Harla Journals

Harla Journal of Social and Behavioral Studies

Journal home page: https://journals.ddu.edu.et/index.php/HJSBS

Harla journal of Social and Behavioral Studies

GIS and Remote Sensing Based Meteorological Drought Risk Assessment: the case of East Hararge Zone, Oromia, Ethiopia

Kefelegn Chernet

Senior Lecturer at Department of Geography and Environmental Studies, College of Social Science and Humanities, Dire Dawa University, Dire Dawa, Ethiopia. Phone: +251920857694,
Email: kefelegn.chernet@gmail.com

Abstract

Ethiopia, located in the Horn of Africa, is one of the sub-Saharan countries highly prone to drought hazards. Drought is a water-related natural disaster that impacts a wide range of environmental factors. It is primarily a climatic phenomenon that cannot be fully eradicated. The study sought to identifies the occurrence of meteorological drought in the study area by using geospatial tools. It examined the spatial and temporal meteorological drought patterns of the study areas using different appropriate meteorological drought indices and identified the most drought-vulnerable areas using geospatial data and modeling techniques in the drought-prone East Hararge Zone of Ethiopia. To assess the spatiotemporal variation of seasonal drought patterns and severity, four drought indices Normalized Difference Vegetation Index (NDVI), Vegetation condition index (VCI), Standard precipitation index (SPI) and Drought severity index (DSI) were applied. MODIS NDVI data and monthly rainfall data from 2012 to 2022 were used as input data, while crop yield data served as ground truth for validating the strength of the drought indices. To validate the drought indices, correlation and regression analyses were conducted between NDVI and rainfall (r = 0.76), NDVI and crop yield (r = 0.74), and VCI and SPI (r = 0.78). The results of this study showed that the region experienced extreme drought in 2016, 2017, 2018, and 2022. The findings indicate that the study area is highly prone to drought, although the severity levels varied across these years. A result map was generated based on the frequency maps of the four indices. The map revealed that 35%, 49.1%, and 13.8% of the total area of the zone were classified as severely, moderately, and mildly vulnerable to drought, respectively. This result map can be valuable for decision makers and policymakers in developing pre and post drought risk management plans.

***Keywords**: East Hararge Zone, Meteorological Drought, MODIS, NDVI, SPI*

**Corresponding author: Kefelegn Chernet, email: kefelegn.chernet@gmail.com , Phone:* +251920857694,

DOI:

Received October 2023; Received in revised form November 2023; Accepted December 2023

1. Introduction

Some of the most difficult issues that modern human societies must deal with are the rising food demand and environmental stressors, which has encouraged new research into the impact of drought on agricultural food production (Fava and Vrieling, 2021). Droughts are climatic disasters, with varying frequencies and intensities worldwide. It can be defined as the deficiency of water or precipitation over an extended period of time that adversely affects ecosystem, environmental productivity and socioeconomic conditions. Particularly, food and ecological security are threatened by drought (Baik et al., 2019).

Meteorological drought is driven by climate change that negatively affects both crops growing and livestock production. It is characterized by a situation when an area has not had rain for an extended period of time (Cravens et al.,2021). Drought is one type of climate extreme that has a substantial impact on environmental quality and threatens food availability in underdeveloped nations like Ethiopia. There is pressure on the sustainability and welfare of natural resources as a result of the significant increase in the effects of meteorological drought. Ethiopia in particular and all of Africa are the most susceptible to drought (Matlou et al, 2021).

Ethiopia faces significant challenges due to climate change, particularly in the form of increasing droughts that have a severe impact on agriculture and food security. As one of the most drought-prone nations in Africa, the country's dependence on rain-fed agriculture makes it especially vulnerable to erratic rainfall patterns. Droughts, which are extended periods of insufficient rainfall, not only disrupt environmental productivity but also have devastating effects on socioeconomic conditions, particularly food and ecological security. In areas like East Hararge Zone, droughts have caused frequent crop failures due to irregular rainfall, exacerbating food insecurity (Fava and Vrieling, 2021; Baik et al., 2019).

Agriculture in Ethiopia is the primary source of livelihood for approximately 85% of the population, which makes it highly sensitive to changing weather patterns. The inconsistency of rainfall in areas like East Hararge leads to insufficient water for crops, causing significant reductions in agricultural yields and threatening food supplies. This vulnerability is compounded by the use of traditional farming methods and the absence of advanced technology for drought prediction and management. As a result, the agricultural sector is at constant risk, undermining Ethiopia's economic development and food security efforts (Temesgen et al., 2009; Rosell, 2011; Mersha and Vijendra, 2020).

In Ethiopia, drought risk assessment has traditionally relied on rainfall data analysis, but this method has proven ineffective in addressing the spatial and temporal variability of droughts. Such conventional approaches fail to provide accurate or timely information, especially in areas with challenging landscapes like East Hararge. In contrast, modern technologies like Remote Sensing (RS) and Geographic Information Systems (GIS) offer an effective means of monitoring droughts, as they provide spatially accurate and consistent data. By incorporating these tools, drought-prone regions can be identified more efficiently, allowing for better management and understanding of drought impacts (Lemma, 1996; Berhan et al., 2011; Dodamani et al., 2015).

Given the increasing severity of droughts in Ethiopia, there is an urgent need for advanced scientific methods to accurately assess, monitor, and manage drought risks. The integration of Remote Sensing and GIS technologies offers a more reliable and timely means of tracking droughts, which will enable targeted interventions and strategies to reduce their impact. These technologies can help in creating detailed maps of drought-prone areas and assessing the extent of their effects, improving overall drought management and resilience (Wilhite et al., 2020).

In conclusion, Ethiopia's struggle with frequent droughts, particularly in areas like East Hararge, necessitates the use of modern technologies for effective drought management. Remote Sensing and GIS can provide valuable data for predicting and monitoring droughts, enabling better preparedness and response strategies. By incorporating these tools into the country's drought risk management, Ethiopia can enhance its resilience to climate change, safeguard its agricultural sector, and ensure food security for its population.

2. Materials and methods

2.1. Description of the study area

East Hararge zone is one of administrative zones of the Oromia Regional State. It is located in the Eastern part of Ethiopia, the administrative center of East Hararge zone is Harar city, which is located East of Addis Ababa the capital city of Ethiopia approximately far about 526 km. It located geographically in 7° 31' 27" to 9°45′ 40″ N Latitude and 41° 10' 15" to 42°58′ 30″ E Longitude. East Hararge zone is bordered on the southwest by the Shebelle river which separates it from Bale, on the west by West Hararge zone, on the north by Dire Dawa and on the north and east by the Ethiopian Somali Region. The Harari Region is an enclave and found inside this zone and it is found within the altitude range of 500 to 3400m above mean sea level. East Hararge zone has a total area of 25161.5 km^2, which comprises of 15 rural woredas and 6 town administrative centers (EHZAO, 2023).

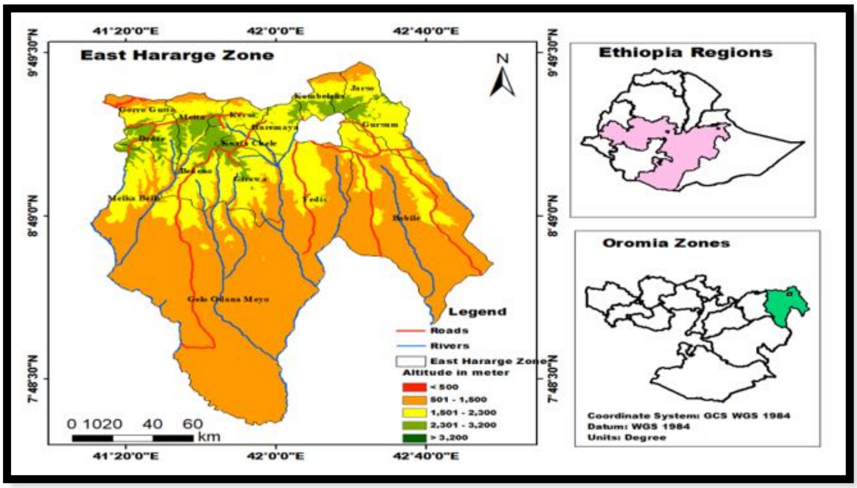


Fig. 1. Location map of the study area

The East Hararge Zone features a diverse topography, including steep slopes in the highlands and mid-highlands, with large plains in the lowland areas. The highlands are primarily used for crop cultivation, but land scarcity often forces farmers to cultivate on steep slopes and forested areas, exacerbating soil erosion. The lowlands, a mix of cultivated and pastureland, also face erosion, worsened by activities like charcoal production. The region experiences two rainy seasons, with annual rainfall varying between 600 and 1200 mm, but the irregularity of rainfall contributes to frequent droughts, impacting agricultural productivity (EHZAO, 2023; Zonal Agricultural Development Department, 2022).

East Hararge's agro-ecological zones include highlands (Dega), midlands (Weyna Dega), and lowlands (Kola), with the highlands covering 10-15%, the midlands 30-35%, and the lowlands 40-45% of the area. The region's average temperature ranges from 25°C to 30°C, with variations based on altitude. In terms of land use, shrubland and cropland dominate the landscape, with significant portions of the land also used for forests, built-up areas, and water bodies. The soils in the region are primarily Cambisols, Vertisols, Regosols, and Xerosols, with brown soils making up the majority (52%) (FAO, 2019; East Hararge Zone Agricultural Department, 2023).

The population of East Hararge is around 2.74 million, with most people living in rural areas and relying on agriculture for their livelihoods. The region is predominantly agrarian and semi-pastoral, but irregular rainfall and droughts have made agricultural productivity unreliable, leading to food insecurity. Key crops grown in the area include maize, sorghum, and cash crops like khat and coffee. Despite these efforts, frequent droughts continue to reduce crop yields, leaving many districts dependent on food aid and external support programs such as the Productive Safety Net Program (PSNP) (East Hararge Administration Office, 2020)

2.2. Data and methods

2.2.1. Data Sources and Type

To achieve the objective, both satellite and ground-based data were collected from primary and secondary sources. Primary data includes satellite image analysis and field observations, while secondary data is gathered from published and unpublished documents. Key sources of secondary data include the Meteorological Agency, Central Statistical Agency, and local governmental organizations. These data will be analyzed based on identified criteria and constraints. Both data types are essential for comprehensive analysis.

Table 1. Data source used for present study

Data set	Variable	Description	Resolution		Period	Source
			Spatial	**Temporal**		
MODIS	NDVI	Satellite	250m	16 days	2012-2022	USGS
CHIRPS	Rainfall	Satellite	10km by 10km	Monthly	2012-2022	Climate hazards center
Agricultural data	Yield	Ground data	Quintal/H	Year	2012-2022	CSS
Metrological Data	Rainfall	Ground data	Average mm	Monthly	2012-2022	NMA

Software package

The following software packages were used at different stages of the study.

Table 2. Types of software packages used

Type	Version	Data type	Purpose
ArcGIS	10.8	NDVI, VCI, DSI	image processing, statistical analysis, graphical display and map preparation
R studio	4.1.1	Rainfall, SPI	Meteorological data Analysis
Microsoft Excel	2019	Rainfall, Crop yield	Data processing and graphical display
SPSS	23.0	Rainfall, Crop yield	Statistical analysis and processing

2.2.2. Satellite Data Acquisition Methods

MODIS (Moderate Resolution Imaging Spectroradiometer) is a key tool for monitoring Earth's ecological, meteorological, and hydrological conditions, providing data from the Terra and Aqua satellites. With a viewing swath of 2,330 km and a data capture frequency of one to two days, MODIS offers enhanced spatial resolution (250 m, 500 m, and 1,000 m) and improved atmospheric corrections compared to other sensors like AVHRR and SPOT VGT. For this study, MODIS products such as the NDVI (MOD13Q1) were downloaded to assess vegetation dynamics from 2012 to 2022, using a scaling factor of 0.0001 for accurate data interpretation.

In addition to satellite data, rainfall data was sourced from two key providers. CHIRPS (Climate Hazards Group Infrared Precipitation with Stations) data, covering the period from 2012 to 2022, was masked to focus on the study area. This data, along with monthly rainfall data from the Ethiopian National Meteorological Service Agency, was analyzed for rainfall variability and used to calculate the Standard Precipitation Index (SPI). A total of seven rainfall stations, unevenly distributed across the study area, provided essential information to explore the relationship between rainfall and vegetation dynamics.

To validate satellite-derived data, ground truth data, including agricultural yield data from the East Hararge Zone Agricultural Office, was collected for the period of 2012 to 2022. This data, combined with expert insights and published materials on agricultural drought impacts, offered a more robust understanding of drought conditions. The relationship between agricultural yield and meteorological conditions was explored through regression analysis, linking crop yield anomalies to changes in NDVI and rainfall patterns to better understand the effects of meteorological drought.

2.3. Data Processing and Analysis Methods

2.3.1. Computation of normalized difference vegetation index

The Normalized Difference Vegetation Index (NDVI) is a widely used metric for assessing environmental conditions, with values ranging from +1.0 to -1.0. Low NDVI values (0.1 or less) typically indicate areas with bare rock, sand, or snow. Moderate NDVI values (0.2 to 0.5) are associated with sparse vegetation, such as shrubs and grasslands, or senescing crops. High NDVI values (0.6 to 0.9) suggest dense vegetation found in temperate and tropical forests or peak crop growth.

Researchers utilize NDVI measurements to create imagery and products that estimate plant types, quantities and conditions globally. NDVI-derived indices can evaluate seasonal crop conditions, as noted by Gizachew Legesse and Suryabhagavan (2014). In this study, calculations were performed using the seasonal maximum NDVI and long-term mean maximum NDVI to assess vegetation drought conditions during the study period (June to September) each year. The results will categorize drought severity into five classes.

The NDVI value calculated from MODIS using this formula

$$\mathrm{NDVI} = \frac{(\mathrm{NIR-RED})}{(\mathrm{NIR+RED})} \quad (1)$$

2.3.2 Computation of Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was developed to measure precipitation deficits across various timescales. It uses an intensity scale with positive values indicating wet conditions and negative values corresponding to dry events. For drought analysis, particular attention is given to the "tails" of the precipitation distribution, especially extreme dry events, which are rare based on the regional climate. A drought event is identified when SPI values for a given timescale become consistently negative and reach -1 or lower. The drought is considered ongoing until the SPI value returns to 0. According to McKee et al. (1993), drought begins at an SPI of -1 or below, though there is no universally accepted threshold. Some researchers may define drought at SPI values below 0 but not as severe as -1, while others strictly classify it at values below -1. The timescales used in SPI analysis highlight how drought impacts various water resources. On shorter timescales, precipitation anomalies significantly influence soil moisture conditions (Shaheen and Biag, 2019). It is determined by:

$$\mathrm{SPI} = \frac{(\mathrm{Xij - Xim})}{\sigma} \quad (2)$$

Where Xij is the seasonal precipitation, Xim is the long term seasonal mean and σ is the standard deviation. Finally, a new classification based on the drought severity class will applied to the findings obtained from seasonal rainfall data for each grid cell.

Table 3. SPI based drought severity class

SPI value	Drought severity class
Above 0	No drought
0.0 to -0.99	Slight drought
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2 and less	Very Severe drought

2.3.3. Vegetation Condition Index (VCI)

Vegetation Condition Index (VCI) used to be measured in percent provides an assessment of spatial characteristic of drought, as well as its duration and severity and is in good agreement with precipitation patterns (Moussa et al. 2021). The Vegetation Condition Index (VCI) serves as an indicator of vegetation cover status by using the NDVI's minimum and maximum values observed over many years for a specific ecosystem. By normalizing the NDVI, VCI facilitates comparisons across different ecosystems, making it a more effective measure of water stress conditions than NDVI alone (Kogan, 1995). However, the accuracy of VCI depends on the availability and quality of images used to determine the absolute minimum and maximum NDVI values.

$$\mathrm{VCI} = \frac{(\mathrm{NDVI} - \mathrm{NDVImin})}{NDVImax - NDVImin} * 100 \qquad (3)$$

Where, MaNDVIi and MiNDVIi represents maximum and minimum Normalized Difference Vegetation Index of year i, NDVIi13 represents the first 10-day NDVI composites image of May (which is the 13th dekad from the beginning of the sensor in 1998), NDVIi27 is the third 10-day NDVI composite data of September. VCI values around 50% indicate fair vegetation conditions, while values between 50% and 100% reflect optimal or above-normal conditions. A VCI value of 100% signifies that the NDVI for the selected month (or decade) is equal to NDVImax, representing the best possible vegetation condition. Conversely, VCI values below 50% indicate varying degrees of drought severity. According to Kogan (2011), a VCI threshold of 35% can be used to identify extreme drought conditions. A VCI value near 0% represents an extremely dry period, where the NDVI approaches its long-term minimum. Persistent low VCI values over consecutive time intervals suggest the development of drought.

For the purpose of delineating drought, seasonal VCI were generated for eleven years. The Vegetation Condition Index (VCI) is measured as a percentage ranging from 1 to 100. VCI values between 50% and 100% indicate slight to optimal/normal conditions, while values close to zero percent reflect an extreme dry season. According to Thenkabail and Gamage (2004), the VCI has been reclassified into five clusters, as shown in Table 4.

Table 4. Vegetation Condition Index threshold classes applied in the study

VCI value	Drought severity class
0 to 20	Very Severe drought
21 to 35	Severe drought
36 to 50	Moderate drought
51 to 60	Slightly drought
61 and above	Optimum/normal

2.3.4. Computation of Drought Severity Index (DSI)

The Drought Severity Index (DSI) was calculated on a seasonal basis using the ArcGIS Raster Calculator. To generate the DSI map for the study area, decadal long-term mean NDVI images were stacked and the monthly long-term mean was computed. In this study, 11 years of long term seasonal mean NDVI maps were derived from MODIS vegetation datasets. The DSI was computed seasonally to identify drought years and classify their severity levels (Table 5). The computation follows the algorithm:

$$\text{DSI} = \frac{NDVIi}{NDVImean,m} \quad (4)$$

Where NDVIi represents the NDVI value for a specific season, and NDVI mean, m is the long-term mean NDVI for the same season m. For instance, in a dataset spanning 2012 to 2022, there would be 11 seasonal NDVI values corresponding to the same season (e.g., 11 NDVI values for June–September).

Table 5. Drought Classes Based on Drought Severity Index (DSI)

DSI Value	Drought Severity
< 0.25	Extreme drought
0.1 to 0.25	Severe drought
0.1 to 0.1	Moderate drought
0.1 to 0.25	Mild drought
> 0.25	No drought

Source: Kogan (2001)

2.3.5. Rainfall Data Set

To assess the temporal variation of rainfall, the researcher utilized the monthly Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) time series data covering the period from 2012 to 2022. CHIRPS were chosen for its strong correlation with rain gauge measurements, as highlighted by Bayissa et al. (2017). This makes it particularly reliable for estimating precipitation in Ethiopia, where accurate rainfall data is critical for agricultural planning and water resource management. The data was sourced from Climate hazards center, ensuring high-quality and consistent rainfall records for analysis.

2.3.6. Crop yield anomaly regression analysis with drought indices

Agricultural yields are sensitive to weather fluctuations, often declining during severe drought periods. The Normalized Difference Vegetation Index (NDVI) has been extensively used for vegetation monitoring, crop yield assessment and drought detection. By leveraging the reflective and absorptive characteristics of plants in the red and near-infrared portions of the electromagnetic spectrum, NDVI has shown strong correlations with vegetation yield and productivity. Consequently, crop yield has also been correlated with NDVI values.

To quantify the impact of meteorological drought on the production of major crops, the correlation between the Standard Precipitation Index (SPI) and zonal-level crop yields will be analyzed. Additionally, yield trends over the last 11 years (2012–2022) will be computed to assess changes in crop production.

3.4. Meteorological Drought Risk Assessment

In this study, seasonal frequency maps derived from meteorological drought indices were standardized onto a common scale based on drought occurrence frequency. To create a drought frequency map, each drought index was reclassified into binary images representing each drought severity class. These binary maps were then summed to determine the frequency of slight, moderate, severe and very severe drought occurrences at each pixel level for meteorological drought. Finally, the resulting severity maps were combined to produce a comprehensive meteorological drought risk map.

In this approach, seasonal frequency maps derived from each drought index were standardized onto a common scale. The frequency of drought occurrence was then grouped into four vulnerability classes based on how often droughts occurred during the study period: areas with 2 to 3 occurrences were labeled as mildly vulnerable, 4 to 5 as moderately vulnerable, 6 to 8 as severely vulnerable and 9 to 11 as extremely vulnerable. Each drought index map was then weighted according to its relative influence and these weighted maps were combined using a weighted overlay analysis in ArcGIS software, resulting in integrated drought vulnerability maps. A schematic presentation of the methodology that has been followed is mentioned (Fig.2)

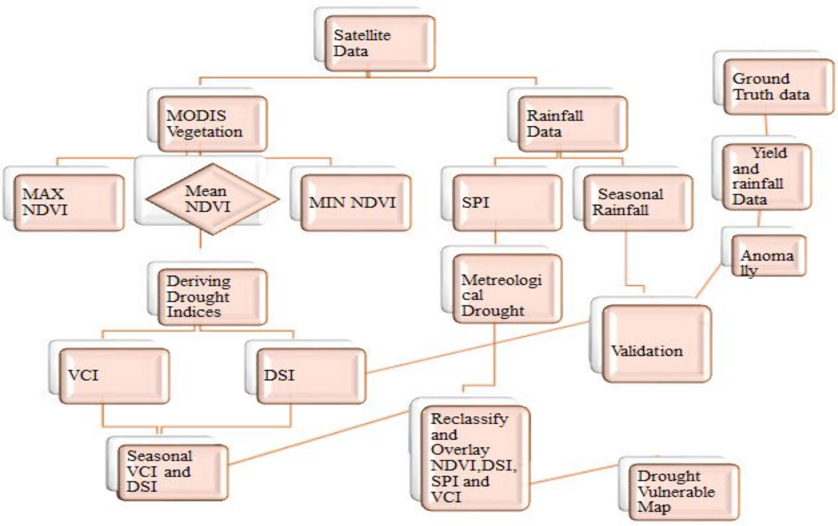


Fig. 2. A schematic presentation of the methodology

3. Results and Discussion

3.1. Normalized Difference Vegetation Index (NDVI)

The NDVI data revealed significant seasonal variations in drought across the study area. Notably, the southern and southeastern parts exhibited the lowest NDVI values, indicating reduced vegetation health and greater susceptibility to drought. In contrast, the northern and northwestern parts displayed higher NDVI values, reflecting more robust vegetation and overall better ecological conditions. This disparity suggests that the northern and northwestern areas are more resilient to drought conditions compared to their southern counterparts. Understanding these variations is crucial for developing targeted strategies for drought management and vegetation restoration in the region.

NDVI values range from -1 to 1, where higher values indicate increased vegetative growth and biomass. Values close to 0 suggest sparse vegetation, while negative values may indicate non-vegetated surfaces, such as water or barren land. This index is invaluable for assessing vegetation health, monitoring drought conditions and analyzing changes in land cover over time. NDVI is particularly effective for detecting changes in plant canopy health and density, influenced by both natural and human factors, such as droughts or deforestation. This index allows for the monitoring of vegetation dynamics over time, providing insights into ecosystem health and resilience.

Results from NDVI analyses are often visualized as maps, which illustrate variations in vegetation across different regions. These maps can highlight areas experiencing stress, such as those affected by prolonged drought, or indicate regions of significant vegetation loss due to deforestation. By offering a clear visual representation of vegetation patterns, NDVI maps serve as valuable tools for researchers, land managers and policymakers in making informed decisions regarding environmental conservation and resource management.

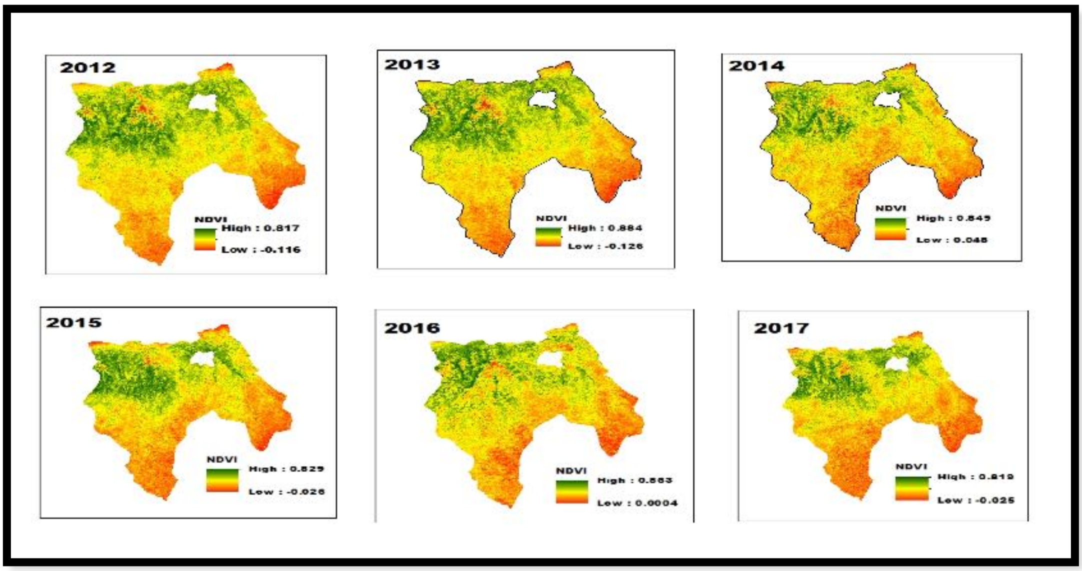


Fig. 3 Mean Seasonal Normalized Difference Vegetation Index for the period from 2012 to 2017

The NDVI analysis revealed significant seasonal fluctuations in vegetation health, indicating periods of stress across the study area. Notably, certain regions exhibited markedly lower NDVI values compared to others, with some areas achieving a maximum NDVI of 0.884.

In 2013, NDVI values extended from -0.126 to 0.884, highlighting a range of vegetation health, Conversely, the lowest values recorded in 2012, 2015, 2017 and 2022 ranged from -0.025 to 0.829. The southern and southeastern parts of the study area consistently showed the lowest NDVI values, reflecting reduced vegetation cover and health.

Historical NDVI data underscored the persistent presence of low vegetation in the southern and southeastern regions of the East Hararge zone, with variations in both quantity and geographic extent over time. This information is critical for understanding the impacts of environmental stressors on vegetation and guiding effective land management strategies.

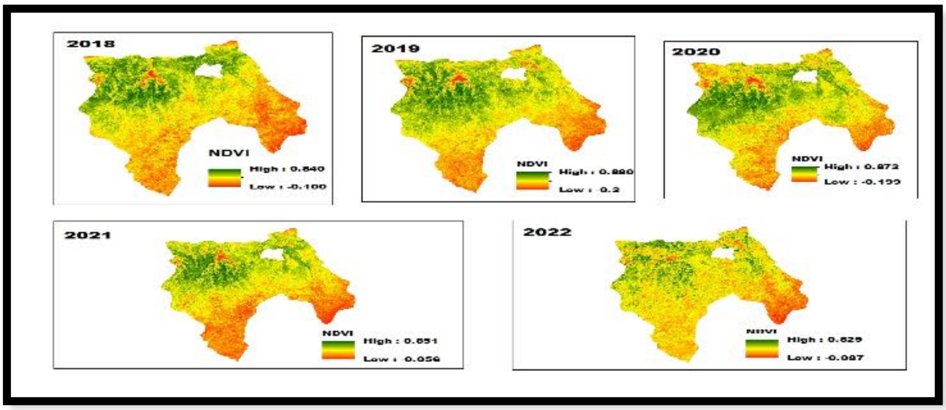


Fig. 4. Mean Seasonal Normalized Difference Vegetation Index for the period from 2018 to 2022

3.2. Relationship between Normalized Vegetation Index (NDVI) and Seasonal Rainfall

The seasonal patterns of rainfall and vegetation condition, represented by NDVI, were analyzed in the study area from 2012 to 2022. Results showed a strong correlation ($r = 0.75$) and ($p < 0.05$) between rainfall and NDVI, indicating that vegetation health is closely linked to seasonal rainfall patterns. This finding is consistent with studies by Eshetu et al. (2017) and Hurgasa (2016), who also observed a strong correlation between NDVI and seasonal rainfall.

During the study period, the seasonal pattern of NDVI generally increased in proportion to seasonal rainfall. However, this does not imply an exact one-to-one pattern. There were slight year-to-year variations in both long-term NDVI and seasonal rainfall values.

Over the 11-year study period, it was determined that 57% of NDVI variability could be explained by seasonal rainfall (Fig.5). Whereas, a study conducted in East Shewa zone by Gizachew and Suryabhagavan (2010) for the period between 1996 & 2008 has reported that 42% of NDVI variability was explained by seasonal rainfall. This highlights how temporal variation in rainfall distribution significantly affects vegetation response in the study area.

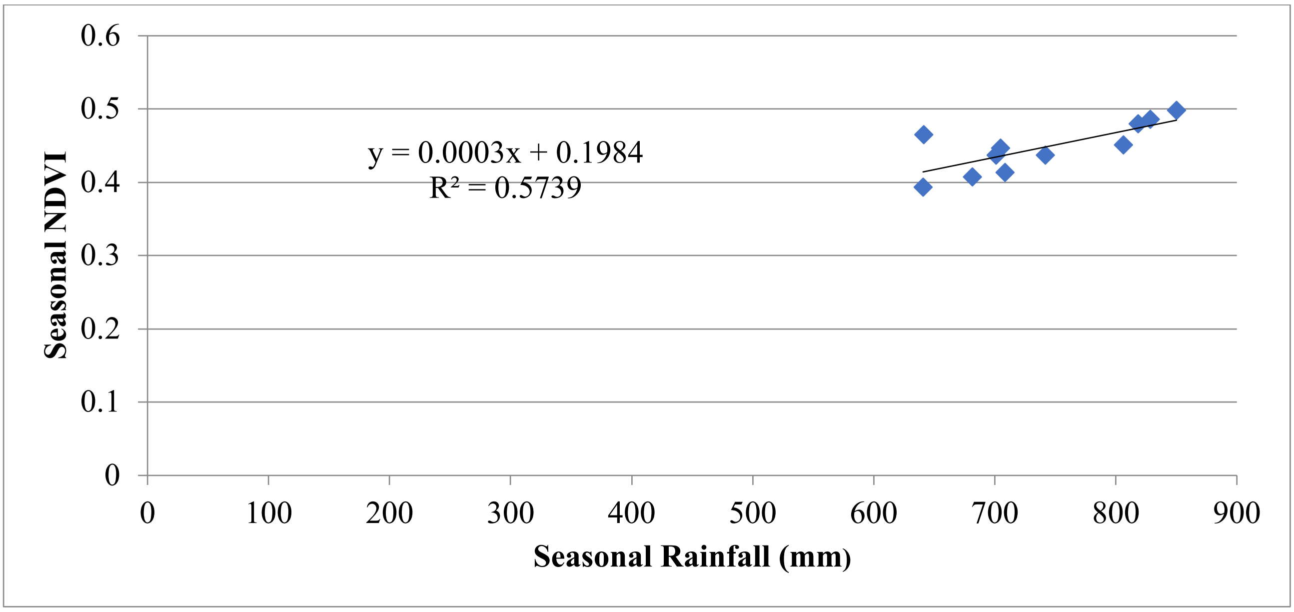


Fig. 5 Seasonal (June to September) pattern of NDVI and Rainfall (2012 to 2022)

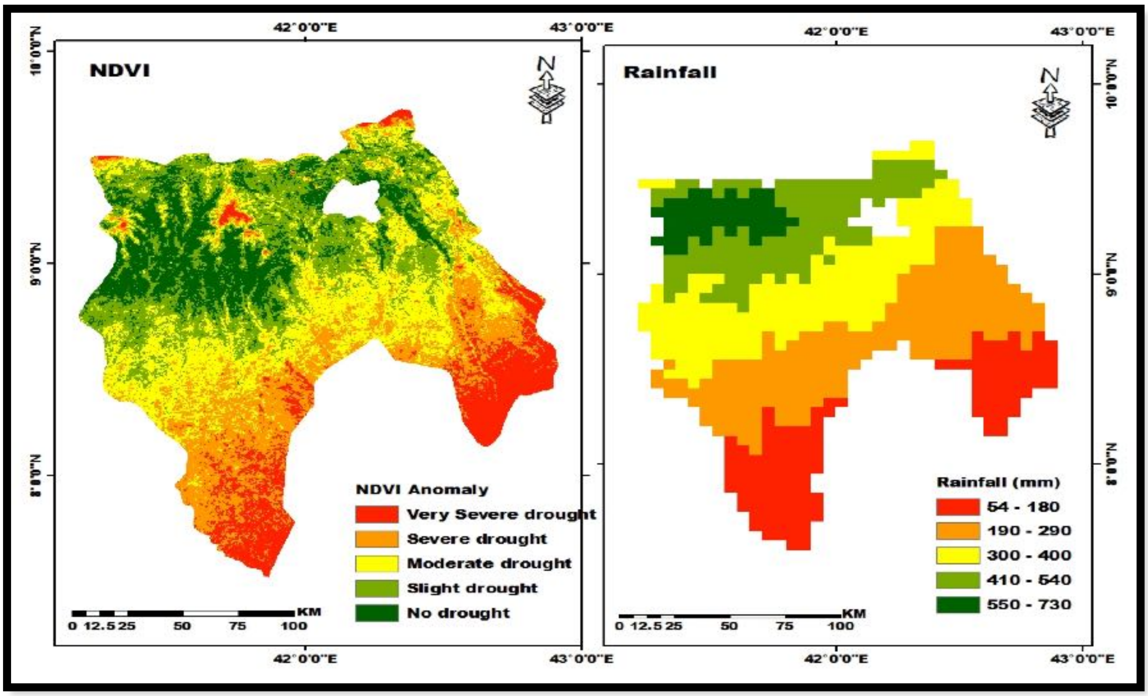


Fig. 6. Spatial pattern of long term seasonal (June–September) Normalized Difference Vegetation Index and rainfall during the period of 2012 to 2022

From 2020 to 2021, the highest NDVI values were observed when seasonal rainfall was well-distributed (Fig.7), while lower NDVI values occurred with minimal rainfall distribution. In rainfall-dependent countries like Ethiopia, the amount and distribution of rainfall during the cropping season are crucial factors. In particular, 2016, 2017, and 2019 were marked as drought years with minimal NDVI and low rainfall, whereas 2020 and 2021 were considered wet years with maximum rainfall and NDVI (Fig.7). Since NDVI, which reflects vegetation greenness, has a strong correlation with seasonal rainfall, it can serve as a valuable drought indicator (Wassie et al., 2022).

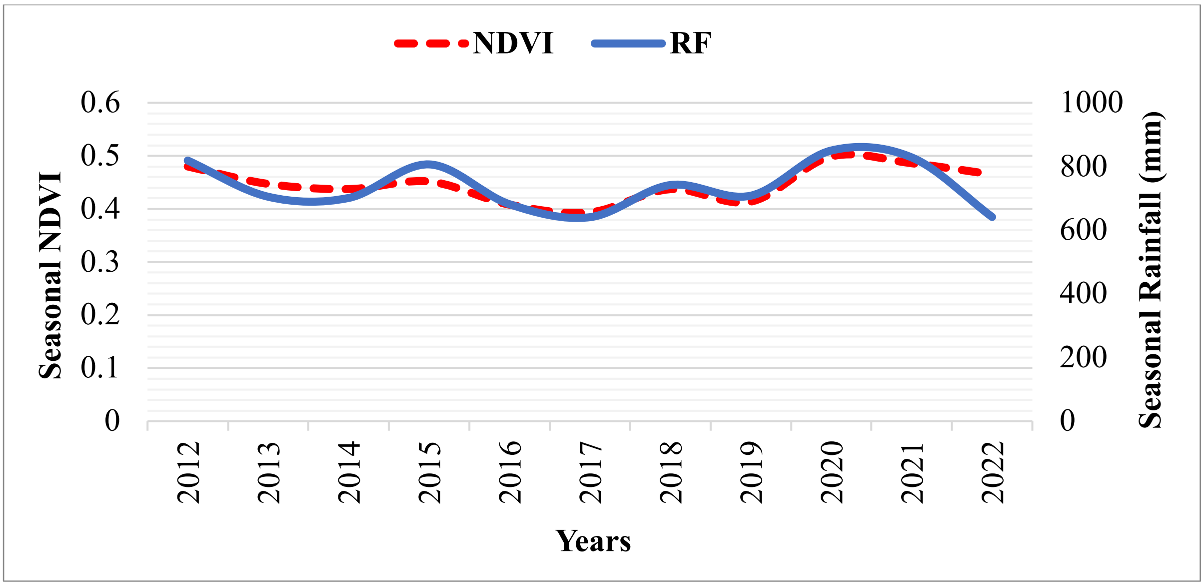


Fig. 7. Temporal trend of seasonal Rainfall and NDVI (2012 to 2022)

3.3. Relation between NDVI and crop yield anomaly

The relationship between NDVI and crop yield anomaly is illustrated in Fig. 8, showing a strong correlation (r = 0.74). This indicates that about 54% of crop yield variability can be explained by NDVI variances. The positive correlation suggests that as NDVI values increases crop yield anomaly also tends to increase, and vice versa. Notably, the largest yield reductions occurred in 2017, 2018 and 2019, both identified as drought years.

Similar studies in other parts of Ethiopia support this relationship. For example, Wondewosen (2016) found a strong correlation (r = 0.77) between NDVI anomaly and crop yield anomaly in the West Hararge Zone, while Gizachew (2010) observed a positive correlation between these variables in East Shewa Zone. Therefore, the NDVI anomaly index demonstrates moderate effectiveness in explaining the spatial and temporal conditions of meteorological drought in the study area.

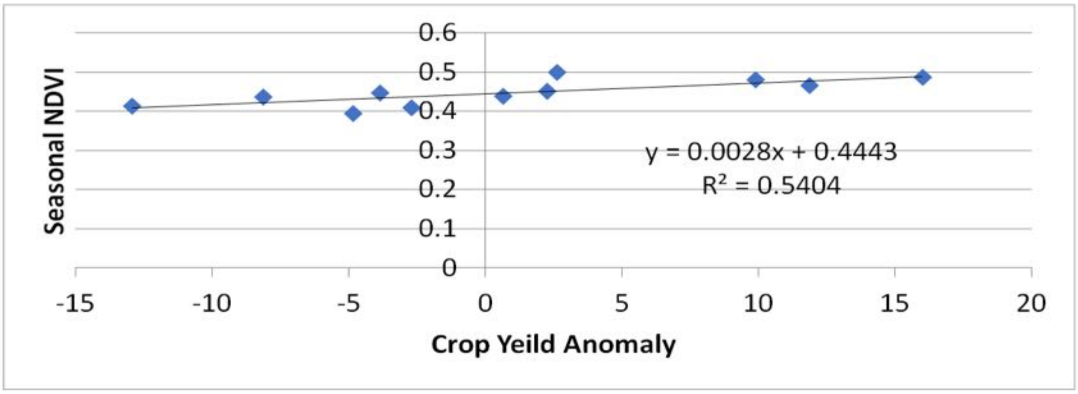


Fig. 8. Relation between NDVI and crop Yield anomaly

3.4. Vegetation Condition Index

The Vegetation Condition Index (VCI) is one of the most widely used satellite-based drought indices for monitoring vegetation health and conditions. It is derived from the Normalized Difference Vegetation Index (NDVI), which evaluates the amount of live green vegetation in a specific area (Kogan, 2011).

The Vegetation Condition Index (VCI) compares the current NDVI to historical NDVI values for the same time period, expressed as a percentage. This percentage reflects where the current measurement falls within the range of values observed in previous years. Lower VCI numbers indicate poor vegetative conditions, suggesting stress or drought impacts, while higher numbers signify more favorable conditions with healthier vegetation. This comparative approach allows for effective monitoring of changes in vegetation health over time, helping to identify areas at risk. Below, figs. 9 and 10 displays the temporal trends of the VCI index for the study area between 2012 and 2022. These figures illustrate the variations in vegetation conditions over the years.

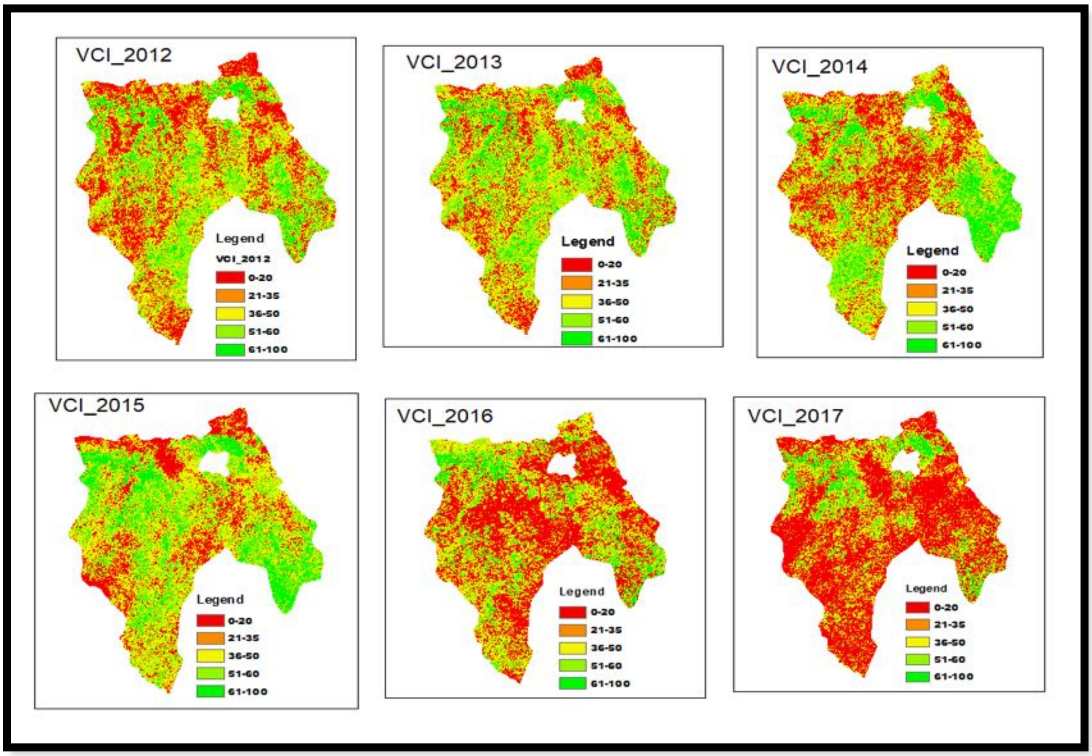


Fig. 9. Vegetation Condition Index during the years from 2012 to 2017

Several studies have effectively utilized the Vegetation Condition Index (VCI) to illustrate drought levels. For example, Fig. 9 and 10 highlights that severe drought conditions were recorded in 2017 and 2022. The VCI maps for the study area from 2012 to 2022 clearly demonstrated both the onset and spatial extent of drought events. The VCI ranges from 0 to 100, where a value of 0 indicates no vegetation and a value of 100 signifies extensive vegetation. This range provides a clear framework for assessing vegetation health and monitoring changes in response to drought.

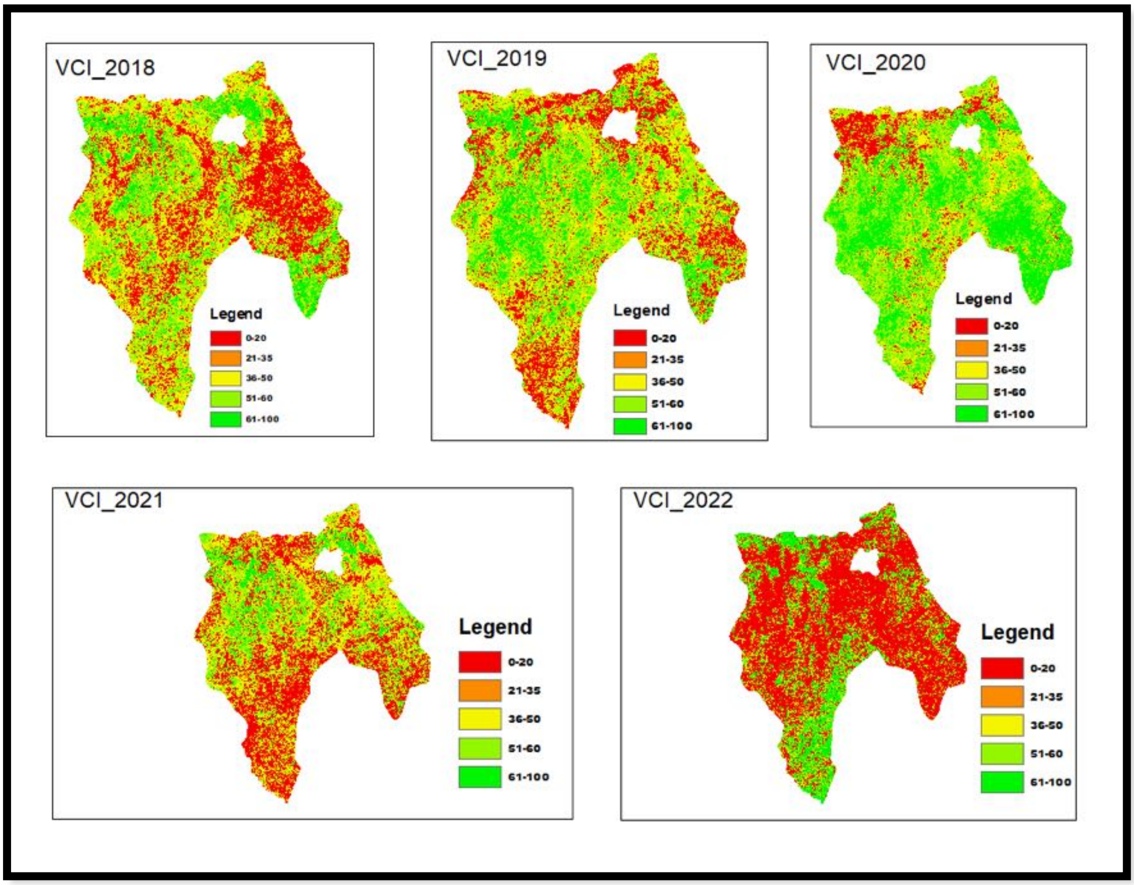


Fig. 10. Vegetation Condition Index during the years from 2018 to 2022

3.5. Relationship between VCI and mean seasonal rainfall

The relationship between the Vegetation Condition Index (VCI) and mean seasonal rainfall in the study area shows a moderate and statistically significant positive correlation, as indicated by a moderate correlation coefficient ($R^2 = 0.68$). This value suggests that approximately 68% of the variability in VCI can be explained by changes in mean seasonal rainfall (Fig. 11).

In 2020, when mean seasonal rainfall peaked at 850.075mm, the VCI was also at its highest level (50.54%), underscoring this close relationship. This moderate correlation indicates that VCI and mean seasonal rainfall tend to increase and decrease in same proportion.

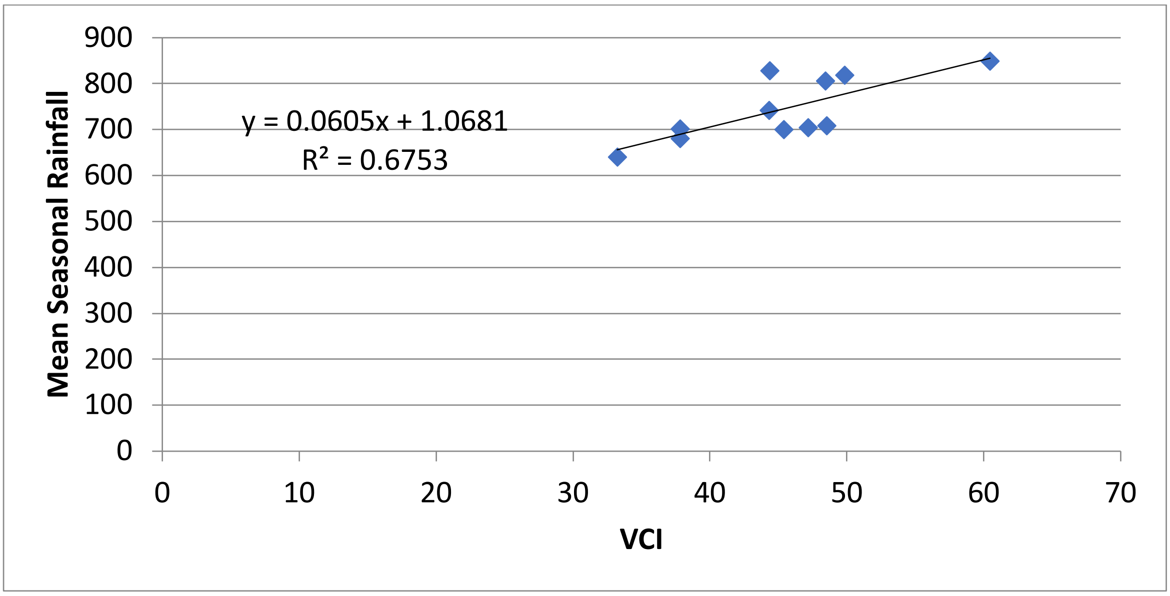


Fig. 11. Relationship between VCI and Mean seasonal rainfall

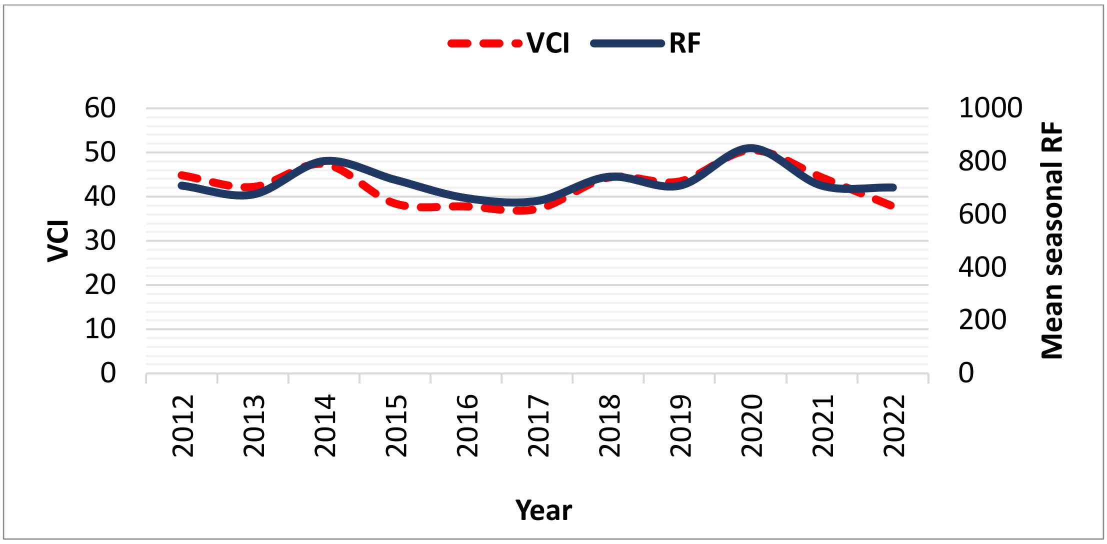


Fig. 12. Temporal trends of mean seasonal VCI and rainfall during years 2012 to 2022

3.6. Relation between VCI and Crop Yield Anomaly

To validate the reliability of satellite-based meteorological drought indices, crop yield data was used as ground truth. The correlation between VCI (Vegetation Condition Index) and crop yield anomaly was positive, showing a strong relationship between the two variables ($r = 0.82$). This suggests that 68% of crop yield variability can be explained by VCI, meaning that as VCI increases, crop yield also tends to increase and vice versa. In particular, significant crop yield reductions were observed in 2016, 2017 and 2022, when VCI values were lowest, whereas the highest yields were seen in 2020, years when VCI values were higher.

This result aligns with findings by Eshetie et al. (2016), who reported a positive correlation between VCI and crop yield anomaly in Eastern Amhara (r = 0.83). Similarly, Kogan (2011) found a strong correlation between VCI and corn crop yield. These findings confirm that VCI is a reliable indicator for assessing meteorological drought conditions.

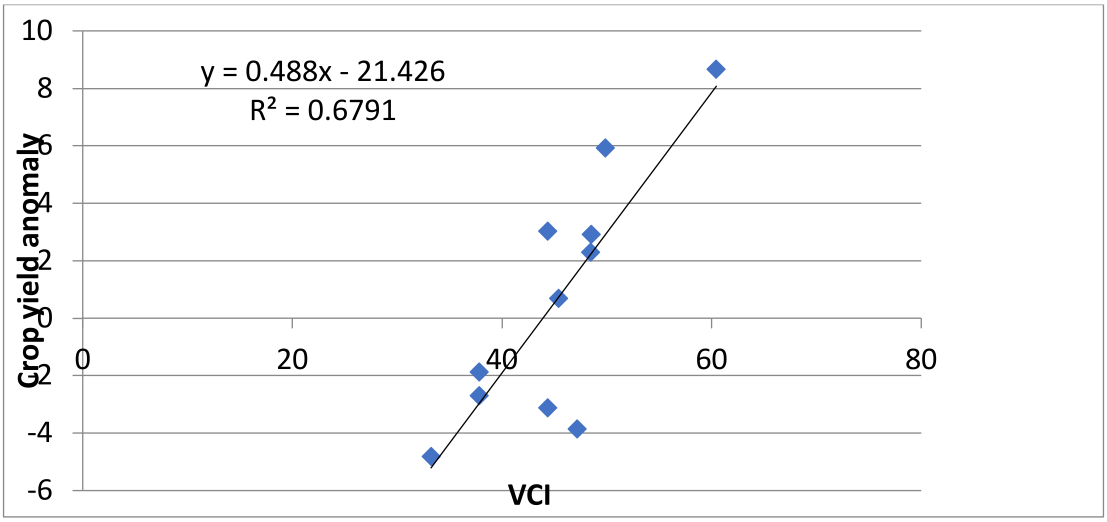


Fig. 13. Relation between VCI and crop yield anomaly

In the drought year of 2016, 2017 and 2022 various regions of the study area experienced different levels of drought severity, including very severe, moderate and severe conditions, as shown in figure 14**.**

Table 6 and Fig. 14 show the area and their percentage affected by meteorological drought as explained by VCI. Accordingly percentage of area stricken by drought during cropping season 2016 was found to be 18.5, 27.2 and 47.2% of the total geographical area for moderate, sever levels and very Severe drought respectively, whereas the corresponding meteorological drought severity for 2017 and 2022 cropping season was 11.0%, 21.7%, 63.1% and 11.9%, 8.9%, 63.5% of the total area were fall under moderate, sever levels and very Severe drought respectively.

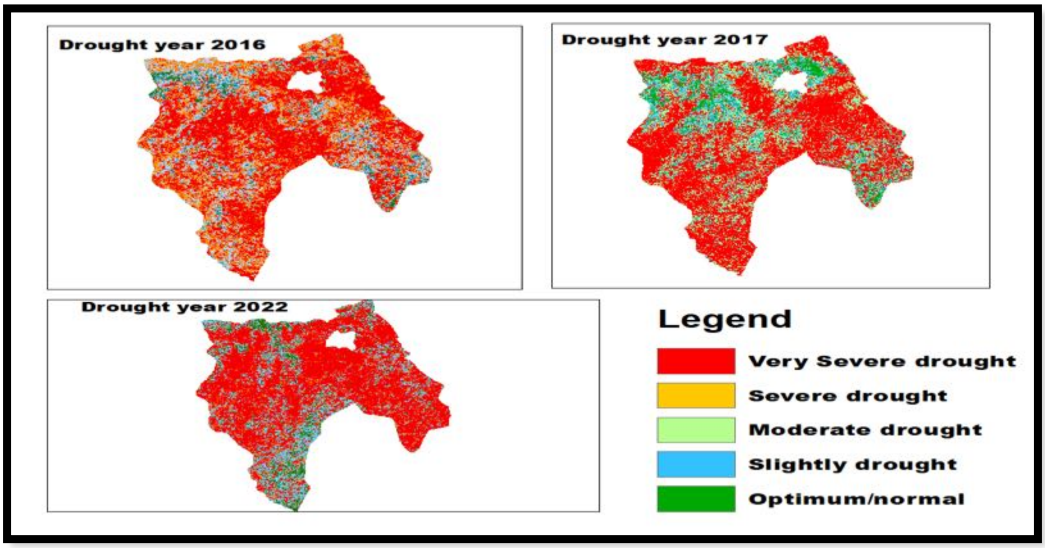


Fig. 14. Spatial pattern of meteorological drought expressed by Vegetation condition index during drought year 2016, 2017 and 2022

Spatial pattern of meteorological drought severity was also computed for wet season of year 2020 using VCI. Only small portion of area were stricken by slight to moderate drought (Fig. 15). The percentage range of meteorological drought severity indicts that during cropping season of 2020 38.8 and 18.8 percent of total geographical area of the Zone were stricken by moderate and slightly drought respectively in most north and North West part of study area.

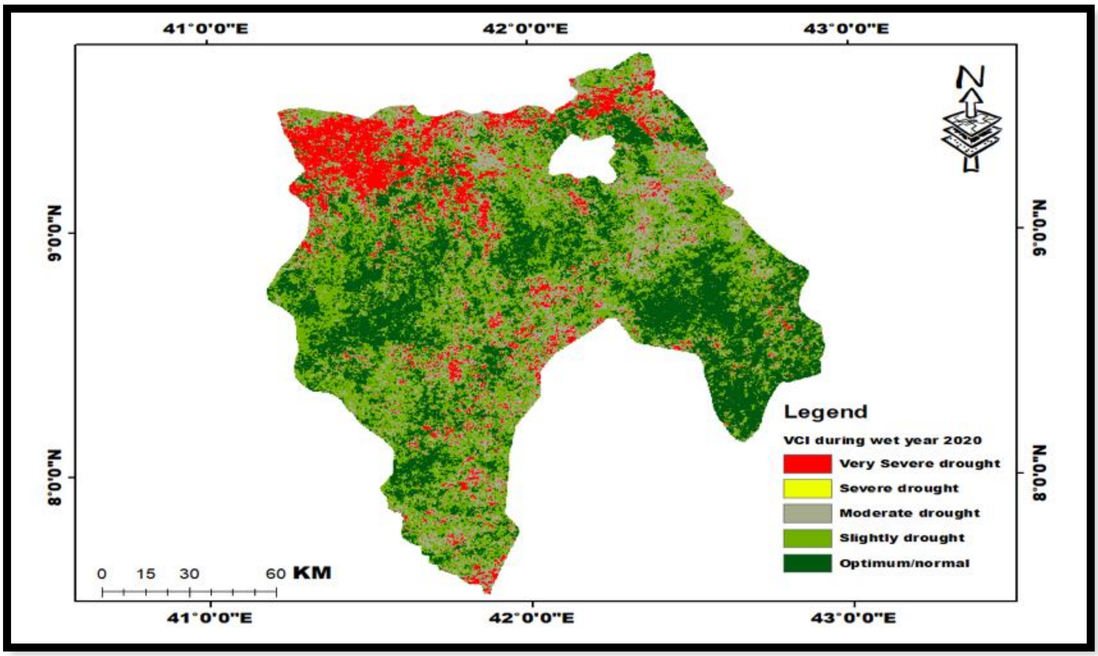


Fig. 15. Spatial pattern of agricultural drought expressed as VCI during wet year 2020

Table 6. Meteorological drought severity for drought year 2016, 2007 and 2022 and wet year 2020 expressed by VCI

Drought severity class	Wet Year	Drought Year		
	2020	2016	2017	2022
	Area%	Area%	Area%	Area%
Very Severe drought	11.3	47.2	63.1	63.5
Severe drought	18.8	27.2	21.7	8.9
Moderate drought	38.8	18.5	11.0	11.9
Slightly drought	18.8	4.4	2.4	8.0
Optimum/normal	12.4	2.6	1.8	7.6
Total	100	100	100	100

3.7. Drought Severity Index

The Drought Severity Index (DSI) values confirmed the presence of drought during the study period in the East Hararge Zone. As depicted in Fig. 16 and 17**,** DSI values ranged from 1 to +1**,** with values less than 0 indicating drought conditions, while values greater than 0 signified a wet season. The mean seasonal DSI values for drought years were as follows: 2016 (-0.02), 2017 (-0.04) and 2022 (-0.1. In contrast, the remaining years were the wet years**.** The temporal trend of the DSI, shown in Fig**.** 16 and 17 revealed that drought was prevalent in several years, although its severity varied spatially and temporally across the region.

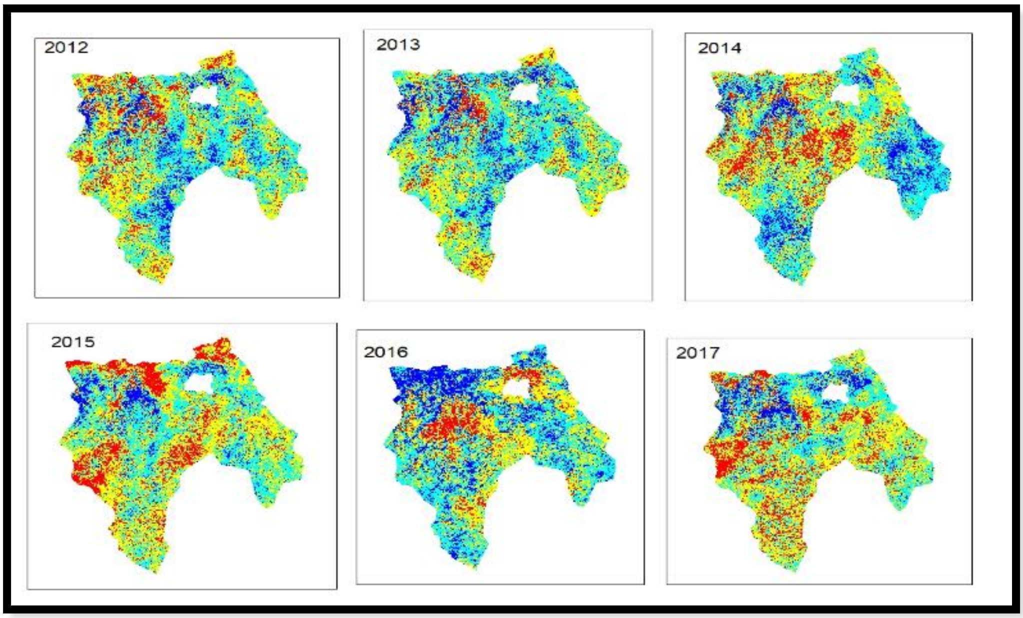


Fig.16. Spatial patterns of drought in study area as revealed by Drought Severity Index during the period from 2012 to 2017

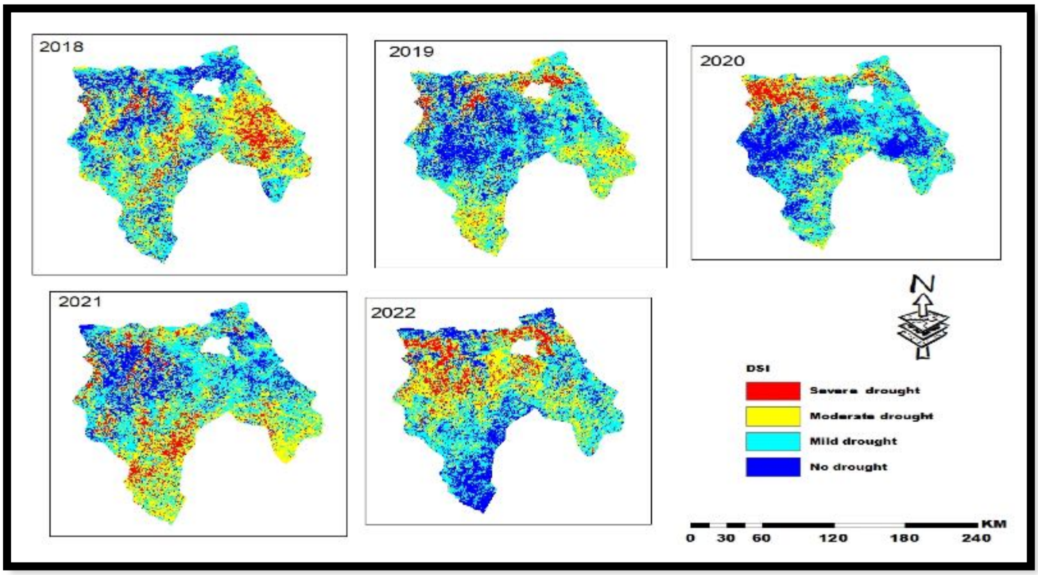


Fig. 17. Spatial patterns of drought in study are as revealed by Drought Severity Index during the period from 2018 to 2022

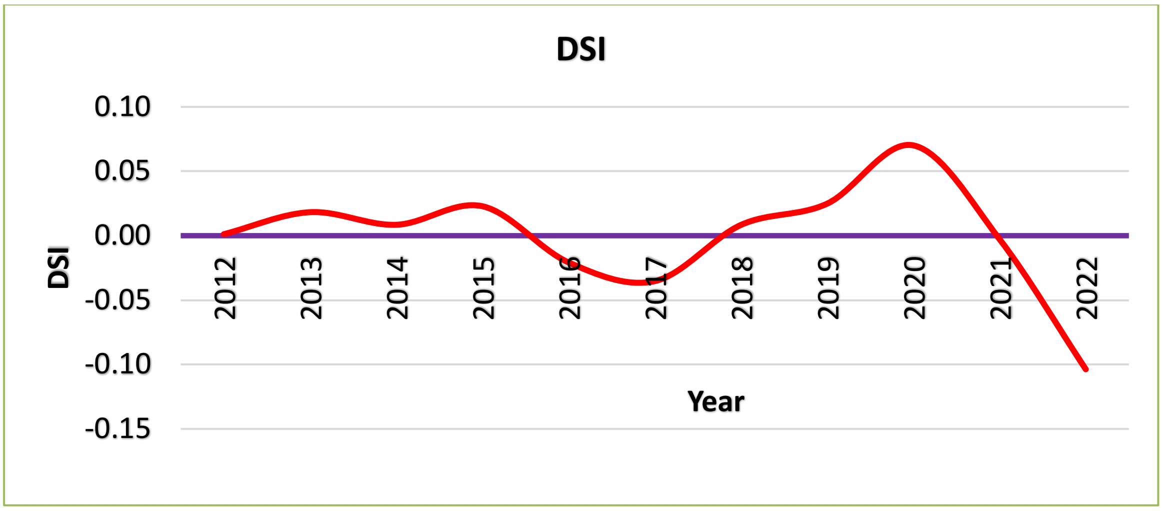
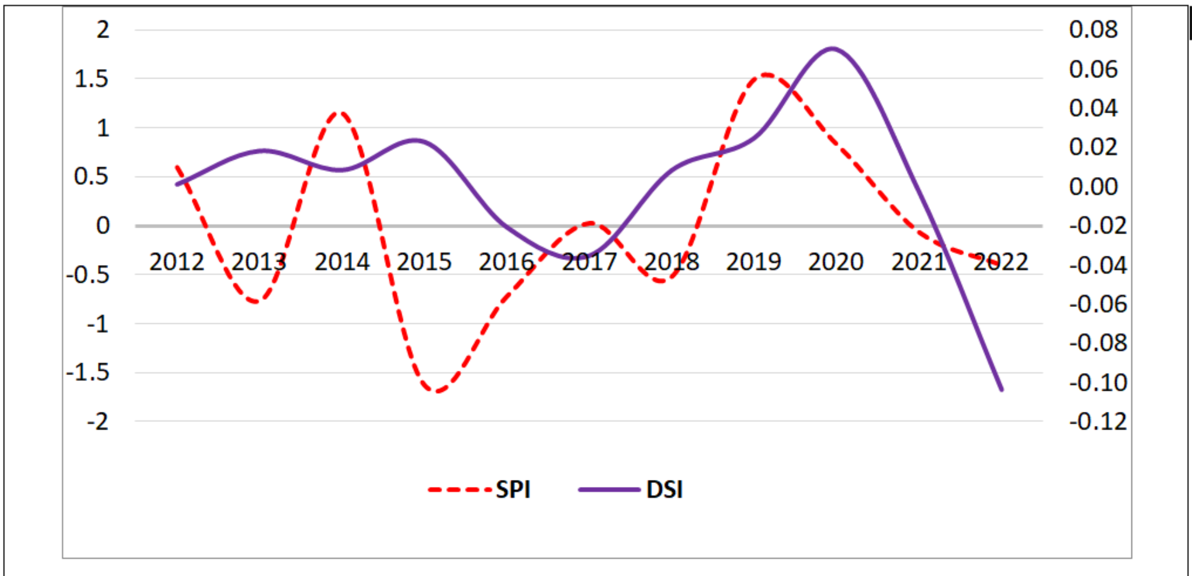


Fig.18. Temporal trend of Drought Severity Index (2012 to 2022)

3.8. Drought Severity Index (DSI) and Standardized Precipitation Index (SPI)

When the Drought Severity Index (DSI) and Standardized Precipitation Index (SPI) were compared, their values showed similar trends, either increasing or decreasing. The DSI values were low in the years 2016, 2017 and 2022 all of which were below 0 (Fig. 19). Similarly, the SPI values were also low during 2013, 2015, 2016, 2018, 2021 and 2022, with values falling below 0. As a result, both drought indices consistently indicated the occurrence of drought in the East Hararge throughout the study period.



Years	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
---Mean SPI	0.60	-0.77	1.15	-1.63	0.72	0.03	-0.52	1.50	0.83	-0.07	-0.40
__ DSI	0.00	0.02	0.01	0.02	-0.02	-0.04	0.01	0.02	0.07	0.00	-0.10

Fig.19 Temporal trends of Standardized Precipitation Index and Drought Severity Index

Fig.19. Temporal trends of Standardized Precipitation Index and Drought Severity Index

3.9. Relationship between Drought severity index and Vegetation condition index

The correlation coefficient plot shows that the DSI and VCI had a positive and moderate relationship (r2 = 0.51) that was statistically significant with coefficient variation, indicating a positive relationship between the two drought indices in the study area.

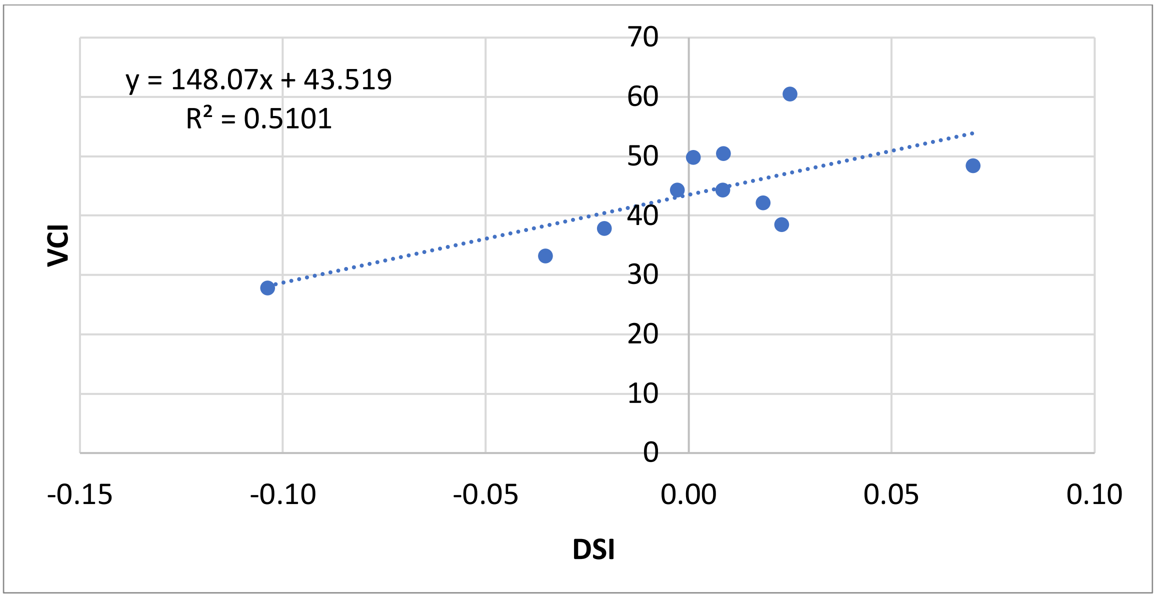


Fig.20. Regression analyses between DSI and VCI

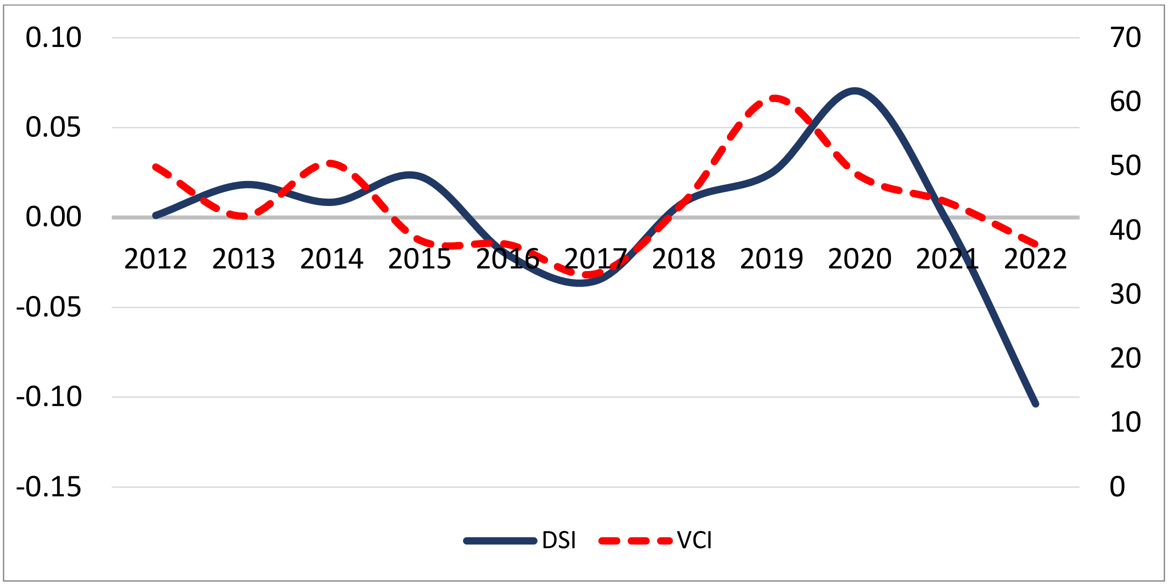


Fig.21. Temporal trends of VCI and DSI

3.10. Metrological Drought characterization based on SPI

The interaction between precipitation and vegetation is highly interconnected, especially in rain-fed cropping systems, where seasonal rainfall variability directly influences vegetation density. Analyzing the impact of rainfall deficiency on drought is crucial and the Standard Precipitation Index (SPI) plays a key role in quantifying precipitation deficits (Eshetie et al., 2016). By providing a clear measure of rainfall variability, SPI helps to assess how insufficient precipitation affects vegetation health and agricultural productivity.

The Standard Precipitation Index (SPI) is an index developed to quantify precipitation deficits across various time scales. In this study, a four-month SPI was computed to provide a seasonal estimation of precipitation for seven stations, using monthly data from 2012 to 2022. The four-month SPI was employed to assess drought conditions during the summer (Kiremt) season, which corresponds to the longer rainy period in the region. This seasonal focus allows for a more accurate evaluation of how precipitation deficits impact vegetation and agricultural practices during critical growing months. By analyzing the SPI specifically for the Kiremt season, we can gain insights into the severity and frequency of drought events.

In Ethiopia, very few studies have been undertaken in various parts of Ethiopia to analyze drought using the Standard Perception Index. Desalegn et al. (2010) conducted a temporal and regional investigation of metrological and hydrological drought in Ethiopia's Awash Basin. The study demonstrated the potential benefits of SPI for drought assessment and investigated the lag time between hydrological and meteorological droughts. Similarly, Bayissa et al. (2015) used SPI and vegetation index to assess drought variability in the Tigray zone of Ethiopia's highlands. The study found that a major portion of the study area is susceptible to drought.

The amplitude, frequency, trend, patterns and probability of drought in south Wollo were investigated using SPI (Yimer et al., 2018). The results showed that the majority of the examined stations had drought events in 1984, 1987/1988, 1992/1993, 1999, 2003/2004, and 2007/2008, which were among Ethiopia's worst drought years. According to the findings, SPI is a critical tool for assessing drought and comparing its characteristics over time and location. The actual impacts of the drought on the agricultural operations in west Hararge Zone's farming villages were thoroughly investigated and analyzed using the NDVI, SPI, and WRSI indices (Wondwosan, 2016).

In line with this result, the results indicate a monthly variation in the Standardized Precipitation Index (SPI). In June, the SPI value turned negative, signifying drought conditions and delayed rainfall. Conversely, September recorded a positive SPI value during the study period. Negative SPI values reflect rainfall amounts below the median, indicating drier conditions, while positive values indicate rainfall exceeding the median, suggesting wetter conditions. Each positive SPI value corresponds to regions experiencing above-average precipitation, whereas negative values denote areas with less than median rainfall, as per Bayissa et al. (2017).

Notably, the lowest SPI values were observed in June and July of 2012 and 2015. This finding coincides with reports from UNOCHA (2022) and FAO (2020), which document significant droughts in Ethiopia during the years 2003, 2008, 2009, 2012 and 2015 all of which were associated with strong El Niño events.

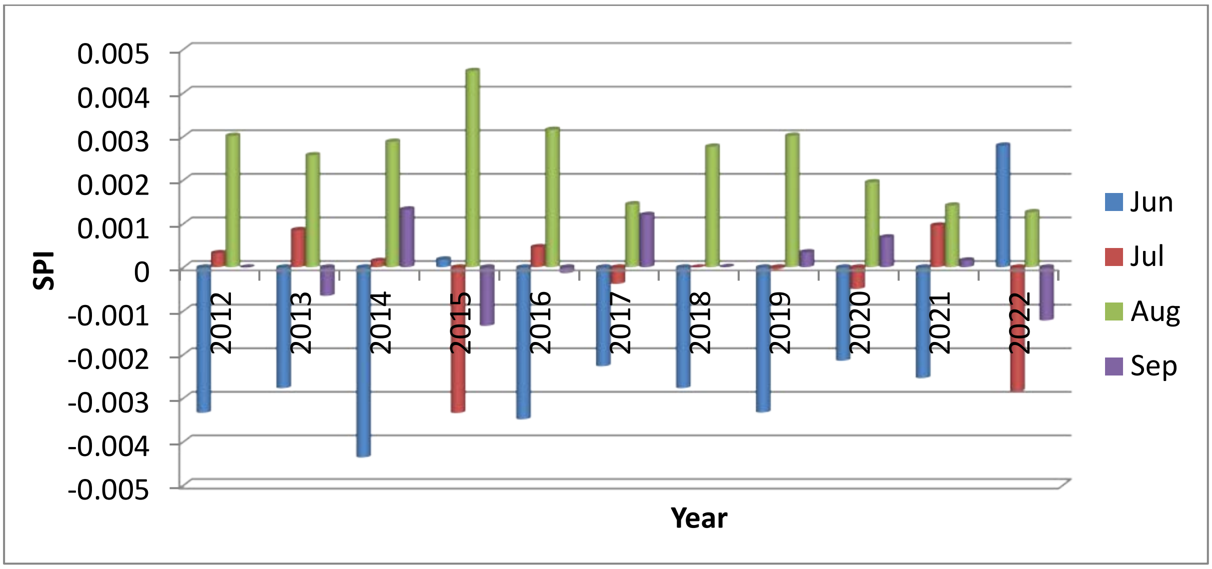


Fig. 22. Monthly variation of Standard Precipitation Index (2012 to 2022)

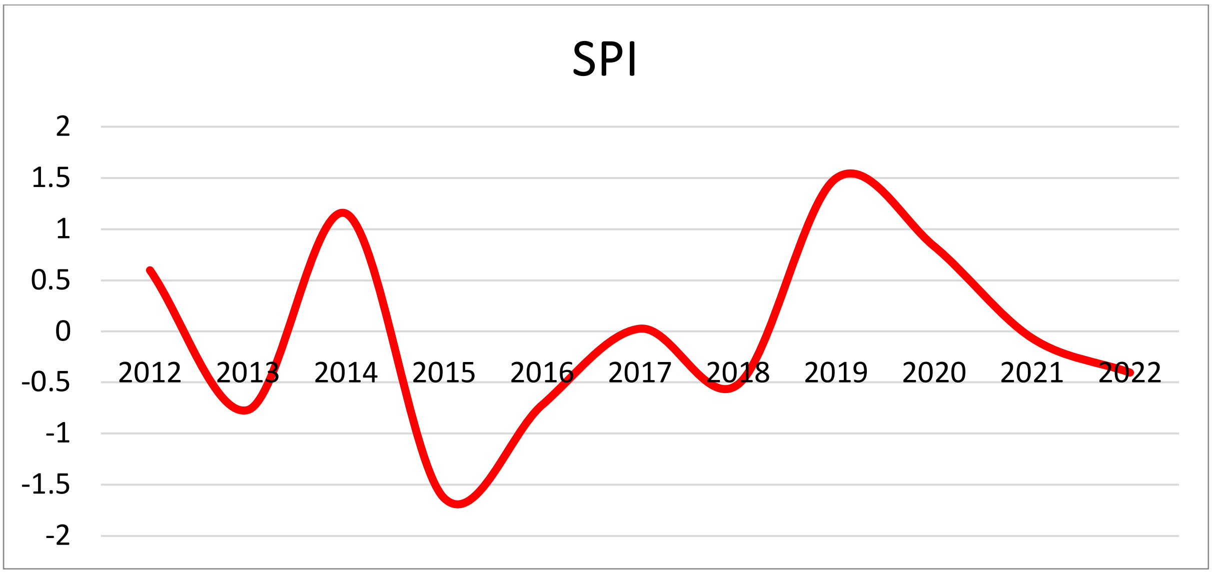


Fig. 23. Temporal trend of Standard Precipitation Index (2012 to 2022)

3.11. Relationship between Standardized Precipitation Index (SPI) and Vegetation Condition Index (VCI)

Fig. 24 shows a positive and statistically significant relationship between mean SPI (Standardized Precipitation Index) and VCI (Vegetation Condition Index), with a correlation of r = 0.78, suggesting a strong correlation between these two drought indices in the study area. Over an 11-year period, about 60% of VCI variability could be explained by SPI, indicating that both indices are effective in drought assessment.

Despite their correlation, VCI and SPI serve different purposes: SPI is a meteorological drought indicator, while VCI is an agricultural indicator. This study found that both indices function as reliable indicators for monitoring drought in the study area. The temporal trends of VCI and SPI are illustrated in Fig. 24, further emphasizing their complementary roles in drought assessment.

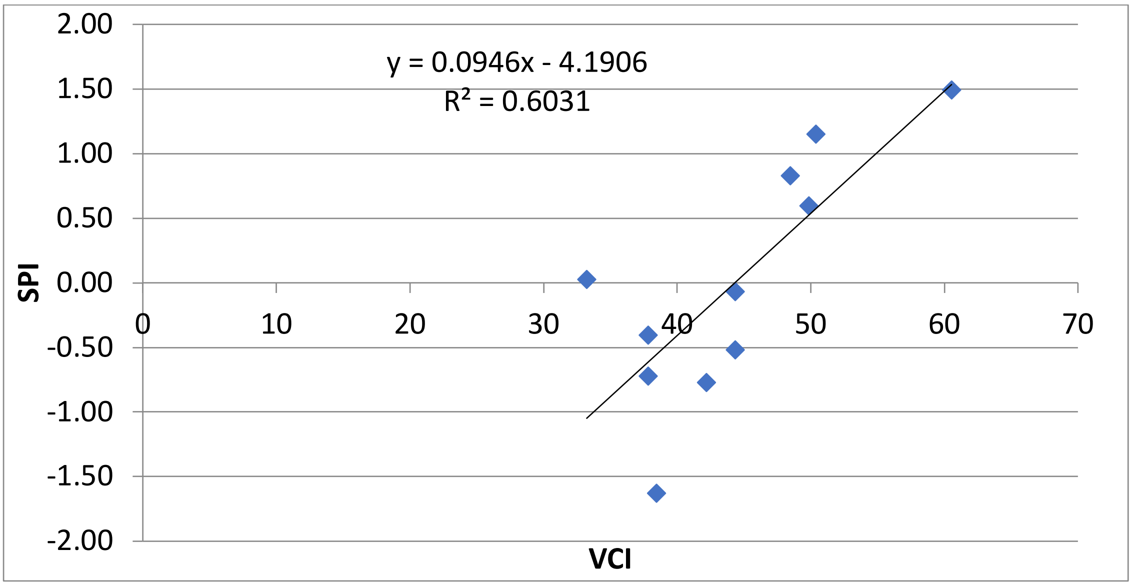


Fig. 24. The relationship between Standardized Precipitation Index and Vegetation Condition Index

3.12. Standard precipitation index (SPI) and Crop Yield Anomaly

The Standard Precipitation Index (SPI) is a valuable tool for assessing water availability for crops as it represents the deficiency or excess of moisture in a region. Positive SPI values indicate excess moisture, while negative SPI values signal a water deficiency, which can lead to yield reductions or crop failure. In the study area, crop failures are often linked to moisture shortages during critical crop-growing periods. The East Hararge Zone Disaster Preparedness and Prevention Office identifies several key weather-related issues that drive drought in the area, including late onset and early withdrawal of the main rainy season, erratic rainfall distribution, and extended dry spells. These adverse conditions have significant impacts on agricultural production, as observed through field assessments that underscore the serious threat posed by decreasing and unpredictable rainfall patterns, ultimately leading to reduced food production and crop failures.

To examine the relationship between SPI and crop yield, a correlation analysis was conducted, revealing a strong positive correlation (r = 0.72) between SPI and crop yield anomaly. This finding suggests that approximately 52% of the variability in crop yield can be attributed to SPI values. These results align with previous research by Gizachew (2010), who found a similar correlation between SPI and crop yield anomaly in the East Shewa Zone, reinforcing the reliability of SPI as a predictor for agricultural performance under variable moisture conditions.

The impact of drought has necessitated substantial relief interventions by both governmental and non-governmental organizations, particularly during severe drought periods. This analysis underscores the potential of SPI as an effective indicator for meteorological drought assessment, providing a quantitative basis for anticipating and mitigating drought impacts on agricultural production. The use of SPI in the study area and similar drought-prone regions can aid in developing early warning systems and informing drought preparedness strategies, thereby enhancing resilience against climate-related agricultural risks.

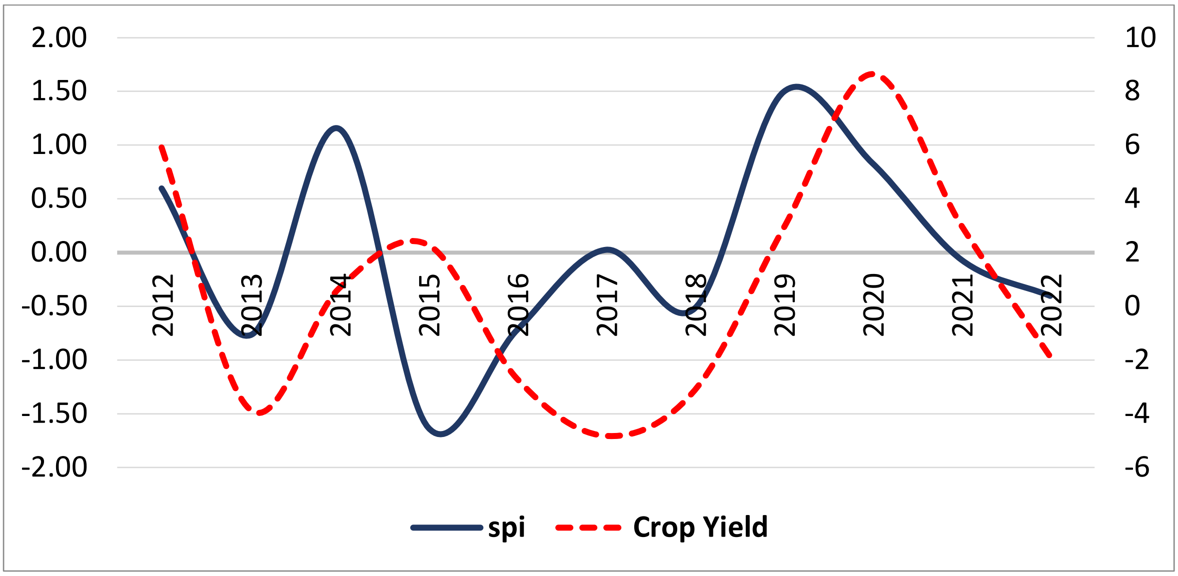
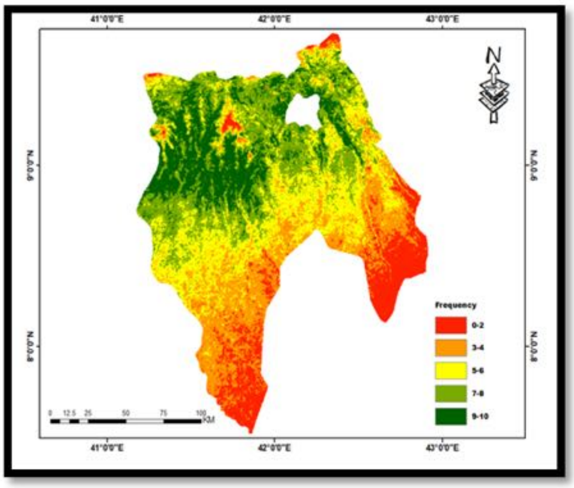
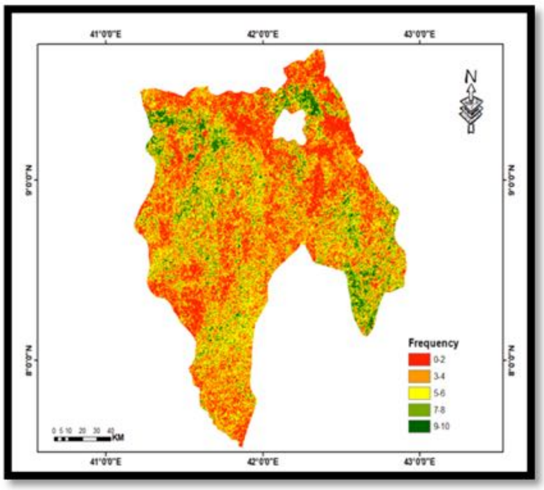


Fig. 25. Relation between SPI and Crop yield anomaly

3.13. Drought Risk Classification

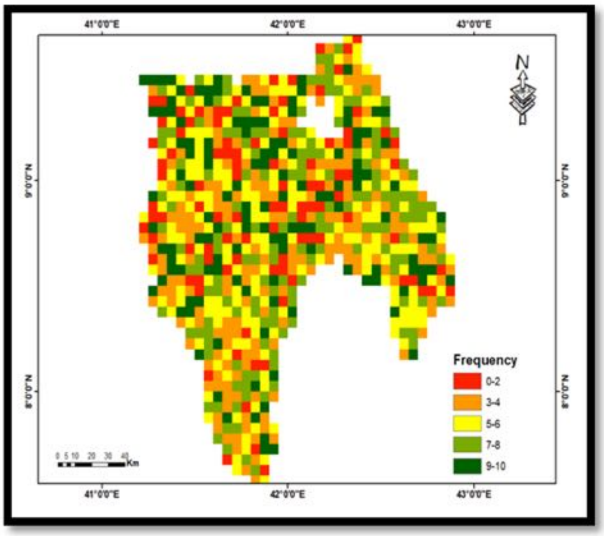
With the aim of isolating and determining the typical drought-prone areas of the Zone, a model map was prepared by integrating drought frequency maps generated from four drought indices: NDVI, VCI, SPI and DSI (Fig. 26 -29). The four layers, representing these drought indices, were combined to create a comprehensive map of drought risk across the study area.

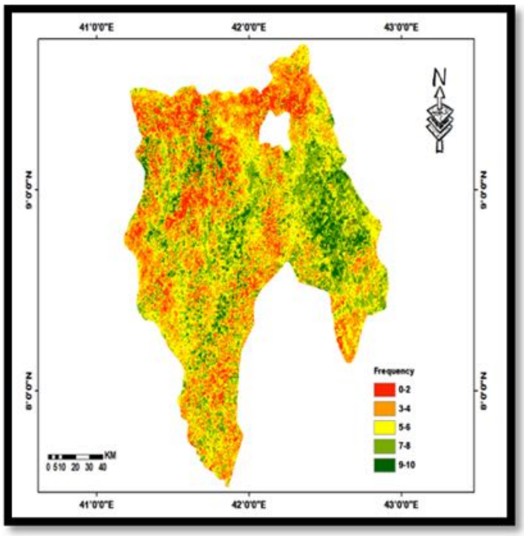




(a)Fig. 26 Drought frequency of Normalized difference vegetation index map

(b) Fig. 27 Drought frequency of vegetation condition index map





(a) Fig. 28 Drought frequency of standard precipitation index map,

(b) Fig. 29 Drought frequency of drought severity index map

The final drought risk map of the study area (Fig. 30) classifies the area into five categories: mild, moderate, severe, extreme and none vulnerability to drought. According to these classifications, approximately 1.7% of the region falls under extreme vulnerability, 35% under severe vulnerability, 49.1% under moderate vulnerability, and 13.8% under mild and only 0.4% none vulnerable to drought (Table 7).

The results indicate that a significant portion of the study area, approximately 35% of the total geographical area, is highly vulnerable to severe drought. This severe drought risk is predominantly concentrated in the south and southeastern part of the study area. Although the entire region is drought vulnerable, the severity of vulnerability varies significantly across the area.

Table 7. Drought Risk Class of East Hararge zone

Severity level	Area (km^2)	Area (%)
None Vulnerable	91.34	0.4
Mild Vulnerable	3105.06	13.8
Moderate Vulnerable	11007.41	49.1
Severe Vulnerable	7844.63	35.0
Extreme Vulnerable	376.55	1.7
Total		100

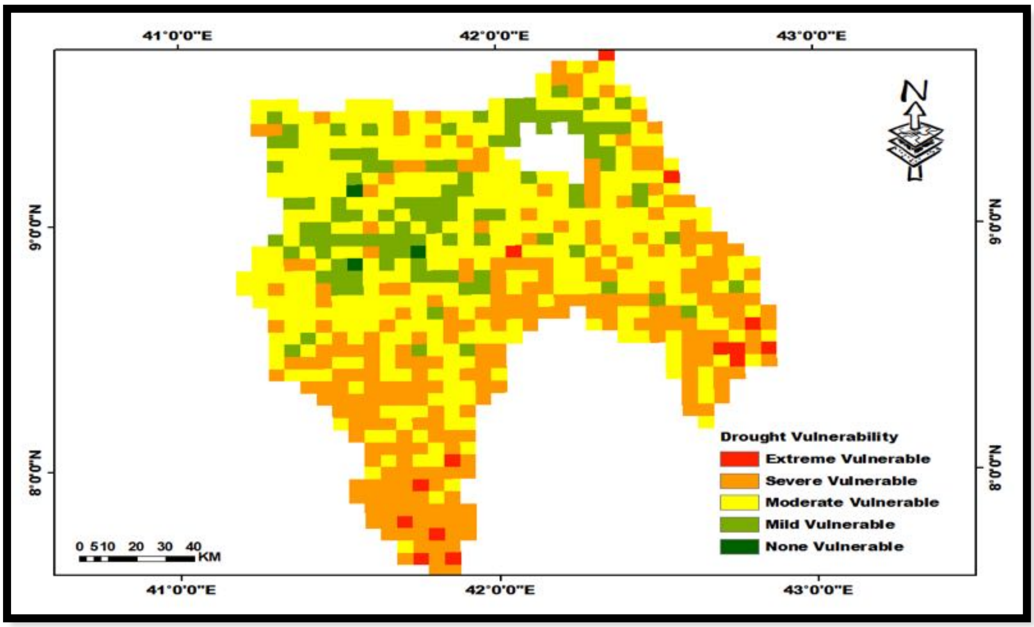


Fig. 30. Drought Risk Map of East Hararge Zone produced by using the four drought indices

4. Conclusion and Recommendation

4.1. Conclusion

Modern Remote Sensing satellite data and Geographical Information System techniques have been used to collect and process eleven years data on drought in East Hararge Zone. To map the spatio-temporal patterns of meteorological drought variation and severity in East Hararge Zone from 2012 to 2022, advanced remote sensing and GIS techniques were employed. Enhanced MODIS (eMODIS) NDVI satellite imagery was used as an input parameter for drought indices such as NDVI, VCI and DSI. While the SPI which is derived from meteorological data on monthly rainfall was used to assess meteorological drought, Ground truth data on crop yield anomalies, derived from crop yield records, was used for validation purposes.

Based on the results of the investigations and analyses, a comprehensive map highlighting the drought-vulnerable areas of the zone has been produced. This study concluded that the spatio-temporal variation of NDVI is closely linked to precipitation data, showing a strong relationship with a coefficient of variation (r = 0.76). The results reveal that between 2012 and 2022, the Zone experienced both severe and slight severe drought conditions. Year 2016, 2017, 2018 and 2022 has been found to be the year of the worst drought, while in year 2014 and 2020 the area was wet year. Similarly, the VCI shows a strong correlation with crop yield anomalies, with a coefficient of correlation (r = 0.82). The Standard Precipitation Index (SPI), which indicates the occurrence of meteorological drought, was also correlated with crop yield anomalies. The results show a strong correlation between the two indices (r = 0.74).

This study highlights the occurrence of recurrent drought in the area. Over the eleven years of the study period, drought events were observed in multiple years. Consequently, it can be concluded that the zone is highly prone to drought. The drought vulnerability map of the zone indicates that it falls within a range of vulnerability from mild to severe. The combined drought risk map showed that 35% of the study area was classified under severe vulnerable, 49% under moderate vulnerable and 13.8% under mild vulnerable conditions.

4.2. Recommendations

Based on the finding the following recommendations was forwarded

- Based on the findings, most of the southern and southeastern parts, as well as certain areas in the northeastern parts of the study area are highly vulnerable to drought. Therefore, effective drought risk management is urgently needed by the East Hararge Zone Disaster Prevention and Preparedness Department.

- According to the study findings, in areas identified as severely and moderately vulnerable to drought, proactive remedial actions should be implemented before drought occurs. In this regard, the National Meteorology Agency of Ethiopia plays a vital role in providing timely and updated information on drought conditions to support effective management and prevention efforts.
- Future studies should focus on using higher resolution satellite data to monitor drought

occurrences in the study area more effectively. Such data will provide enhanced spatial and temporal detail, leading to more accurate drought assessments. This will improve early warning systems and support the development of targeted prevention strategies.

References

Baik, J., Zohaib, M., Kim, U., Aadil, M., & Choi, M. (2019). Agricultural drought assessment based on multiple soil moisture products. Journal of Arid Environments, 167, 43–55. https://doi.org/10.1016/j.jaridenv.2019.04.007. ScienceDirect+1

Bayissa, Y. A., Moges, S. A., Xuan, Y., van Andel, S. J., Maskey, S., Solomatine, D., van Griensven, A., & Tadesse, T. (2015). Spatio-temporal assessment of meteorological drought under the influence of varying record length: The case of Upper Blue Nile Basin, Ethiopia. Hydrological Sciences Journal, 60(11), 1927–1942. https://doi.org/10.1080/02626667.2015.1032291. Taylor & Francis Online+1

Bayissa, Y., Tadesse, T., Demisse, G., & Shiferaw, A. (2017). Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. Remote Sensing, 9(7), 669. https://doi.org/10.3390/rs9070669.

Berhan, G., Hill, S., Tadesse, T., & Atnafu, S. (2011). Using satellite images for drought monitoring: A knowledge discovery approach. Journal of Strategic Innovation and Sustainability, 7, 135–153.

Central Statistical Service (CSS). (2007). Population and housing census of Ethiopia. Addis Ababa, Ethiopia.

Chemeda, D., Babel, M. S., & Gupta, A. D. (2010). Drought analysis in the Awash River Basin, Ethiopia. Water Resources Management, 24(7), 1441–1460. https://doi.org/10.1007/s11269-009-9508-0

Cravens, A. E., Henderson, J., Friedman, J., Burkardt, N., Cooper, A. E., Haigh, T., Hayes, M., McEvoy, J., Paladino, S., Wilke, A. K., & Wilmer, H. (2021). A typology of drought decision making: Synthesizing across cases to understand drought preparedness and response actions. Weather and Climate Extremes, 33, Article 100362. https://doi.org/10.1016/j.wace.2021.100362

Dodamani, B. M., Anoop, R., & Mahajan, D. R. (2015). Agricultural drought modeling using remote sensing. International Journal of Environmental Sciences and Development, 6(5), 326–331. https://doi.org/10.7763/IJESD.2015.V6.612. E-Pubs ICAR

Eshetie, S. M., Demisse, G. B., & Suryabhagavan, K. V. (2016). Evaluation of vegetation indices for agricultural drought monitoring in East Amhara, Ethiopia. International Journal of Scientific Research, 5(10), 535–540. https://doi.org/10.36106/ijsr. ResearchGate+1

Gebre, E., Berhan, G., & Lelago, A. (2017). Application of remote sensing and GIS to characterize agricultural drought conditions in North Wollo Zone, Amhara Regional State, Ethiopia. Journal of Natural Sciences Research, 7(17), 41–?.

Food and Agriculture Organization of the United Nations (FAO). (2020). FAO-Adapt framework programme on climate change adaptation. Rome, Italy: FAO.

Fava, F., & Vrieling, A. (2021). Earth observation for drought risk financing in pastoral systems of sub-Saharan Africa. Current Opinion in Environmental Sustainability, 48, 44–52. https://doi.org/10.1016/j.cosust.2020.09.006.

Food and Agriculture Organization of the United Nations (FAO). (2013). UN lays foundations for more drought resilient societies: Meeting urges disaster risk reduction instead of crisis management. Rome, Italy: FAO.

Gonfa, L. (1996). Climate classification of Ethiopia. In Meteorological Research Report Series

No. 3. Addis Ababa.
Hurgasa, A. H. (2016). Drought assessment and prediction of drought years using the standardized precipitation index (SPI) in East Shewa Zone, Ethiopia. Cogent Environmental Science, 2(1), https://doi.org/10.1080/23311843.2016.1229882
Legesse, G. (2010). Agricultural drought assessment using remote sensing and GIS techniques (Unpublished master's thesis). Addis Ababa University, Addis Ababa, Ethiopia.
Legesse, G., & Suryabhagavan, K. V. (2014). Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia. Tropical Ecology, 55(?), ?–?.
.Kogan, F. N. (2001). Operational space technology for global vegetation assessment. Bulletin of "the American Meteorological Society, 82(9), 1949–1964. https://doi.org/10.1175/1520-0477
Kogan, F. N. (2011). [Possible duplicate / wrong year entry] The canonical vegetation assessment paper cited in drought/vegetation work is the 2001 BAMS paper above.
Matlou, R., Bahta, Y. T., Owusu-Sekyere, E., & Jordaan, H. (2021). Impact of agricultural drought resilience on the welfare of smallholder livestock farming households in the Northern Cape Province of South Africa. Land, 10(6), 562. https://doi.org/10.3390/land10060562. MDPI
McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January 17–22). The relationship of drought frequency and duration to time scales. Paper presented at the 8th Conference on Applied Climatology, Anaheim, CA. (Conference paper; widely cited in drought literature; published proceedings pp. 179–184).
Mersha, E., & Boken, V. K. (2020). Agricultural drought in Ethiopia: Monitoring and predicting agricultural drought — A global study. New York: [publisher missing].
Negesse, W. (2016). Agricultural drought risk assessment in West Hararge, Ethiopia (Unpublished master's thesis). Addis Ababa University, Addis Ababa, Ethiopia.
Rosell, S. (2011). Regional perspective on rainfall change and variability in the central highlands of Ethiopia, 1978–2007. Applied Geography, 31, 329–338. https://doi.org/10.1016/j.apgeog.2010.07.005.
Shaheen, A., & Baig, M. A. (2019). Drought severity assessment in arid area of Thal-Doab: Using remote sensing and GIS. International Journal of Water Resources and Arid Environments, 2, 92–101.
Temesgen, M., Hoogmoed, W. B., Rockström, J., & Savenije, H. H. G. (2009). Conservation tillage implements and systems for smallholder farmers in semi-arid Ethiopia. Soil & Tillage Research, 104(1), 185–191. https://doi.org/10.1016/j.still.2008.10.026.
Thenkabail, P. S., & Gamage, M. (2004). The use of remote sensing data for drought assessment and monitoring in Southwest Asia. Research report. International Water Management Institute, Colombo, Sri Lanka.
United Nations Office for the Coordination of Humanitarian Affairs (OCHA). (2022). Ethiopia: Drought update No. 1 (January 2022). OCHA (published report).
Wassie, S. B., Mengistu, D. A., & Birlie, A. B. (2022). Agricultural drought assessment and monitoring using MODIS-based multiple indices: The case of North Wollo, Ethiopia. Environmental Monitoring and Assessment, 194(10) https://doi.org/10.1007/s10661-022-10455-4
Wilhite, D. A., Hayes, M. J., & Svoboda, M. D. (2000). Monitoring drought using the Standardized Precipitation Index. In D. A. Wilhite (Ed.), Drought: A Global Assessment (Vol. 1, pp. 168–180). Routledge.

Yimer, M., Yimer, F., Tadesse, M., & Tesfaye, K. (2018). Meteorological drought assessment in the north-east highlands of Ethiopia. International Journal of Climate Change Strategies and Management, 10(1), 142–160. https://doi.org/10.1108/IJCCSM-03-2018-0049.

Acknowledgment

The author would like to express his sincere gratitude to all individuals who contributed to the completion of this research.

Conflict of Interest

The author declares no conflict of interest.

Funding

The author declares that this study received no external funding.