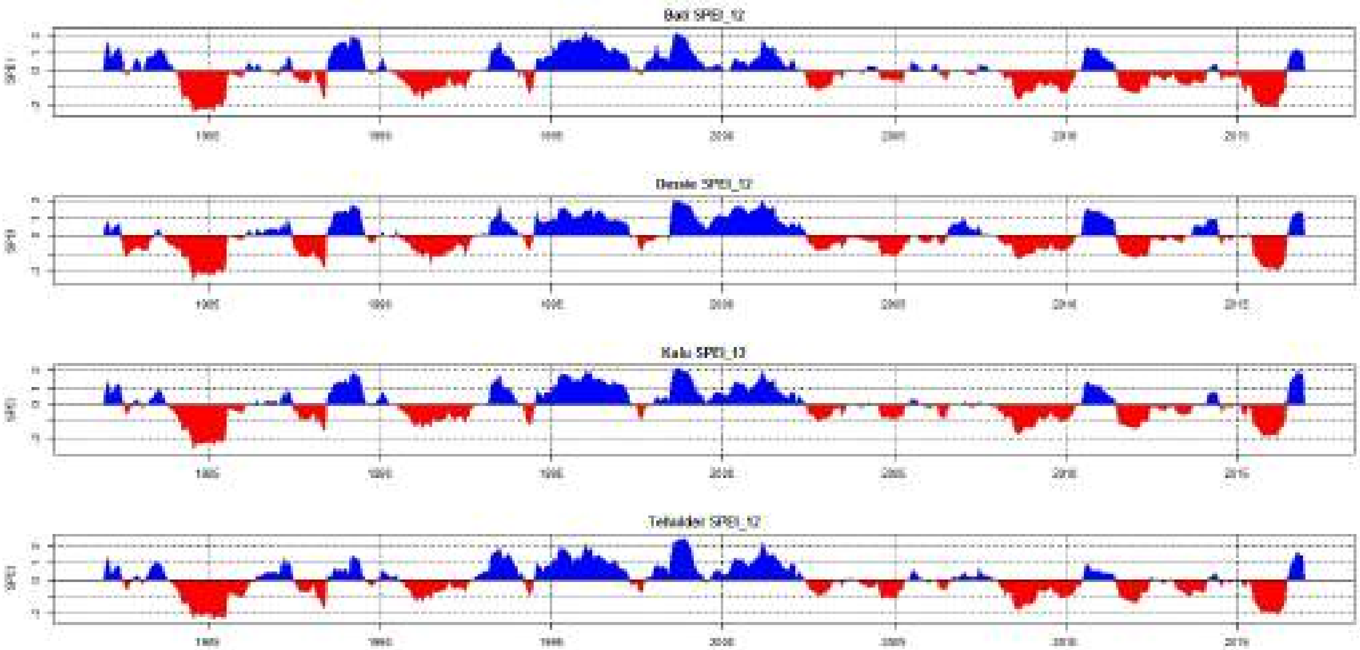


Figure 15 Annual cumulative sum of SPEI from representative points in four districts (1981_2016)

Duration of drought is significant parameter to characterize drought severity, which is determined by included start time of period and end of the events shows in table 3. However, the magnitude of SPEI shows very highest in drought years during 1983/4 and 2015, while it has different duration of drought in all of the districts. That means three years of drought duration observed during 1983/4 but only one-year drought observed in 2015. Even if drought magnitude becomes strong, its negative impact depends on its frequency and duration. This implies that the negative impact of drought during 1983/4 very strong because of drought duration and high magnitude.

Table 3 Drought duration in monthly incidence from (1981-2016) in summer season

No	Onset	Cessation	Bati	Dessie	Kalu	Tehuldere
1	1982	1986	3	3	2	2
2	1987	1988	1	1	1	1
3	1990	1992	2	2	2	2
4	2002	2003	1	1	1	1
5	2004	2005	1	1	1	1
6	2008	2010	2	2	2	2
7	2011	2014	2	1	2	1
8	2013	2014				1
9	2015	2016	1	1	1	1

Table 4 is shows the probability and frequency of drought in district level. In fact, the probability of highest severe drought is less returning period, but the reverse is true when the severity is low. For instance, the probability of extreme severe drought in Bati district 5 times, but meld drought is 27 times out of hundred years. General, frequency of drought in the study area becomes at least once from three consecutive years in different level of severity. Also from field survey respondents stated that, the frequency of drought becomes increase compare from previous decades at least one from consecutive three years. In agreement with this study Gebrehiwot et al., (2011) documented that before the century, frequency of drought occurrence in the country was once every 10 years but now, it is occurring once every five years. Gidey et al., (2018) studied in Raya Alamata reported that at list once from the range of 1.35 to 7.5 years during the main rainy seasons. This implies that frequency of drought become increase in to the recent time.

Table 4 Annual Drought probability value and returning period from 1981-2016

Woreda	**Probability in percent**				**Returning Period in years**				**Total Drought years**
	Extreme	Severe	Moderate	Meld	Extreme	Severe	Moderate	Meld	
Bati	5	0	14	27	19	0	7	4	13
Dessie	3	5	14	27	37	19	7	4	12
Kalu	3	5	11	24	37	19	9	4	12
Tehuldere	3	5	14	27	37	19	7	4	12

3.6 Characteristic of agricultural drought and risk map using IDI

Agricultural drought risk map of the study area was produced by the method of integrated drought indicator using 2001_2018 remote sensing products. It is derived from the scaling of SPI, NDVI and LST in monthly and seasonal level during the main rain season depend on drought category in table 2. In this section, drought year in 2015 is selected in monthly level. Furthermore, 2002, 2004, 2008, and 2009, 2011 and 2015 are selected in seasonal level to indicate drought severity map over the study area. The highest severity drought index of spatial coverage is observed in the eastern lowland relative to the western highland during June and August in 2015 drought year figure 16. Similar to this result, FEWS NET, (2015) documented that, poor crop production were observed during 2015 drought year, whereas, North Wollo, South Wollo, and North Shewa (adjacent to the study area). Also output map included Bati district that affected by poor crop production. Furthermore, the result of the current study reported in the above is an agreement with Gidey *et al*., (2018). The studded was in Raya Alamata, who noted that the advanced remote sensing drought indices using the Vegetation Health Index (VHI) can help to assess the incidence of agricultural droughts onset and cessation during 2011 and 2015 respectivily.

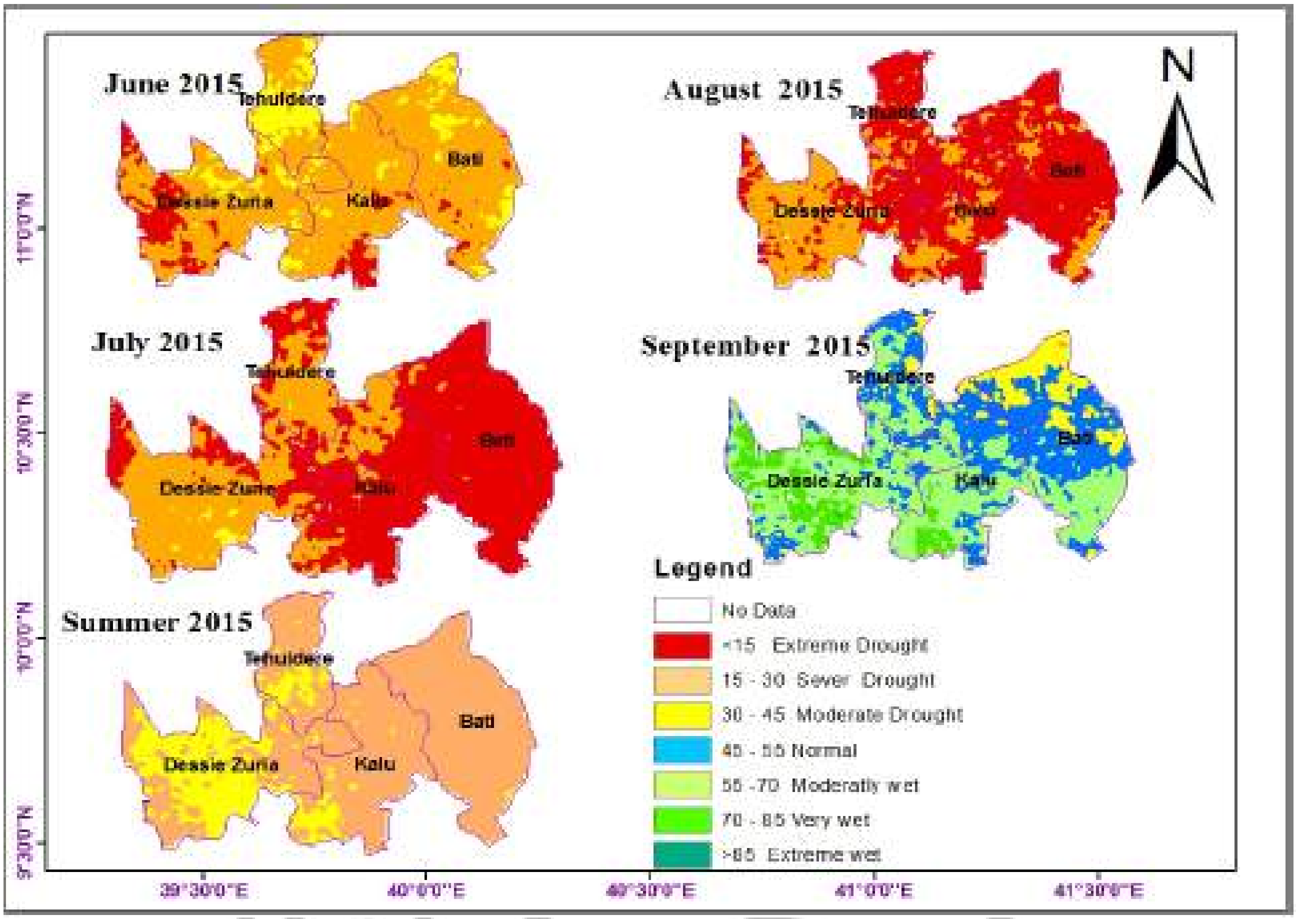


Figure 16 Monthly CDI during summer season in 2015

Summer seasonal drought outputs is shows in figure 17. The result showed that, below the normal scale of indices. During 2002, 2004, 2008, 2009, 2011 and 2015 are clearly observed drought event at different level of severity in most part of the area. Specially, more spatial coverage of severe drought is measured during 2002, 2011, and 2015 on the map. For instance, drought during 2015 was linked to the lack of rainfall in the main rainy season (June to September), moreover, increment of temperature observed over the area. Mostly, the result indicated that in most part of the study area observed a moderate drought in selected drought years except the whole part of Bati district during 2015. Thus, severe drought had observed in most part of Bati district during 2015. Generally the eastern lowland area more vulnerable compared from the western highland. We said that, from figure 14 and 15 show that monthly drought indicator clearly show the severity and area coverage rather than seasonal output.

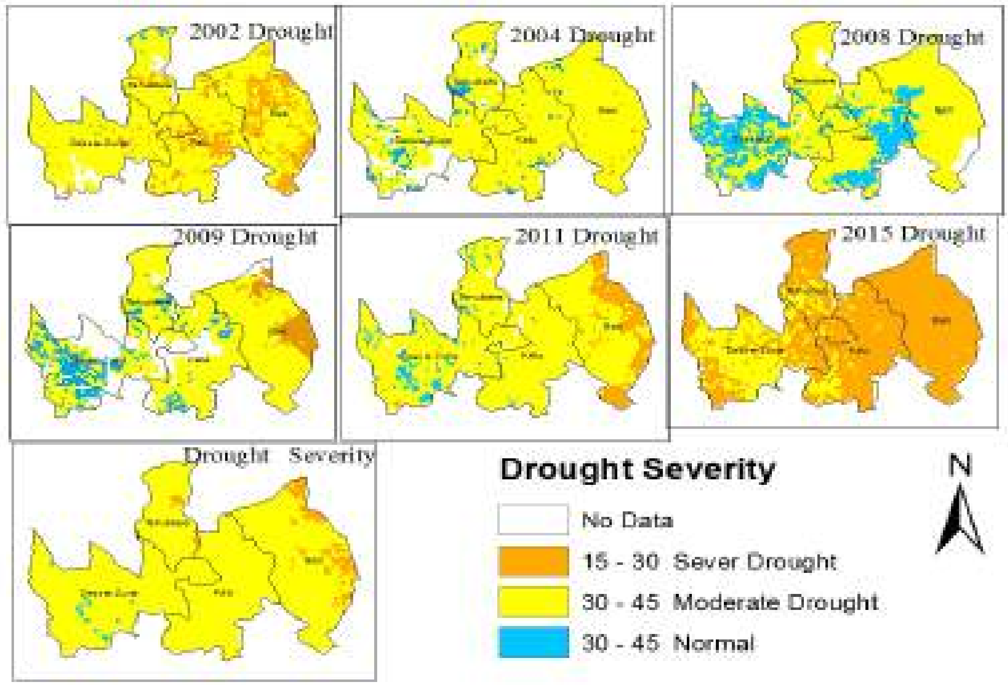


Figure 17 Seasonal classification of drought during selected drought years

Figure 18 is indicating that the seasonal dryness and wetness condition of the study area from the time scale of 2001 - 2018. The magnitude of the events is expressed in percent of area coverage. As the figure shown in 2002, 2004, 2011 and 2015 almost the whole part of the study area dry condition. Which means, this area affected by drought. But the magnitude and severity varied in time and location. Scholars such as Mohamed, (2017) and Korecha, (2013) reported similar results in the current study. They noted that in 2002, 2011, and 2015 are the period of drought observed over Ethiopia, even though they have not well defined the percentage of area coverage of the event. Generally, couples approach of agricultural drought indicators using satellite sensors is a good method to capture drought severity in terms of temporal and spatial distribution.

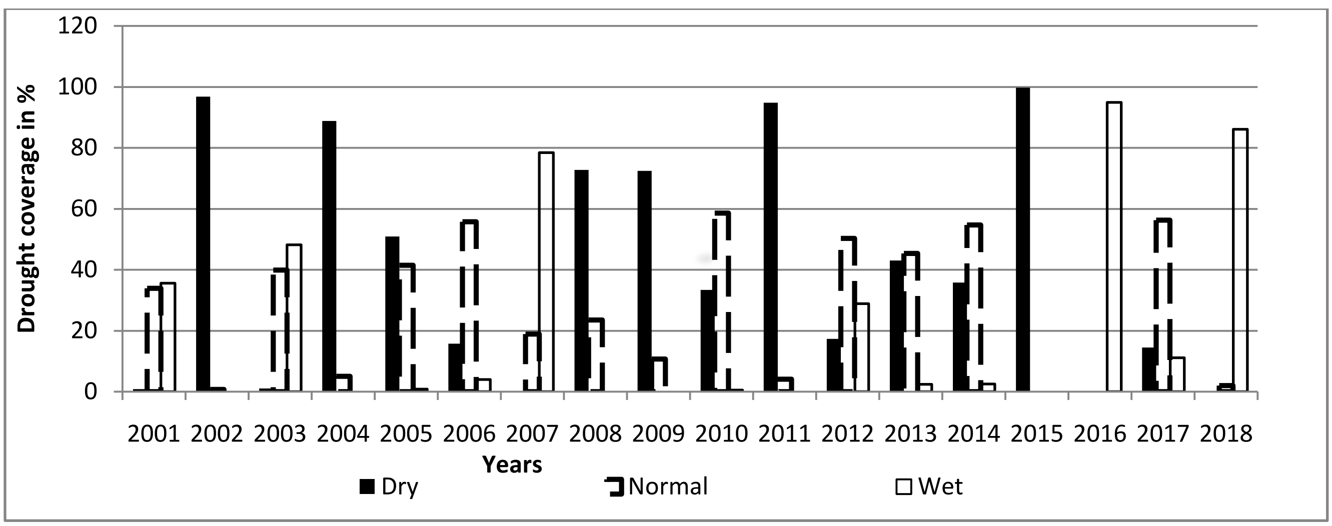


Figure 18 drought magnitude and coverage in percent on the study area (2001_2018)

Figure 19 is shows seasonal drought risk map during 2011 and 2015. Its impact increase from west to east part and slightly increase the severity of drought in the northern direction. The right-hand said of the map shows that the number of total pixels affect by drought severity based on the scale in table 2.

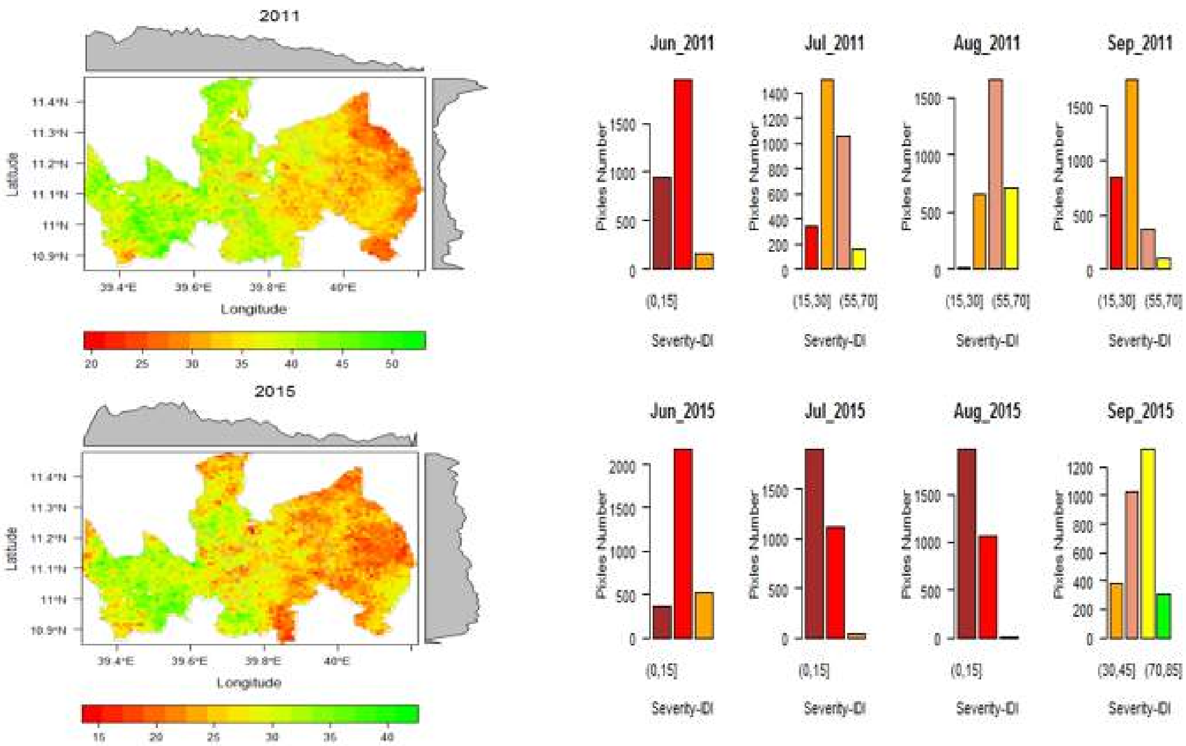


Figure 19 *summer season drought risk map in 2011 and 2015)*

3.7 Adaptation and mitigation practice

The main concept of the socioeconomic data survey is to assess drought period and its impact on crop production in the study area on eight samples Kebele, in order to investigate best adaptation and mitigation strategy. Based on field surveys, there is frequent occurrence climatic related disaster such as drought, flood and unseasonal rainfall. During 2015, recent memorized strong severe drought happened due to the failure of annual crop production. Agricultural expert and farmers are responding that there was supported different type of goods when crop production failed in order to resist during the events and to recover after the event.

Supporting for household not only during drought years, but also still now like safety net program sport some selected households, who have been suffered from frequent drought events. Such as, they provided nutrition, medicine, mental treatments and financial support for short-term prevention and provide construction of irrigation canals and preventing environment by facilitating water and soil conservation in long-term mitigation and adaptation strategy. Supporting for current study according to Mera, (2018) documented that in order to recover the impact of 2015 drought event, Ethiopian government spent more than a billion dollars to provide food grain by purchase from abroad. In addition, Mohammed et al., (2017) documented that, due to the lack of rainfall during rainy seasons in 2015 significant impact by limiting agricultural production leads to food insecurity among the vulnerable households in this area.

Table 5 the main adaptation and mitigation practice from field survey

		Responses		Percent of Cases
		N	Percent	
Adaptation and Mitigation	Soil and water conservation	74	21.1%	82.2%
	Crop rotation	52	14.8%	57.8%
	Compost	60	17.1%	66.7%
	Using irrigation	36	10.3%	40.0%
	Afforestation	36	10.3%	40.0%
	Using fertilizers:	54	15.4%	60.0%
	Using selected seeds	39	11.1%	43.3%
Total		351	100.0%	390.0%

Based on the field survey, the main climate related effect on the study area was frequent drought event, shortage of rainfall, un-seasonal rainfall and river flooding. Therefore, need to develop long-term adaptation and mitigation strategy plan by focused local coping practices. For example, the main action plan attempts to protect their environment using afforestation, soil and water conservation; construct irrigation canals, use fertilizers and selected seeds to increase their productivity by taking long strategic plan action table 5. While these local coping practices need high potential to construct well organized irrigation practice using water harvesting in rainy season, excavate underground water and river diverting special in low land such as Bati and Kalu districts. Because highland area is source of water for lowland if properly utilized. Even if agricultural yield production more related with, the amount of rainfall, also depends on agricultural activity, such as plow, weeding, environmental protection and the use of fertilizer. Therefore, in order to obtain good crop production needs to plan use of current agricultural technology and better to apply weeding activity to protect crop from diseases.

4. Conclusion and recommendation

South Wollo Zone and Bati district in the north eastern part of Ethiopia affected by frequent agricultural drought events. However, most studies used single drought indicator to capture agricultural drought severity recent articles recommended that to develop weather based integrated drought indicators, which are best significant to develop an early warning system rather than single drought indicators. Therefore, this study focused on the coupled approach to estimate agricultural drought severity using result of satellite sensor such as SPI, NDVI and LST. The relation between monthly integrated drought indicator with SPI and VHI in the study area have better correlation coefficients, which are greater than 0.5 and its significant value less than 0.05. The result CDI with SPEI correlation in the Bati district was 0.85 whereas in Dessie district was 0.76. On the other hand, IDI with VHI have correlation coefficient 0.79 and 0.71 at Bati, and Dessie_Zuria respectively. Crop production with IDI shows a good correlation in district level Bati was 0.72 and Dessie-Zuria was 0.56. Even if area coverage and drought severity are differ each other during 2002, 2004, 2008, 2009, 2011 and 2015 indicated that drought events. During 2002, 2011 and 2015 drought year indicates that whole part of the area was covered about 97 %, 95 %, and 100 % respectively affected by drought in different level of severity. Especially, during 2015 more than 77% of the areas were affected severe drought. The result of this study shown that 2015 the whole part of the study area suffered by drought, but its severity and spatial coverage is high in Bati district, whereas Dessie-Zuria district shown that better performance than others. The other output of this study have an advantage to compute or assess drought events in a 1000m pixel seize, in order to advice any organization working with climate based activity. Frequency of drought in the study area either using IDI or SPEI at list one drought year was happening in the consecutive three years; while, the probability of extreme drought occurred five times out of hundred years. The main adaptation and mitigation strategy in the community of the study area before, after and during drought event solved by providing permanently implement of constrictive project. Such as, constrict irrigation canal in drought affecting areas, either river diverts or excavate of underground water and water harvest during rainy season; on the other hand improving crop production by using fertilizers, selective seeds and facilitate soil and water conservation.

IDI is a result of high resolution and timely updated weather based remote sensing products with ground based information. We have believed highly important for decision makers in order to build any strategic plan in the study area related to drought events. Another recommendation that to verify the scale of this IDI result to show dry and wet months, also verify this method by taking into account below district level proper agricultural production, soil type and also considers land use land cover of the area because those characters are factored in crop production. Based on the findings of the study, finally recommended that future studies can build upon this work to solve cloud factors by taking daily satellite products and other scientific techniques because this study excludes the area that enclosed by cloud.

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