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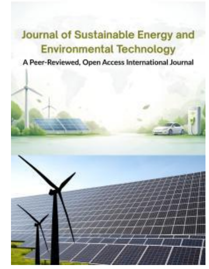

Research Article

Application of GIS and Remote Sensing for Delineation of Food Insecure Areas in South Omo Administrative Zone SNNPRS/Ethiopia

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Abstract: Food insecurity is a matter of both limited food availability and restricted access to food. Food availability is the availability of sufficient quantities of food of appropriate quality, supplied through domestic production or imports. The main objective of this study is to detect and delineate of food insecure areas in South Omo Administrative Zone using remote sensing and GIS. The necessary information was generated from satellite images, meteorological data and other ground data. The data analysis technique evolved generation of major parameters to detect drought prevalence that determining food insecurity. Because there are numerous factors determining food insecurity, the researcher selected drought and land use land cover change as determinant factors from crop production. Deviations of NDVI from the long term mean and anomalies derived from Landsat 5 and 8 NDVI images for 12 different years were used for drought detection. The results were validated using ground truth data such as crop production, food aid beneficiaries and the amount of food aid distributed including the number. The drought severity level in the study area was detected by using Index's like Standard Precipitation index, Normalized Difference Vegetation Index and anomalies. These determinant factors were then weighted and overlaid in the ArcGIS environment to generate a map indicating food insecure areas. Of the total areas of the Zone 11.6 % is found to be generally food secure, 19 % moderately food insecure, 29.4% highly food insecure and 39.9 % is chronically food insecure for the existing Drought year. The result of the research indicated that food insecure areas can be mapped by both Administrative and ecological boundary, which could be very important during area targeting for food aid and solve the problem under of area targeting only traditional view. In the research it is recommended that delineation of food insecure areas using Remote Sensing and GIS at local level should be encouraged. This system could be scaled up at zonal and regional level after incorporating other factors determining food insecurity. In doing so, Wastage of resource was controlled and Facilitate Emergency response for real targeted areas and peoples what was there in the area before.

Keywords: *Food Insecurity, Drought Indices, Drought Detection (Agricultural and Meteorological drought), Land Use Cover Change*

1. INTRODUCTION

1.1 Background of the Study

Food insecurity is defined as "a condition in which people lack the basic food intake necessary to provide them with the energy and nutrients required for fully productive lives" (FAO, 2008). Can be chronic or transitory. A constant failure to access food is distinguished as chronic, while a temporary decline to access food is considered as transitory. It is a matter of both limited food availability and restricted access to food (FAO, 2010).

On this base of FAO, 2012. In its working paper suggest that the global population is in danger for the future years to achieve its food security, problems relating El Niño driven drought. Horn of Africa: Over 15 million peoples in the region are food insecure (WFP, 2015). Ethiopia: Due to El Niño driven drought; over 8 million food insecure people receive support under the PSNP (OCHA, 2015/2016).

At present, proper identification of food insecure areas is important for aid and development activities. So remote

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sensing and GIS technologies were helpful to delineate food insecure areas quickly and effectively (Birhanu G, 2009). This technology was also used by different researchers to detect areas affected by seasonal drought.

Study done by (Gizachew, 2010) identify vegetation based drought index, etc. used for agricultural drought assessment whereas, Land Surface Temperature and land use land cover change for agricultural drought area mapping used by (Surenra et al, 2012). As the main concern the research wants to fill the gap between detecting the prevalence of drought and mapping food insecure area using remote sensing and GIS by using selected drought parameters.

According to UN (2017) for the last two year (2016/17) In Ethiopia drought caused by Eli Niño, led many peoples to become food insecure. 8.5 million People require relief food assistance. In South Omo Zone 240,000 peoples were led to emergency food assistance (ZPSNPR, 2017).

But for the purpose of food aid and food assistance Both the Government and NGOs use poor over poor (Yedeha Deha) targeting system following administrative boundaries' so this result weak targeting including inclusion and exclusion errors (WFP, 2017). The study Conducted by (Birhanu G, 2009) states that "GIS and RS provide as spatial framework for delineating food insecure areas switching from administrative to ecological boundaries."

Off course satellite sensors are tangible to do so but delineating food insecure areas standing from current unfavorable climatic condition that cause food insecurity is missed as existing in Ethiopia for the last two years so this study will show the possibilities for delineating food insecure areas which was resulting from current drought impact to cope food insecurity problems syntifically through proper identification of areas through GIS & RS tequniqes.

1.2 Statement of the Problem

Food insecurity remains one of the most pressing challenges facing Ethiopia, particularly in the South Omo Administrative Zone of the Southern Nations, Nationalities, and Peoples' Regional State (SNNPRS). Despite various interventions by government and humanitarian organizations, the identification and targeting of food insecure areas has been hampered by inadequate methodologies that rely primarily on administrative boundaries and traditional assessment approaches.

The existing targeting system, known locally as "Yedeha Deha" (poor over poor), follows administrative boundaries without adequate consideration of the spatial and temporal dynamics of food insecurity (WFP, 2017). This approach has resulted in significant inclusion and exclusion errors, where some food insecure populations are missed while others who are not in need receive assistance. Such inefficiencies lead to wastage of scarce resources and failure to address the needs of the most vulnerable populations.

Furthermore, the current system does not adequately account for the spatial variation in drought severity, land use changes, and other environmental factors that influence food production and availability. The conventional approach of using administrative boundaries for food aid targeting fails to capture the ecological and environmental realities that determine food insecurity at the local level.

The lack of spatial tools and methodologies for delineating food insecure areas has resulted in delayed emergency responses, misallocation of resources, and persistent food insecurity in the region. This study addresses this gap by applying GIS and remote sensing techniques to detect and delineate food insecure areas in South Omo Administrative Zone, providing a more accurate and scientifically based approach for targeting food aid and development interventions.

1.3 Objectives

1.3.1 General Objective

The main objective of this study is to detect and delineate food insecure areas in South Omo Administrative Zone using remote sensing and GIS.

1.3.2 Specific Objectives

1. To detect the prevalence of drought in South Omo Administrative Zone using remote sensing indices (NDVI, NDVI deviation, and NDVI anomaly)
2. To analyze land use and land cover changes in the study area over the past 30 years
3. To assess meteorological drought conditions using Standard Precipitation Index (SPI) and rainfall anomaly analysis
4. To generate a food insecurity map by integrating drought indices and land use cover change data
5. To validate the results using ground truth data including crop production and food aid beneficiary information

1.4 Research Questions

1. What is the extent and severity of drought in South Omo Administrative Zone?
2. How has land use and land cover changed in the study area over the past 30 years?
3. What is the relationship between meteorological drought, agricultural drought, and food insecurity in the study area?
4. Which areas of South Omo Administrative Zone are most vulnerable to food insecurity?

5. How can GIS and remote sensing techniques improve the targeting of food aid and development interventions?

1.5 Significance of the Study

The findings of this study are expected to provide valuable information for various stakeholders:

Government Agencies: The study will provide a scientific basis for food aid targeting and resource allocation, helping to ensure that assistance reaches those who need it most.

Humanitarian Organizations: The methodology developed in this study can be used to improve the effectiveness of food assistance programs and emergency response.

Policy Makers: The results will inform policy decisions related to food security, drought preparedness, and sustainable land management.

Academics and Researchers: The study contributes to the body of knowledge on the application of GIS and remote sensing for food insecurity assessment in Ethiopia.

1.6 Scope and Limitations

This study focuses on the South Omo Administrative Zone in SNNPRS, Ethiopia. The research utilizes Landsat 5 and 8 satellite imagery, meteorological data, and ground truth information to assess drought conditions and food insecurity. The study is limited to the analysis of drought as a determinant of food insecurity, recognizing that other factors such as conflict, population pressure, market access, and policy issues also contribute to food insecurity.

2. LITERATURE REVIEW

2.1 Conceptual Framework

Food insecurity is a complex phenomenon determined by multiple interrelated factors. The conceptual framework for this study recognizes that food insecurity results from the interaction of biophysical, socioeconomic, and institutional factors. Drought and land use land cover change are key biophysical determinants that affect agricultural production and food availability.

2.2 Food Insecurity in Ethiopia

Ethiopia has experienced recurrent food insecurity due to its vulnerability to drought, environmental degradation, and poverty. The country's food security situation has been characterized by chronic food deficits, particularly in the lowland areas of the country (Abdulsalami, 2017). The South Omo Administrative Zone is one of the most food insecure areas in the country, with recurrent droughts affecting agricultural production and pastoral livelihoods.

According to FAO and WFP (2017), the reasons for famine and food insecurity in the region include drought, conflict, environmental degradation, and policy failures. The El Niño drought of 2015/16 had particularly severe impacts, leading to emergency food assistance for hundreds of thousands of people in the zone (ZPSNPR, 2017).

2.3 Drought and Food Insecurity

Drought is a major driver of food insecurity in Ethiopia. Drought can be classified into meteorological, agricultural, and hydrological drought (Wilhite, 1993). Meteorological drought refers to a deficiency of precipitation compared to the long-term average. Agricultural drought occurs when soil moisture is insufficient to support crop growth, and hydrological drought refers to a deficiency in surface and groundwater resources (AMS, 2004).

Agricultural drought is of particular concern for food security because it directly affects crop production. In the South Omo Zone, drought has led to reduced crop yields, livestock losses, and increased food insecurity (Bewket, 2009; Woldeamanual, 2009).

2.4 Application of Remote Sensing and GIS in Food Security Assessment

Remote sensing and GIS technologies have been widely used for food security assessment and drought monitoring. These technologies provide cost-effective and timely information on vegetation conditions, land use changes, and environmental factors affecting food production (Suraiya & Mehrun, 2013).

Normalized Difference Vegetation Index (NDVI) is one of the most widely used remote sensing indices for vegetation monitoring. NDVI is calculated from the reflectance in the red and near-infrared bands of the electromagnetic spectrum (Rouse et al., 1974). Lower NDVI values indicate stressed vegetation, which may be caused by drought or other environmental stresses.

NDVI Anomaly and Deviation are useful for detecting drought conditions. NDVI anomaly is the difference between the current NDVI and the long-term mean NDVI, expressed as a percentage. NDVI deviation measures the departure of NDVI from its long-term mean. Negative deviations indicate below-normal vegetation conditions, suggesting drought (Quiring & Ganesh, 2010).

Standard Precipitation Index (SPI) is a widely used meteorological drought index. SPI is calculated based on the probability of precipitation for a given time scale (McKee et al., 1993). SPI values can be used to classify drought severity, with values below -1 indicating drought conditions.

Land Use Land Cover Change (LULCC) analysis is important for understanding the environmental context of food insecurity. Changes in land use and land cover can affect agricultural productivity, water availability, and ecosystem services (Butt et al., 2015).

2.5 Previous Studies

Several studies have applied GIS and remote sensing for food security assessment in Ethiopia and other parts of Africa:

Birhanu (2009) conducted a study on delineation of food insecure areas using remote sensing and GIS in South Gondar Zone, Ethiopia. The study demonstrated the potential of these technologies for area targeting of food aid.

Gizachew (2010) conducted agricultural drought assessment using remote sensing and GIS techniques in Ethiopia, showing the utility of NDVI-based indices for drought detection.

Hadish (2010) conducted drought risk assessment using remote sensing and GIS in southern zones of Tigray Region, Ethiopia, highlighting the importance of these tools for drought preparedness.

Aswathy (2014) conducted drought monitoring and assessment for Karur district in Tamil Nadu, India, using remote sensing and GIS techniques, demonstrating the applicability of these methods in different contexts.

Suraiya and Mehrun (2013) showed that remote sensing technology contributes towards food security in Bangladesh, particularly through crop monitoring and early warning systems.

2.6 Research Gap

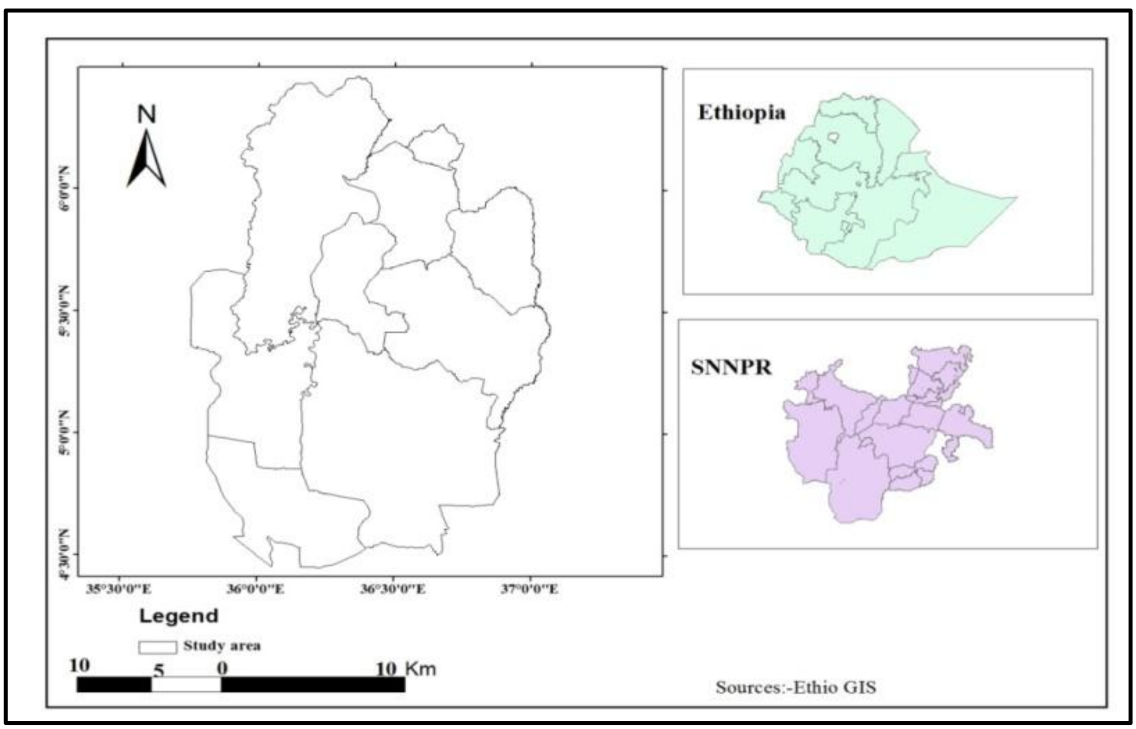
While previous studies have applied GIS and remote sensing for drought assessment and food security analysis, there is limited research that specifically focuses on the South Omo Administrative Zone. Furthermore, there is a need for integrated approaches that combine multiple drought indices and land use information for comprehensive food insecurity mapping. This study aims to fill this gap by applying a multi-indicator approach to delineate food insecure areas in South Omo Zone.

3. METHODOLOGY

3.1 Study Area Description

South Omo Administrative Zone is located at the south-western extreme part of the country, as well at the southern tips of SNNPRS. Astronomically it is roughly lies between 4°43' to 6°46' North latitude and 35°75'E to 37°07'E longitude.

(Figure 3: Study Area Map)



Geographical Location: The zone is located between 05°47'06" North Latitude and 036°33'44" East Longitude. It is located in SNNPRS, Ethiopia, 755 km from Addis Ababa and 525 km from Hawassa.

Administrative Divisions: The zone has eight Woredas (districts) and 1 city administration (Jinka).

Boundaries: It shares borders with Kenya and South Sudan in the south, on the southwest by the Ilemi Triangle, on the west by Bench Maji Zone, on the northwest by Kefa and Sheka Zones, on the north by Gamo Gofa Zone, on the northeast by the Alee and Konso Woredas, and on the east by the Oromia Region.

Population: According to the FDRE-Central Statistical Agency (August 2013), population projections for the year 2016, more than 700,000 people were projected to be living in the zone. The Ari ethnic community is the dominant group in the zone with a total population of more than 300,000.

Climate and Agriculture: The zone experiences a semi-arid to arid climate with bimodal rainfall patterns. The main agricultural activities include crop farming, pastoralism, and agro-pastoralism.

3.2 Data Sources

3.2.1 Satellite Data

Landsat has the potential to offer a long-term NDVI product at both a regional and global scale which is superior to that of low spatial resolution NDVI products of AVHRR. Since 2013 NASA has been acquired Landsat 8 image with high spatial resolution and standardized normalized difference vegetation index (NDVI) data, which has been widely used for biophysical feature extraction green cover, climate change, ecological and hydrological modeling for the past years.

Landsat 5 and 8 NDVI images are found aggregated in a decadal basis, 12 year images stacked together for a single year. The Landsat image for the year 1987, 1988, 1989, 1990, 1991, 1992 and 2012, 2013, 2014, 2015, 2016 and 2017 with path number 169/170 and row number 56/57 with an acquisition date of 04/30/2018 is downloaded from the internet/USGS. In order to obtain actual NDVI values for each year. NDVI time series between 1987, 1988, 1989, 1990, 1991, 1992 and 2012, 2013, 2014, 2015, 2016 and 2017 (4 composites per a month, 432 layers per year with 15m and 30m resolution respectively. To do Land Use Cover Change, NDVI, NDVI anomaly, seasonal NDVI deviation maps of each year to drive agricultural drought severity an area.

3.2.2 Climate Data

34 year rainfall data was collected from the Ethiopian national meteorological agency. Especially 4 by 4 km grid data which are distributed unevenly in the zone and Derived from 11 meteorological stations of the study area. Rainfall data are essential to support SPI and Rain fail Anomaly data for drought risk assessment and meteorological drought map production.

3.2.3 Ground Truth Data

Ground truth data were collected from various sources:

- Crop production data from the Zonal Agricultural and Natural Development Department
- Food aid beneficiary data from the Zonal Productive Safety Net Program (PSNP) Branch
- Food aid distribution data from the World Food Programme (WFP)

3.3 Image Processing

Satellite image was downloaded from Earth Explorer: http://earthexplorere.usgs.gov, to structure the study area. The researcher take four different points (points from Jinka path 169 raw 056, Turmi path 169 raw 057, Bench Maji path 170 raw 056 and Kaaling Keneya path 170 raw 057) than the downloaded images were Extracted individually with in performed folder.

Next to that each extracted layers were staked with in Erdas 2014 environment following the next steps: Go to Raster, Spectral, select Layer Stacking than input each extracted layers, select all, assign the output file name and at the end click OK to make layers to stack.

This was held for all downloaded images, after that all stacked image layers were come in to a single image through the process of mosaicking following the next steps with in Erdas 2014: Go to Raster, select mosaic, click on mosaic, click on mosaic pro, go to edit click on add images, after adding four stacked images than go to process and click on Run mosaic after finishing the process close the process.

3.4 Image Classification

Supervised classification was held by linking google earth; spectral signatures were developed from specified locations in the image. These specified locations were given the generic name 'training sites'. The training sites used as inputs for ERDAS 2014 to develop spectral signatures for the selected areas.

After the training sites were developed ERDAS used this information, along with the various images of different bandwidths, to create spectral signatures from the specified areas. These signatures then used to classify all pixels in the scene. Landsat ETM+ bands used were bands 1-5 and 8 in case 4, 3, 2 band combinations were used. The classification program then acts to cluster the data representing each class.

3.5 Driving Agricultural Drought

3.5.1 Land Use Land Cover Change Detection

Analysis of detected change is the measure of the distinct data framework and thematic change information that can lead to more tangible discernment to underlying process involved in upbringing of land cover and land use changes (Ahmad, 2012).

Thus per-pixel signatures are taken and stored in signature files by using this knowledge and the raw digital numbers (DN) of each pixel in the scene are therefore converted to radiance values (SCGE, 2011). Similar technique was used to detect changes observed in a nearby watershed (Rawal watershed, Islamabad, Pakistan) and achieved up to 95% accurate results (Butt et al., 2015).

3.5.2 Drought Detection by NDVI

The Researcher drive NDVI data from Landst 5 and 8 Band combination 4, 3, 2 to analyze weather on the study area contains vegetation or not, by using in the Visible and Near-Infrared bands of electromagnetic spectrum.

So the NDVI numerical value is calculated from the reflectance measurement in R and NIR portion of the spectrum while in using the formula:

$$NDVI = (NIR - RED) / (NIR + RED)$$

with in Erdas 2014 environment by using band combinations in a multispectral imagery.

3.5.3 Drought Detection by NDVI Anomalies

Maximum NDVI and long-term mean maximum NDVI in the growing season (April to September) were computed in order to derive seasonal NDVI anomaly. NDVI anomaly percentage was derived for years 1987-1992 and 2012-2017.

$$NDVI\ Anomaly\ (\%) = [(NDVIi - NDVIm) / NDVIm] \times 100$$

Where:

- NDVIi = NDVI for a specific year
- NDVIm = Long-term mean NDVI

For example: 1987 NDVI anomaly = -20, 2017 NDVI anomaly = -31.8

3.5.4 Drought Detection by NDVI Deviation

The severity of drought can be Defined as NDVI deviation from its long-term mean (DEVNDVI). When DEVNDVI is negative, it indicates the below-normal vegetation Condition and, therefore, suggests a prevailing drought situation.

The greater the negative departure, the greater the magnitude of a drought is therefore the researcher advocates NDVI deviation with in Arc map environment by reclassifying the Normal NDVI result to detect and map drought severity level.

3.6 Driving Meteorological Drought

3.6.1 Drought Detection by Seasonal Rainfall Data

For the period from 1983-2016 years monthly Rain fall data was calculated from stations in which its source is Ethiopian National Meteorological Agency. Meteorological data was used to get the response of the variability of rain fall in each Woredas through interpolation /ordinary kriging method be made for distributing the influence of each year rain fall over the zone.

3.6.2 Drought Detection by Standard Precipitation Index

To know the dryness, witness and to detect meteorological drought condition of an area the researcher calculate Standard Precipitation index by using monthly rain fall data during 1983-2016 for crop growing season 6-month (October-march) So, it is help full to detect metrological drought in the study area.

Therefore, Z score = SPI value:

$$SPI = (X - Pa) / \sigma$$

Where:

- X = Precipitation for particular month
- Pa = Mean rainfall for six month
- σ = Standard deviation

Then Precipitation is normalized using a probability distribution function, so that value of SPI are actually seen as standard deviations from the median and accumulated value can be used to analyze drought severity.

The researcher use the latest version SPI program SPI_SL_6.exe/software. Can be down loaded from online internet program by using steps like file with daily precipitation the number of scales to calculate SPI as Input data and output file name for calculated SPI value to get the Result.

3.6.3 Drought Detection by Rainfall Anomaly

Here, the researcher choose Geostatistical Interpolation technique Kriging to develop both Rain fall Anomaly and meteorological drought map which was driven from Seasonal rain fall and SPI six month result because the estimates of Kriging was unbiased and have a minimum variance as well as it were exact interpolators.

Therefore to ensure maps the researcher accesses the data for 11 rainfall stations by averaging 17100, 4 by 4 km point data around each station with in Arc Map 10.3 by selecting Ordinary Kriging to get estimated unbiased result to develop map for the quality of prediction. The data was also validated by comparing filed value /measured value from SNNPRS Meteorological Agency and remote sensing based predicted data from National Meteorological Agency by taking high number of point data.

3.7 Drought Classification

3.7.1 Meteorological Drought Classification Based on Rainfall

Meteorological drought is defined as a situation when the seasonal rainfall received over an area is less than 75% of its long-term average value. Recently 44.1% is taken as a threshold for drought severity (Dunkel, 2009). It is further classified into:

- Slight drought: rainfall is 25% less than normal
- Moderate drought: rainfall is 50% less than normal
- Severe drought: rainfall is 44.1% less than normal (WMO, 2017)

3.7.2 SPI Classification

SPI values and drought classification:

- SPI > 2.0: Extremely wet
- 1.5 to 1.99: Very wet
- 1.0 to 1.49: Moderately wet
- -0.99 to 0.99: Near normal
- -1.0 to -1.49: Moderately dry
- -1.5 to -1.99: Severely dry
- SPI < -2.0: Extremely dry

3.8 Data Integration and Overlay Analysis

The determinant factors (agricultural drought, meteorological drought, and land use cover change) were weighted and overlaid in the ArcGIS environment to generate a map indicating food insecure areas. The integration process involved:

1. **Reclassification:** Each factor was reclassified into severity classes
2. **Weighting:** Factors were weighted based on their relative importance
3. **Overlay Analysis:** Weighted factors were overlaid using weighted overlay technique
4. **Validation:** Results were validated using ground truth data

3.9 Validation

The results were validated using ground truth data including:

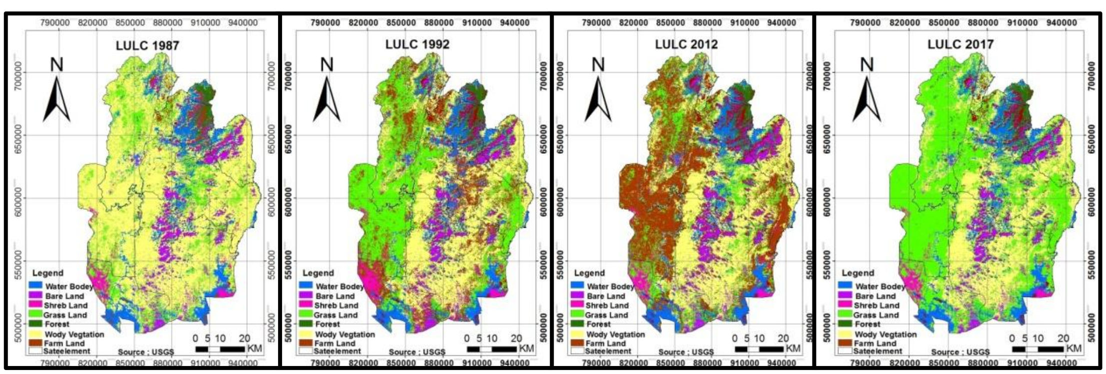
- Crop production data
- Food aid beneficiary numbers
- Amount of food aid distributed

3.10 Ethical Considerations

This research utilized publicly available satellite data and secondary data sources. All data sources are properly cited and acknowledged. No primary data collection involving human subjects was conducted, therefore ethical approval was not required.

4. RESULTS

4.1 Land Use and Land Cover Change Analysis



The data at **(Figure 9)** shows that land use cover change of water body, woody vegetation, grass land, forest and shrub land was decreasing where as other land use features were increasing in the study period.

Accordingly farmlands and Settlement showed positive rate of change for the past 30 years. Alvaraz, (2008) monitoring land use/land cover change and suggest on its finding atypical checkup of land use cover change within a given area sustain individual need.

Archer, (2010) analyzed the land use/land cover cause disturbance over the given environment. Verburg et al (2014) advocates the causality of land use land cover change to in drought phorn areas who applied the same technique taking this into account the researcher done land use land cover change in relation to detect drought for the year 1987, 1992, 2012 and 2017 as a base for existence of drought condition.

The study area has undergone a series of land use cover change over the last 30 years. From 1987 to 2017 the water body of the study area has been shrinking about -0.22% of the total area.

Table 1: Land Use and Land Cover Change Analysis (1987-2017)

Land Use Type	Change (%) 1987-2017	Direction
Water body	-0.22%	Decreasing
Bare land	+5.3%	Increasing
Shrub land	-2.9%	Decreasing
Grassland	-18.21%	Decreasing
Forest	-7%	Decreasing
Woody land	-17.1%	Decreasing
Settlement	+17.3%	Increasing
Farmland	+23.13%	Increasing

The high bare land which is dominant in the south western periphery of the study area encompasses about +5.3% of the total area. The main shrebland is mainly found in southern and central part of the study area and it covers only -2.9%. -18.21% of the study area is covered with grassland; the high forest covered -7% of the study area. -17.1% woody land converted to another land uses +17.3% scattered settlement and +23.13% farm lands.

Therefore, land use land cover change from the year 1987 to 1992 and 2012 to 2017 reflect that the amount bare land, Farm land and Settlement were increasing were as the rate of Water bodies, Shrub land, Grass land, Forest and Woody land were decreasing Especially the rate of Grass land and Woody land were decreasing by half 16.91% and 16.76% respectively.

4.2 Agricultural Drought Detection

4.2.1 Drought Detection by NDVI (1987-1992)

The drought condition of an area driven for the year 1987, 1988, 1989, 1990, 1991 and 1992 indicated that the lower values are reflects continuous vegetation stress which show the existence of drought with the least value of -0.87 to -0.99 while all the positive value shows approximately good vegetation condition with the value of 0.73 to 0.88.

4.2.2 Drought Detection by NDVI (2012-2017)

Compared to the previous year's 2012, 2013, 2014, 2015, 2016 and 2017 was highly affected by drought with vegetative condition of an area with the lowest value -0.49 to -0.7 and with the highest value of -0.37 to -0.68 respectively but the map indicated the good condition of vegetation in the area this is because of sugarcane plantation in the southern and western parts of the area at list for 5-6 sugar factories. Therefor only greenness of an area can't make free from drought.

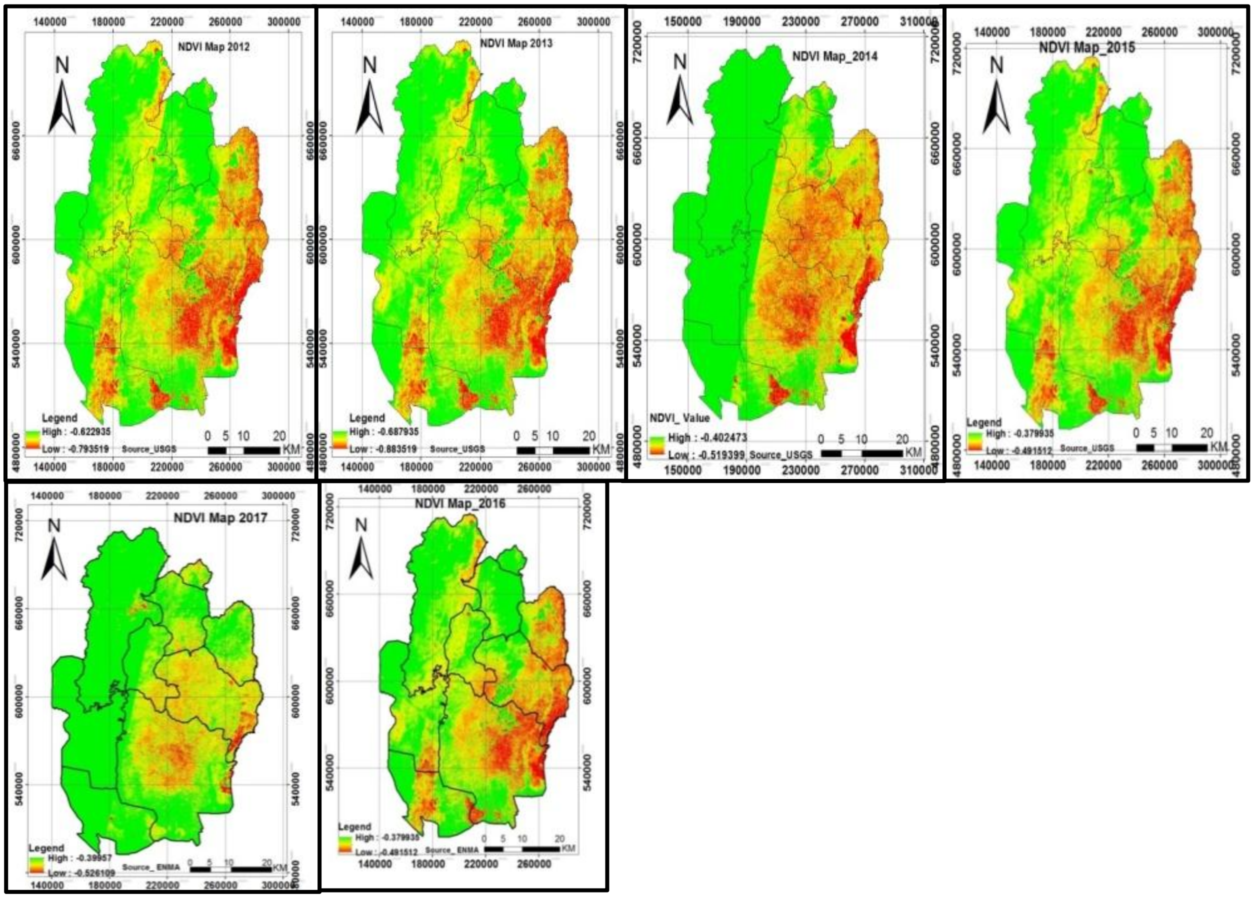
Therefore, all negative value below 0 indicated that the prevalence of drought with in the area may be with the occurrence of different natural phenomena /shortage of water etc. / though this shows the prevalence of historical drought in the study area.

This work was in line with the work conducted by (Shang et al, 2014) that Lower NDVI values below 0 are indicates prevalence/existence of drought conditions with the occurrence of natural phenomena like Cloud, water, snow, ice and non-vegetated surfaces have negative NDVI values but in our case drought was the main cause.

4.2.3 Drought Detection by NDVI Deviation

NDVI deviation was conducted for selected year and years with low NDVI deviation values are taken for the purpose of comparison. As a result of seasonal NDVI deviation the rate of drought severity covers large area since 2017 compared to that of 1987. Therefore drought condition of the study area was harsh to that of 2017.

(Figure 11: Seasonal NDVI for the year 1987 and 2017 for South Omo Zone)



The trend of drought in South Omo Administrative zone shows that some areas are frequently affected. The NDVI deviation of the zone varies through time. Song et al (2004) states seasonal NDVI deviation ranges from <-2.5 to >2.5. The maximum/positive NDVI deviation was recorded in 1987 and the negative/minimum NDVI deviation was recorded in 2017 years of the study period shows that there is an increase in the number of severe drought affected Woreda therefore this work is in line with the work done by (Hassan et al, 2008).

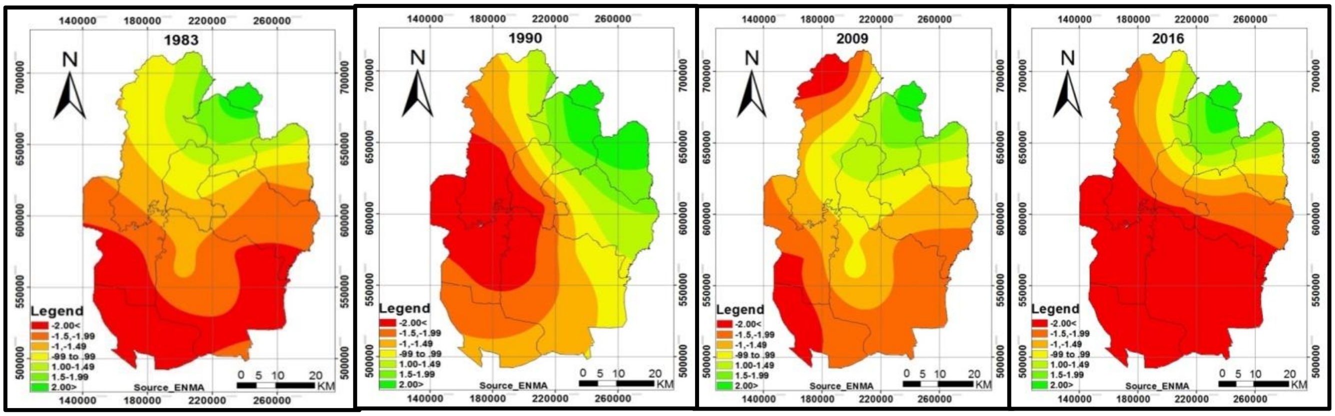
Table 2: Extent of Drought Affected Woredas in Time

Description	1987 (%)	2017 (%)	Remark
Very severe drought	0	62.5	Increasing
Severe drought	37.5	12.5	Decreasing
Moderate drought	37.5	25	Decreasing
Slight drought	12.5	0	Decreasing
No drought	12.5	0	Decreasing

The drought severity map generated from seasonal NDVI deviations shows that Nangatom, Dassench and Hammer Woreds recorded very severe drought conditions 37.5%, Salamago and Benatemay Woreda recorded severe drought condition of 25%, Male Woreda recorded Moderate Drought 12.5% and North and South Ari Woredas recorded Slightly Drought of 25% and No woreda was out of Drought risk in the year 1987.

On the other hand in the year 2017 Nangatom, Dassench, Hammer, Benatemay, Male Woredas recorded Very severe drought condition 62.4% of the study area, Salamago Woreda recorded severe drought 12.5% and North and South Ari Woredas recorded Moderate Drought 25%. Because stress of vegetation in the area results drought severity over the area (Wu J et al, 2011 and Rhee J 2010).

(Figure 12: Agricultural drought map generated from seasonal NDVI deviation for the year 1987-2017)



4.2.4 NDVI Anomaly Analysis

The result of the study indicated that NDVI anomaly in the years 1987, 1988, 1989 reaches -17.8, -18.2, -18.9 respectively and the area record Moderate drought whereas in the years 1990, 1991, 1992 it reaches -20.6, -20.3, -20.1 respectively and the area reaches to Severe drought.

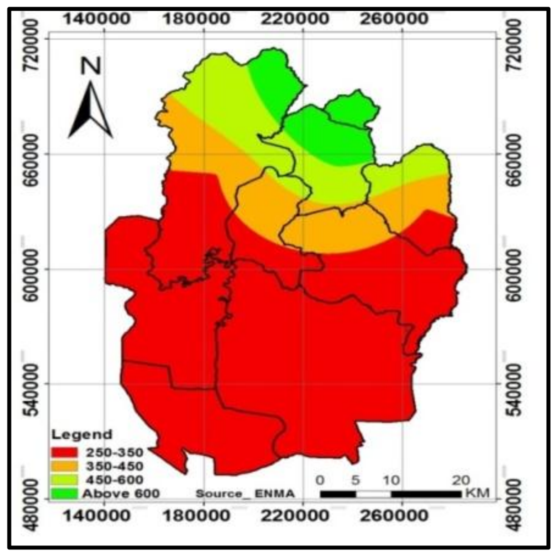
While in the years 2012 and 2013 recorded -22.4 and -26.1 respectively and it reaches severe drought whereas in the years 2014, 2015, 2016 and 2017 it goes to -31.3, -31.7, -31 and -30.8 so the area was affected by very severe drought.

Study done by advocates by on its agricultural drought risk classification -10% to 20% was under moderately drought and -30 and above was very severe drought, so the researcher agree with the previous research results.

4.3 Meteorological Drought Detection

4.3.1 Rainfall Analysis

The average yearly rainfall indicated that except 1994, 1995, 1996, 1998, 2000, 2001, 2003, 2005, 2006 and 2013 all years recorded low amount of rain fall, so it reflects the shortage of rain fail /existence of drought. Meteorological drought is defined as a situation when the seasonal rainfall received over an area is less than 75% of its long-term average value. Recently 44.1% is taken as a threshold for drought severity (Dunkel, 2009). It is further classified into slight drought when rainfall is 25% less than the normal, moderate drought when rainfall is 50% less than the normal and severe drought when rainfall is 44.1% less than the normal (WMO, 2017).

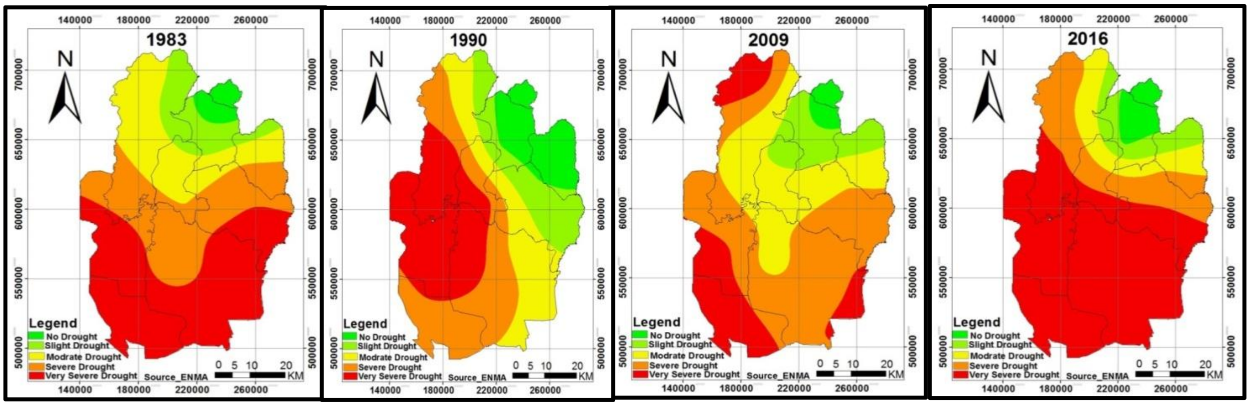


(Figure 16: Meteorological Drought Map Generated from long term rainfall data)

The result indicates the deficiency of rainfall compared to normal rainfall in a given region. Places where long-term average rainfall is less, year-to-year variability is greater and so the likelihood of drought is greater (Tsiaris, 2004). The area gets average annual rain fall above 600 mm might not be attacked by meteorological drought and it is ever green whereas b/n 250-350 mm which was affected by meteorological drought.

4.3.2 Drought Detection by Standard Precipitation Index (SPI)

McKee et.al 1993 states that drought events are indicated when the result of SPI, for which ever time scale was being investigated, become continuously negative and reach a value of -1. As shown the result the dryness of the area was increasing through the year from 1983 to 1990 and from 2009 to 2016 the wetness of an area were decreasing.



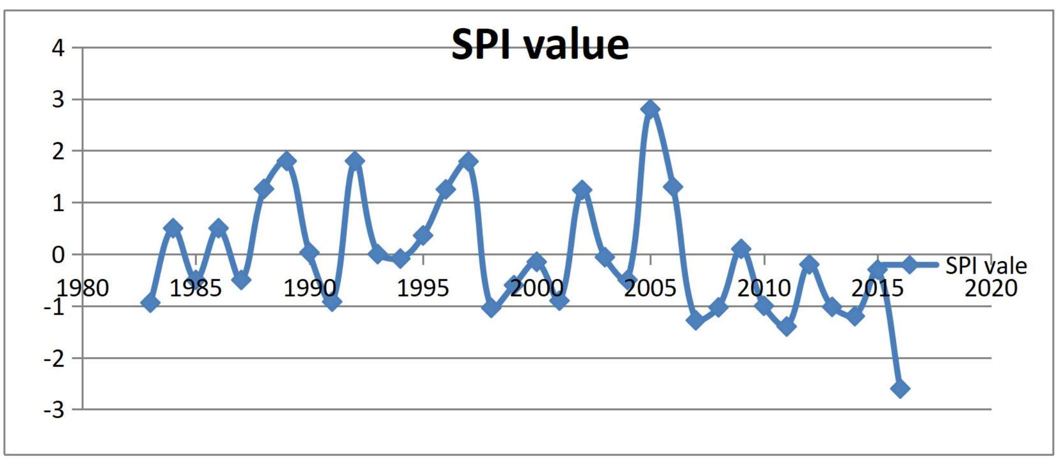
(Figure 17: Six month Standard Precipitations Index value map for the study year)

As shown the result the dryness of the area was increasing through the year from 1983 to 1990 and 2009 and 2016 where as the wetness of an area were decreasing over the past year. The final drought trend graph and map which has been obtained from six month (October to march) SPI value from 1983-2016 was generated from a Standard Precipitation Index.

Six Month SPI result shows that around 8.8% of the area was extremely dry 23.5% of the area severely dry 32.3% of the area cover moderately dry area which was below the normal condition of which 11.8% was moderately wet 8.8% of the area was very wet and only 2.9% of the area was extremely wet, therefore the SPI value that covers 64.6% gets low rain fall event over time period specified as drought affected area therefore there was Metrological drought occurred in the area this is in line with the work conducted by (Tigkas D, 2008).

(Figure 18: Meteorological Drought Severities for Different years)

Based on the drought condition probability the dry and wet percent was identified. Therefore 64.6% of the area was under extreme drought 11.7% of the area was No drought and the rest 29.9% of the study area should be recorded severe, moderate and slight drought for the study year.

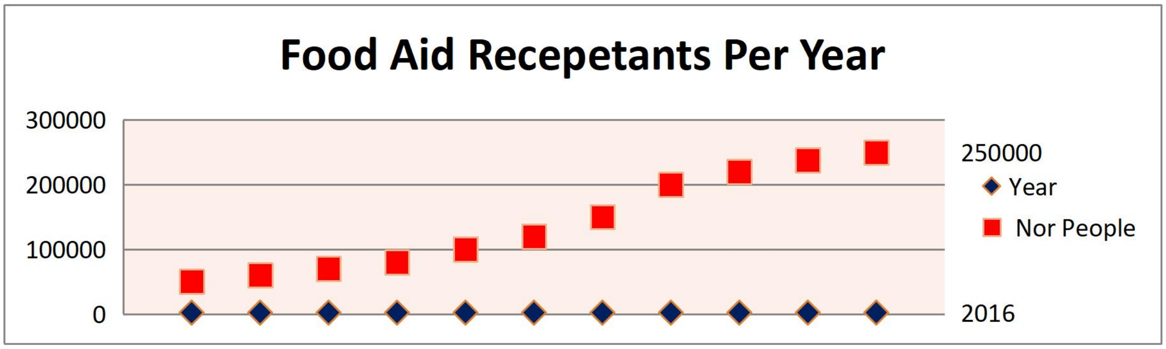


(Figure 19: Six Month Metrological Drought Trend Graph 1983-2016)

As the result shown starting from 1983 to 2016 ElNino/LA Nina Driven drought was occurred with the maximum SPI value averagely 8-9 years (Wolde G, 2010) or by repeating its year of periodical occurrence as shown in the graph 1983, 1990/91, 1998/2001, 2007/08, 2016.

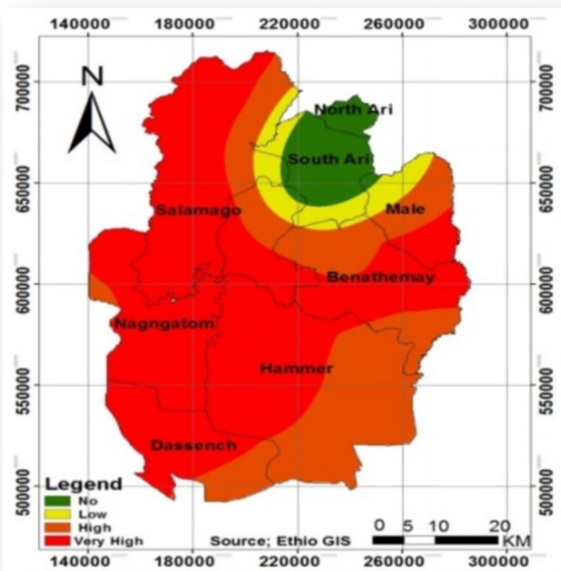
As explained by (Yirdaw, S et al, 2016) High SPI value (closer to 3): heavy precipitation event over time period specified Medium SPI value (approximately = 0): normal precipitation event over time period specified Low SPI value (closer to – 3): low precipitation event over time period specified (drought).

4.4 Food Insecurity Trend Analysis



(Figure 22: Food insecurity trend 2006-2016)

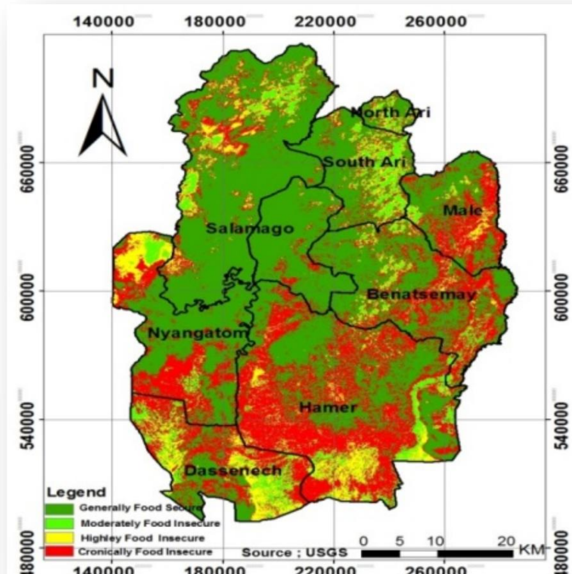
This also implies that averagely 37.1% of the people were food insecure. There for the number of food insecure population increases from 5.3% in the year 2006 to 37.1% in the year 2016 with the annual rate of 2.8% within each year. Annual food aid distributed in the zone during the study period proves high. The total beneficiaries in 2007 as a result of severe drought conditions in 2016 crop growing season was the highest of all years.



(Figure 23: Map that show maximum number of food aid beneficiaries)

As shown in the map except North Ari and Some parts of South Ari other parts of the study area were food aided this implies that 75% of the area was attacked by seasonal drought over the study year.

4.5 Delineation of Food Insecure Areas



(Figure 24: Delineation of Food Insecure Areas Map)

As the map shows that North, South ari Woredas and Salamago were generally food secure it covers 39.8 %. Western parts of Male and Benatsemay were moderately food insecure which covers 11.6 %. Southern parts of Dassench and Nangatom were highly food insecure which covers 15.1% and Hammer woreda, central parts of Benatsemay, eastern and central and southern parts of Male and Nangatom Woredas face chronic food insecurity which covers 33.5 %.

5. DISCUSSION

5.1 Land Use and Land Cover Change

The study revealed significant land use and land cover changes in South Omo Administrative Zone over the past 30 years. The most notable changes include the expansion of farmland (+23.13%) and settlements (+17.3%) at the expense of grassland (-18.21%), woody land (-17.1%), and forest (-7%). These changes are consistent with the findings of Alvarez (2008), who reported similar trends in the Omo National Park area, and Archer (2010), who analyzed the impact of land use changes on environmental conditions.

The conversion of natural vegetation to agricultural land and settlements indicates increasing pressure on natural resources due to population growth and economic activities. However, the reduction in vegetation cover also contributes to increased vulnerability to drought and food insecurity, as vegetation plays a crucial role in regulating hydrological cycles and maintaining soil fertility (Midgley et al., 2010).

The loss of grassland (-18.21%) and woody vegetation (-17.1%) is particularly concerning for the pastoral and agro-pastoral communities in the zone. These communities depend on natural vegetation for livestock grazing, and the reduction in vegetation cover directly affects their livelihoods and food security.

The expansion of farmland, while reflecting the importance of agriculture to the local economy, also raises concerns about land degradation and reduced agricultural productivity in the long term. As land becomes increasingly fragmented and degraded, agricultural yields may decline, contributing to increased food insecurity (ATA, 2010).

5.2 Agricultural Drought

The NDVI analysis revealed significant drought conditions in the study area. The presence of negative NDVI values indicates vegetation stress, which is associated with drought conditions. The results show that drought conditions were more severe in 2017 compared to 1987, with 62.5% of Woredas experiencing very severe drought in 2017, compared to 0% in 1987.

This finding is consistent with the work of Shang et al. (2014), who reported that lower NDVI values below 0 indicate the prevalence of drought conditions. The increasing severity of agricultural drought is also consistent with the findings of Gizachew (2010), who reported increasing drought trends in various parts of Ethiopia.

The agricultural drought analysis also revealed spatial variation in drought severity. Areas in the southern and eastern parts of the zone (Nangatom, Dassench, Hammer) were more affected by drought compared to the northern and western areas (North and South Ari). This spatial variation is important for targeting food aid and development interventions.

The NDVI anomaly analysis further confirmed the increasing trend of drought in the zone. The anomaly values decreased from -20.6 in 1992 to -31.8 in 2017, indicating worsening vegetation conditions. This finding is consistent with the agricultural drought risk classification, which suggests that values below -30% indicate very severe drought.

5.3 Meteorological Drought

The rainfall analysis revealed that the study area has experienced recurrent meteorological drought, with significant rainfall deficits during many years. The SPI analysis confirmed the occurrence of meteorological drought, with 64.6% of the area experiencing dry conditions. The most severe drought events occurred in 1983, 1990/91, 1998/2001, 2007/08, and 2016, which coincides with El Niño events.

This finding is consistent with the work of Wolde (2010), who reported that El Niño driven droughts in Ethiopia occur every 8-9 years. The recurrence of drought events highlights the vulnerability of the study area to climatic variability and climate change.

The analysis of rainfall anomalies showed that areas with annual rainfall between 250-350 mm are most affected by meteorological drought. These areas are located in the lowland parts of the zone, where rainfall is highly variable and insufficient for reliable crop production. In contrast, areas with rainfall above 600 mm are less likely to experience severe meteorological drought.

The relationship between meteorological drought and agricultural drought is evident in the study findings. Areas that experienced severe meteorological drought also had low NDVI values, indicating the impact of rainfall deficits on vegetation conditions. This relationship is important for early warning systems and drought preparedness.

5.4 Food Insecurity

The food insecurity analysis revealed that the majority of the study area (88.4%) is food insecure, with varying degrees of severity. About 39.9% of the area was classified as chronically food insecure, 29.4% as highly food insecure, and 19% as moderately food insecure. Only 11.6% of the area was classified as generally food secure.

The number of food insecure people increased from 5.3% in 2006 to 37.1% in 2016, with an annual increase rate of 2.8%. This increasing trend is consistent with the worsening drought conditions in the zone. The highest number of food aid beneficiaries was recorded in 2007, following the severe drought of 2016.

The spatial distribution of food insecurity corresponds well with the distribution of drought severity. Areas with severe drought (Nangatom, Dassench, Hammer, Benatemay, Male) had high levels of food insecurity, while areas with less severe drought (North and South Ari, Salamago) had lower levels of food insecurity.

This finding is consistent with the work of Birhanu (2009), who reported that GIS and remote sensing can be used to delineate food insecure areas and improve food aid targeting. The use of spatial data for food insecurity mapping can help overcome the limitations of traditional administrative boundary-based approaches and reduce inclusion and exclusion errors.

The relationship between land use change and food insecurity is also evident in the findings. Areas with high rates of land degradation (particularly grassland and woody vegetation loss) tend to have higher levels of food insecurity. This reflects the importance of natural resource management for food security in the zone.

5.5 Comparison with Previous Studies

The findings of this study are consistent with previous research on drought and food insecurity in Ethiopia. Birhanu (2009) reported that GIS and remote sensing can be used to delineate food insecure areas in South Gondar Zone, with similar methodological approaches. The current study extends this work to the South Omo Administrative Zone, demonstrating the applicability of these methods in different contexts.

Gizachew (2010) reported increasing agricultural drought trends in various parts of Ethiopia, which is consistent with the findings of this study. The use of NDVI-based indices for drought detection is well established in the literature (Quiring & Ganesh, 2010; Shang et al., 2014).

The SPI analysis confirms the findings of previous studies on meteorological drought in Ethiopia (Wolde, 2010; Hadish, 2010). The recurrence of El Niño driven droughts every 8-9 years is consistent with the findings of Yirdaw et al. (2008).

The food insecurity analysis aligns with the findings of the Zonal PSNP Branch report (ZPSNPR, 2017), which identified similar areas as food insecure. The agreement between the research findings and ground truth data validates the methodology used in this study.

6. CONCLUSION

This study has successfully demonstrated the application of GIS and remote sensing techniques for delineating food insecure areas in South Omo Administrative Zone. The findings reveal that the majority of the zone (88.4%) is food insecure, with varying degrees of severity. Chronic food insecurity affects 39.9% of the area, while 29.4% is highly food insecure and 19% is moderately food insecure. Only 11.6% of the area is generally food secure.

The study identified several key determinants of food insecurity in the zone:

1. Drought: Both agricultural and meteorological droughts are major drivers of food insecurity. The analysis revealed that drought conditions have worsened over the past 30 years, with 2017 being particularly severe. The recurrence of drought events, associated with El Niño, has led to recurrent food insecurity crises.

2. Land Use and Land Cover Change: Significant changes in land use and land cover have occurred over the past 30 years, including the expansion of farmland and settlements at the expense of natural vegetation. This has contributed to environmental degradation, reduced agricultural productivity, and increased vulnerability to drought.

3. Spatial Variation: Food insecurity varies significantly across the zone. Areas in the southern and eastern parts (Nangatom, Dassench, Hammer, Benatemay, Male) are more food insecure compared to the northern and western areas (North and South Ari, Salamago).

4. Validation: The results were validated using ground truth data, including crop production figures and food aid beneficiary numbers. The agreement between the research findings and ground truth data confirms the validity of the methodology.

The use of GIS and remote sensing techniques provides several advantages for food insecurity assessment and food aid targeting:

1. **Objective and Timely Assessment:** Remote sensing provides objective and timely information on vegetation conditions and drought severity, which is critical for early warning systems.
2. **Spatial Targeting:** GIS enables the identification of food insecure areas at a detailed spatial scale, facilitating more targeted food aid interventions.
3. **Integration of Multiple Factors:** The overlay analysis allowed for the integration of multiple factors (agricultural drought, meteorological drought, and land use change) for comprehensive food insecurity mapping.
4. **Reduced Inclusion and Exclusion Errors:** The spatial approach reduces the inclusion and exclusion errors associated with traditional administrative boundary-based targeting systems.

7. RECOMMENDATIONS

7.1 To Government and Humanitarian Organizations

1. **Adopt GIS-Based Targeting:** Government and humanitarian organizations should adopt GIS-based methods for targeting food aid and development interventions. This approach is more accurate than traditional administrative boundary-based systems and can reduce inclusion and exclusion errors.
2. **Strengthen Early Warning Systems:** The methodology developed in this study should be integrated into existing early warning systems for drought and food insecurity. Regular monitoring of NDVI, rainfall, and other indicators can help predict food insecurity and trigger timely interventions.
3. **Scale Up the Approach:** The approach should be scaled up to the zonal and regional levels after incorporating other factors that determine food insecurity, such as conflict, population pressure, market access, and policy issues.
4. **Support Natural Resource Management:** Programs that promote sustainable land management, reforestation, and rangeland improvement should be supported to reduce

environmental degradation and enhance resilience to drought.

5. **Strengthen Drought Preparedness:** The recurrence of El Niño driven droughts every 8-9 years suggests the need for long-term drought preparedness strategies, including water harvesting, drought-resistant crops, and livelihood diversification.

6. **Improve Data Availability:** Efforts should be made to improve the availability and quality of meteorological data, satellite imagery, and ground truth data to support ongoing food insecurity monitoring and assessment.

7.2 To Local Government and Institutions

1. **Community-Based Monitoring:** Local government agencies and institutions should establish community-based monitoring systems to complement satellite-based assessments. Local knowledge can provide valuable insights into food insecurity dynamics.

2. **Capacity Building:** Training should be provided to local technical staff on the use of GIS and remote sensing for food insecurity assessment, enabling them to maintain and update the mapping system.

3. **Participatory Approaches:** Participatory approaches should be incorporated into food insecurity mapping to ensure that local perspectives and priorities are considered.

4. **Integration with PSNP:** The delineation of food insecure areas should be integrated with the Productive Safety Net Program (PSNP) to improve program targeting and effectiveness.

7.3 To Researchers

1. **Incorporate Additional Factors:** Future research should incorporate additional factors that determine food insecurity, such as conflict, market access, household assets, and gender dynamics.

2. **Longitudinal Studies:** Longitudinal studies are needed to track changes in food insecurity over time and assess the effectiveness of interventions.

3. **High-Resolution Data:** The use of high-resolution satellite imagery and other spatial data sources should be explored to improve the accuracy and detail of food insecurity mapping.

4. **Community Validation:** Participatory mapping and community validation of results should be conducted to enhance the relevance and acceptability of the research findings.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

8.1 Limitations

1. **Data Constraints:** The availability and quality of meteorological data, satellite imagery, and ground truth data posed challenges for the study. Some areas had limited data coverage, which may have affected the accuracy of the results.

2. **Temporal Limitations:** The study focused on specific time periods and may not fully capture the inter-annual and decadal variability of drought and food insecurity.

3. **Spatial Resolution:** The use of Landsat imagery (30m resolution) may not capture fine-scale variations in vegetation conditions and land use, particularly in heterogeneous landscapes.

4. **Limited Factors Considered:** The study focused on drought and land use change as determinants of food insecurity, but other factors such as conflict, population pressure, market access, and policy issues also contribute to food insecurity.

8.2 Future Research Directions

1. **Multi-Factor Analysis:** Future research should incorporate a wider range of factors determining food insecurity, including socioeconomic, political, and institutional factors.

2. **Climate Change Scenarios:** The impact of climate change on drought frequency and severity in the zone should be assessed using climate models and scenario analysis.

3. **Livelihood-Based Analysis:** Research should examine the differential impacts of drought and food insecurity on different livelihood groups (farmers, pastoralists, agro-pastoralists) in the zone.

4. **Intervention Evaluation:** The effectiveness of food aid and development interventions in reducing food insecurity should be evaluated using spatial and temporal analysis.

5. **Participatory GIS:** Participatory GIS methods should be incorporated to integrate local knowledge and perspectives into food insecurity mapping.

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