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Mapping the Spatial and Temporal Variation of Agricultural and Metrological Drought Using Geospatial Techniques, Ethiopia

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Abstract

Background

Geographic Information System (GIS) and Remote Sensing play an important role for near real time monitoring of drought condition over large areas. The objective of this study was to assess spatial and temporal variation of agricultural and metrological drought using temporal image of *eMODIS NDVI* based vegetation condition index (VCI) and standard precipitation index (SPI). To validate the strength of drought indices correlation analysis was made between VCI and crop yield anomaly as well as SPI and crop yield anomaly. The results revealed that the year 2009 and 2015 were drought years while the 2001 and 2007 were wet years. There was also a good correlation between NDVI and rainfall (r=0.71), VCI and crop yield anomaly (0.72), SPI and crop yield anomaly (0.74). Frequency of metrological and agricultural drought was compiled by using historical drought intensity map.

Result

The result shows that there was complex and local scale variation in frequency of drought events in the study period. There was also no year without drought in many parts of the study area. Combined drought risk map also showed that 8%, 56%, 35% and 8% of study area were vulnerable to very severe, severe and moderate drought condition respectively.

Conclusion

In conclusion, the study area is highly vulnerable to agricultural and meteorological drought. Thus besides mapping drought vulnerable areas, integrating socioeconomic data for better understand other vulnerable factors were recommended.

Background

Drought is one of the most frequent climate-related disasters occurring across large portions of the African continent, often with devastating consequences for the food security of agricultural households (Rojas et al., 2011). The effects of droughts are severe particularly in East African countries due to high rainfall variability in space and time (Bayissa et al., 2017). East Africa is highly vulnerable to the impact of frequent droughts and flood exacerbating the existing challenges to satisfy the food demands of an increasing population and improve the population’s livelihood(Tadesse et al., 2014). A catastrophic drought occurred in the region in 1984, which killed an estimated 450,000 people in Ethiopia and Sudan(El Kenawy et al., 2016). More recently, a severe drought in Somalia and southern Ethiopia in June 2011 resulted in more than 10 million people seeking humanitarian aid, as well as 380,000 refugees impacting neighboring countries (Vicente-Serrano et al., 2012). Among these countries, Ethiopia encounters frequent droughts (occurring once in every 2-3 years). In support of this finding recently, severe drought events have occurred in Ethiopia in 2011, 2012, 2014 and 2015, with most of them covering the whole country (Edossa et al., 2010; Viste et al., 2013). In line with these Gebrehiwot et al.

(2011) reported that Ethiopia, a highly populated country whose economy largely depends on rain-fed agriculture, drought is a recurrent climate phenomenon, with a frequency of occurrence approaching one event per decade.

Drought characterization at regional and local scales has significant implications for drought management such as early warning system. Thus far, few drought studies have been conducted on drought management using the historic time series of hydro-meteorological variables at a local level (e.g. zones or basins) in Ethiopia(Legesse & Suryabhagavan, 2014; Bayissa et al., 2017; Edossa et al., 2010;Gebrehiwot et al.,2011; Mohammed et al., 2017;Mekonen et al., 2020). More specific studies need to be conducted to better describe and characterize drought and to associate its characteristics with temporal and spatial variability of rainfall at a local level (e.g. at sub basin level).

In Ethiopia in general and study area in particular the livelihood of community is mainly depends on rain feed agriculture; however drought and crop failure are the common problem in which agriculture provides minimum food requirement for rapidly growing population. To reduce its possible consequences it is important to identify the extent of the areas prone to severe drought conditions and its frequency yet there is limited scientific study conducted on these issues. In recent years, GIS and remote sensing data which consistently available, cost-effective and can be used to detect the onset of drought, its duration and magnitude has been used to monitor drought conditions of an area. Thus the objective of this study was to assess agricultural and metrological drought by using GIS and remote sensing techniques.

Materials And Methods

Description of study area

This study was conducted in Waghimra Zone Easter part of Amhara National Regional state, Ethiopia. It is located 435 km far from Bahir Dar, and 720 Km from Addis Ababa. Geographically Waghimra Zone is located between 12°15´and 13°16´ N latitude and 38°20´and39°17´ E longitude (Fig.1). The most common features of the zone is its rugged topography characterized by mountains, steep escarpments and deeply incised valleys(Tadesse, 2015). It has a mean annual rainfall of 150 to 700 mm in which the highest rainfall occur during summer season which starts in mid-June and ends in early September. The rainfall pattern in the area is relatively erratic and unpredictable.

Data Source and methods of data collection

For this study an expedited MODIS (eMODIS) NDVI Terra image at 250m spatial resolution were used to monitor vegetation condition. Since this study aims to assess agricultural drought only data for crop growing season months from June to September for the 17 years period (2000 to 2016) were downloaded from (https://earthexplorer.usgs.gov website). Enhanced/expedited/expandable MODIS (eMODIS) data provides separate Geostationary Earth Orbit Tagged Image File Format (GeoTIFF) for each product in a 10 day interval, allowing the users to download only the files they need. For example, the eMODIS NDVI imagery for the month of June 2015 includes NDVI data from June 1st-10th, 6th- 15th, 11th-

20th, 16th-25th, 21st-30th, and 26th-July 5th (Zhumanova et al., 2018). In this study 21st to 30th day interval of eMODIS NDVI imagery were taken for analysis purpose for the growing season of crops.

Monthly rainfall data recorded for 17 years were collected from Ethiopia national metrological service agency. Rainfall data was used to analyze relation between NDVI with variability of rainfall to drive standard precipitation index (SPI). In addition seasonal rainfall map was prepared from latitude/longitude files of those stations (Table 1 and Figure 2). To validate rainfall and satellite derived indices agricultural production yield data was collected from Waghimra Zone Agricultural office from the period 2000 to 2016.

Table 1. List of weather stations and their geographic coordinate

No	Station Name	Easting	Northing
1	Tsiketema	38.80	12.78
2	Amdework	38.71	12.43
3	Asketema	39.02	12.41
4	Chilla	38.84	12.41
5	Kewazba	38.92	12.48
6	Lugmura	39.16	12.40
7	Sekota	39.03	12.63
8	Yechila	38.99	13.28
9	Tekeza Hydro power	38.77	13.36
10	Wedisemro	39.34	12.76
11	Lalibela	39.04	12.04
12	Guhala	38.05	12.24
13	Chenek/Semen terra	38.18	13.27
14	Kobbo	39.63	12.33

Data processing and analysis

One weekly or 10 day's composite eMODIS data sets include NDVI, quality, acquisition image, acquisition table and metadata files. In this study, NDVI and quality data has been used to calculate NDVI metrics. Quality files have been used to get the reliability of eMODIS NDVI image product which is computed in ArcGIS 10.5 spatial analysis tool (eq 1).

$$\text{Reliable NDVI} = (\text{QC} == 0) * (\text{NDVI} > 2000) * \text{NDVI} \qquad (1)$$

Where, reliable NDVI=reliable NDVI image which have values range from 0 to 10000, QC = quality image which have values from 0 to 10 where 0 is good values and 10 is fill values, NDVI is image which have values ranges from -2000 to 10,000 where -2000 is fill values and -1999 to 10,000 is valid range. After applying scale factor (the scale factor is 0.0001) NDVI values range from-0.2 to1.0 where valid/normal valid or normal NDVI ranges from 0.0 to 0.1(Zhu et al., 2013)(eq2).

$$\text{NormalNDVI} = \text{Reliable NDVI} * 0.0001 \qquad (2)$$

Time series NDVI variation was derived from the calculation of NDVI using the eMODIS NDVI data set for the year 2000 to 2016 and also used to generate the maximum, minimum and average NDVI values of each season for the year 2000 to 2016 using ArcGIS 10.5 environment spatial analysis tool. Based on the threshold value Vegetation Condition Index and Normalized Vegetation Index anomaly was computed. To determine average value of monthly and seasonal composites of NDVI values, float (math) and cell statistics toolset of ArcGIS 10.5 were applied.

Vegetation Condition Index (VCI)

Normalize Different Vegetation Index (NDVI) has been extensively used in the past for vegetation monitoring; it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. The vegetation condition index reflects the overall effect of rainfall, soil moisture, weather and agricultural practices(Kogan, 1995).Accordingly in areas like *Waghimra* which have different ecosystems and non-homogenous topography VCI is important for one to compare the weather impact in areas with different ecological and economical resources, since the index captures rainfall dynamics better than the NDVI particularly in geographically non homogeneous areas.

The VCI has been used to estimate the climate impact on vegetation. This index is most useful during the growing season because it is a measure of vegetation vigor. When the vegetation is dormant (not in the summer season), the VCI cannot be used to measure moisture stress or drought. Anything that stresses the vegetation including insects, disease, and lack of nutrients will result in decreases in plant growth and therefore lower VCI values. Also, areas that have significant irrigation may not respond to precipitation deficiencies(Quiring & Papakryiakou, 2003). For each monthly and seasonal NDVI image, VCI will be processed from 2000 to 2016 using the ArcGIS raster calculator (eq 3).

$$\text{VCIj} = \frac{(\text{NDVIj} - \text{NDVImin}) * 100}{\text{NDVImax} - \text{NDVImin}} \qquad (3)$$

Where, NDVImax and NDVImin are calculated from the long-term record for that month, and j is the index of the current month in ArcGIS cell statistics. VCI value is being measured in percentage ranging from 1 to 100. The VCI values between 50% and 100% indicates slight or optimal/normal conditions whereas VCI values close to zero percent reflects an extreme dry season (Thenkabail et al., 2004)(Thenkabail, 2004).The VCI was reclassified into five clusters (Table 2).

Table 2. Classification of VCI values in terms of drought

VCI value (%)	category
0 to 20	very severe drought
21 to 35	severe drought
36 to 50	moderate drought
51 to 60	slight drought
61 and above	optimum/normal

Standardized Precipitation Index (SPI)

Standard Precipitation Index, developed by Mckee *et al.* (1993) is the most widely used index for calibrating the magnitude and duration of drought events. In this study the SPI values at two time-scales, (three months SPI-3) was computed. Seasonal rainfall data have been used as an input to compute the SPI for the periods 2000 – 2016. Spatial distribution of metrological drought was prepared from latitude/longitude files of those stations (Table 1 and Fig.2).

The software which automatically calculates SPI value by using observed monthly rainfall data to detect historical drought at 1, 3, 6, 9, 12, 36 and 48 months' time scale. It is freely available at (https://drought.unl.edu/droughtmonitoring/SPI/SPIProgram.aspx) website.

Mathematically SPI is calculated based on following empirical formula (eq4)

$$SPI = \{(Xij - Xim) / \sigma\} \qquad (4)$$

Where, (*Xij=* is the seasonal precipitation and, *Xim* is its long-term seasonal mean and σ is its standard deviation). SPI results computed from seasonal rainfall data were assigned to each grid cell of the study area and reclassified based on drought severity classes (Table 3).SPI values of metrological stations have been spatially interpolated using inverse distance weight of ArcGIS spatial analysis tool box to create drought severity map of study area at multiple time scale.

Table 3.metrological drought risks classification using SPI value (McKee etal, 1993)

SPI values	Drought category
<−2.00 and less	Extreme drought
−1.50 to −1.99	Severe drought
−1.00 to −1.49	Moderate drought
0 to −0.99 Near	Normal or mild drought
Above 0	No drought

Drought frequency analysis

In this study the seasonal frequency maps derived from agricultural and metrological drought indices were reclassified into common scale based on the frequency of drought occurrence. To generate drought frequency map, each drought indices have been reclassified in to binary images for each of the drought severity class. Those maps are added to obtain the frequency of slight, moderate, severe and very severe drought occurrence at each pixel level for both agricultural and metrological drought. The resultant severity maps were then added to get agricultural and metrological drought risk maps. The probability of drought occurrence in a given area can be classified into high, moderate and low drought probability zones when drought occurs in more than 50 %, 30 to 50 %and less than 30 %of the years, respectively (Lemma ,1996). Based on these criteria, the frequency maps of each drought classes are reclassified into five classes based on the frequency of drought occurrence in study periods: 0-2 classified as no drought; 3-4 as slight drought; 5-8 as moderate drought; 9-13 as severe drought; 13-16 as very severe drought. Finally, maps from agricultural and meteorological drought frequency maps were weighted according to the percentage of influence, and then combined using weighted overly analysis (Fig 3).

Results And Discussions

Relationship between Seasonal Rainfall and Normalized Vegetation Index (NDVI)

The results of rainfall and vegetation condition revealed that there is a good correlation (r=0.71) between rainfall and NDVI (Fig 4). This indicates that it is possible to generalize that in all the 17 years 51% of NDVI variability can be explained by seasonal rainfall. Highly rainfall dependent country‘s like Ethiopia the amount and distribution of rainfall during cropping season are more critical and determinates (Tesfaye & Walker, 2004). From the period 2000 to 2016 the highest NDVI was observed when seasonal rainfall was in better distribution (Fig. 5).

While, lower NDVI was observed when amount and distribution of rainfall was minimum. According to the result the year 2009 and 2015 were considered as drought year in which minimum NDVI was observed and rainfall was registered. While, in the years 2001 and 2007 maximum rainfall and NDVI was observed and considered as wet year (Fig 5).

Vegetation Condition Index (VCI) and Agricultural Drought

In this study Vegetation Condition Index (VCI) which was derived from NDVI was computed from 2000 to 2016 to analyze severity of agricultural drought. According to Kogan (1995) report VCI is better indicator of water stress condition than NDVI. In this study majority of the area where influenced by drought during drought year of 2009 and 2015. Drought year of 2015 majority of the area were stricken by very severe drought (Table 4). While, Southern part of study area were not influenced by agricultural drought in 2015 as expressed by VCI, whereas other parts of study area were hit by very severe to slight drought(Fig. 6). This indicated that areas which are low in altitude were sensitive to agricultural drought. Vegetation Condition Index (VCI) below 35% can be identified as sever and very severe drought condition(Felix N. Kogan, 1997), which is found in poor vegetation condition. The results of this study also reveal majority of study area were found under poor vegetation condition during cropping season of those drought years. Generally VCI confirm that in the year 2009 and 2015 almost all part of the study area were affected by agricultural drought condition.

Similarly vegetation condition indexes (VCI) for wet years were computed. As shown drought map (Fig. 7) majority of study area were not under influence of drought in both 2001 and 2007. The value of VCI was above 50% in most of study area. This indicates the value of VCI was above the average indicting good condition of vegetation during cropping season of those years. This means that there is no vegetation stress due to water shortage. During 2001 cropping season the percentage area which were not hit by agricultural drought accounts to 83% whereas in the year 2007, 79% of the total areas were free from drought. However, Very small areas were hit by very severe to slight drought during cropping season of 2001 and 2007 (Table 4) and (Fig. 7).

Table 4. Agricultural drought severity for drought year 2009 and 2015 and wet year 2001 and 2007

No	class	Drought year		Wet year	
		2009	2015	2001	2007
		Area (%)	Area (%)	Area (%)	Area (%)
1	Very severe drought	32.2	45.6	1.1	3.8
2	Severe drought	28.3	17.4	2.2	4.1
3	Moderate drought	23.5	14.7	6.0	7.2
4	Slight drought	9.23	7.38	7.5	6.2
5	Optimal/normal drought	6.86	15	83	79
	Total	100	100	100	100

Relation between VCI and Crop Yield Anomaly

To validate the reliability of satellite based agricultural drought indices crop yield data was taken as a ground truth data. The correlation between VCI and crop yield anomaly was positive and it revalued that

there is good relation between two variables with r=0.72(Fig. 8). This indicates 52% of yield variability can be explained by using vegetation condition index. As vegetation condition index increase crop yield can also increase and vise-versa. This implies higher crop yield reduction was observed in year 2009 and 2015 when the value of VCI was lowest. While, highest yield were found in year 2007 and 2001 when the value of VCI was higher. Thus, this study verifies that VCI can explain existence of agricultural drought in a good and reliable manner

Metrological Drought Characterization based on SPI

The computed SPI value for 3 months time scale during summer season revealed that occurrence of negative SPI or drought were observed in the year 2003, 2004, 2005, 2008, 2009, 2011, 2014 and 2015 while in other years positive SPI value was observed in study period (Fig. 9). Negative SPI values indicated that the rainfall of the area is less than median rainfall and positive indicate that the rainfall is greater than median rainfall. Every positive SPI value indicates greater than the mean precipitation is wet region and every negative value less than the median across the normal distribution are drier regions(McKee et al., 1993). This finding is coinciding with UNOCHA (2015) and FAO (2014) reports as year 2008 documented droughts of Ethiopia which were all strong ElNino years. This indicated that entire study area is considered as metrological drought prone. However, the lowest SPI value was observed in 2009 next to 2015 which were considered drought year while the highest SPI was observed in 2007 next to 2001 which were considered as wet year using vegetation indices. This is an agreement with results found through analysis of satellite data through NDVI index and rainfall data from metrological stations found in and around study areas.

This study examined spatial pattern of metrological drought across the study area using time series (2000 to 2016) SPI value. The analysis of SPI revealed that drought has been occurred at different level of severity across study area during the main cropping season. Standard Precipitation Index (SPI) during selected drought years of 2009 and 2015 and wet years of 2001 and 2007 have been presented to show the spatial pattern of SPI during these years. Drought occurred on large spatial extent mainly on summer season of year 2015 and 2009. It can be seen that during the drought year of 2009 and 2015 SPI value was lowest. This indicates that there has been low rainfall in study area during those years. Majority of the area (99.5%) were stricken by very sever and severe drought in year 2015 (Table 5).In agreement with this finding Mekonen et al. (2020) reported that the year 2015 were the driest year recorded in *Kirmet* season in north east highland of Ethiopia. Spatial and temporal severity map showed that Eastern part of the study area was highly strike by very severe drought relative to western part which was strike by severe drought. The worst drought of 2015 -2016 in northern and central part of Ethiopia because of *belg* rains had failed and soon after *Kiremt* rains were severely delayed, erratic and below the long term average (deficit of 167mm)(Jiemba et al., 2017).While, in year the 2009 majority of the study area (66%) were strike by moderate drought. Northern part of study area was affected by slight drought (Fig. 10). This indicted that there was low rainfall distribution during the main crop growing season. Therefore, those years were seen as the worst dry season in study period.

Table 5. Metrological drought during 2009 and 2015 as expressed by SPI

No	class	Drought year	
		2009	2015
		Area (%)	Area (%)
1	Very severe drought	0.2	45
2	Severe drought	24.5	54.5
3	Moderate drought	66	0.5
4	Slight drought	9.3	-

According to analysis spatial pattern of SPI were used to identify wet years. In this regard 2001 and 2007 were identified as wet year in the study area. The highest SPI value which is above zero was observed in those years (Fig 9). This indicts that there is good distribution of seasonal rainfall. All areas were not under the influence of drought. This implies growing season of 2001 and 2007 were not characterized by water deficit and can be considered as good agricultural time (Fig.11).

Standard precipitation index (SPI) and Crop Yield Anomaly

To validate this correlation analysis between SPI and crop yield anomaly was conducted. As shown in (Fig.12) there is a positive correlation between two variables with r= 0.74. This implies 55% of crop yield can be explained by SPI. Thus an overall analysis of this can be summed that SPI can be used as an indicator of metrological drought assessment.

Frequency of drought risk map

Frequency of metrological and agricultural drought was compiled by using historical drought intensity map. The result shows that there is complex spatial variation in frequency of drought events in the study area. North part of the study area were frequently affected by very sever agricultural drought (Fig.13). While southern and central part of the study area were frequently affected by slight to sever agricultural drought condition. This implies that in the study area short return period of agricultural drought was recorded. As shown in (Fig.15) a combined frequency of agricultural drought almost all areas were highly vulnerable to frequent agricultural drought. Of the total recorded drought years (1953-2016) in Ethiopia, northern part of the country experienced about 72% of drought events (Little et al. 2006).

Frequency of metrological drought occurrence resulted in severe drought was occurred in one year which affect southwestern and north western part of the study area. Ethiopia is often stricken by drought in the 1970s and 1980s which resulted in widespread of poverty, economic, stagnation, depletion of household assets, saving and excess mortality (Dorosh and Rashid 2013).Metrological drought is the main driver leading to the more likely occurrence of agricultural drought. Areas where there is low vegetation cover

were prone to agricultural and metrological drought (Fig 15). This indicates that there is no year without drought in many parts of study area.

Combined drought risk map

The final drought risk map was prepared by overlaying agricultural and metrological drought maps. The weighed was given according to their degree of influence in pairwise comparison in which 55 % was given for agricultural drought. The results reveal that majority of the study area were vulnerable with severe drought which covers around 56% of total geographical area which is dominated in northern part of the study area. In addition central parts of the study area were vulnerable to moderate drought which covers 35% of total geographical area. While, small portion of the study area were affected by slight and very severe drought which encompass 0.4 and 8.3% of the study area respectively (Fig16).

As confirmed from informal interviews of zonal agricultural experts Waghimra Zone is known for prolong and recurring drought features, this study also agree with this fact that the area experienced successive drought events during the last 17 years.

Table 6.Area under drought severity class

Drought severity class	Area (%)
Slight	0.4
Moderate	35
Severe	56
Very severe	8.3
Total	100

Conclusions

The present study revealed that drought can be delineated by remote sensing indices like vegetation condition index derived from vegetation data and standard precipitation index derived from monthly rainfall data. This study concluded that spatial and temporal variation of NDVI is closely linked with precipitation data and there is strong relation during crop growing period. In addition good correlation was observed between VCI and crop yield anomaly, SPI and crop yield anomaly. The result reveals that from the year 2000 to 2016 *Waghimra* zone experiences sever and slightly severe drought. The Year 2009 has been found to be the year of the worst drought next to 2015 while in the year 2001 and 2007 the area were wet year which shows good crop yield. In Waghimra zone there is spatial variation in frequency of drought events. According to the result, northern part of the study area were frequently affected by very sever agricultural drought while southern and central part of the study area were affected by sever to slight drought condition. Combined drought risk map showed that 8%, 56%, 35% and 8% of study area were vulnerable to very severe, severe and moderate drought condition respectively. This revealed that

study area is frequently vulnerable to agricultural and metrological drought. Therefore, using geospatial data to assess agricultural drought is a paramount importance in order to assess past and current drought condition which generate baseline information that helps to monitor real time situation in the future for different adaptation options within relatively large geographical area coverage and repetitively time scale.

List Of Abbreviations

AVHRR Advanced Very High Resolution Radiometer

AWC Available Water Content

CMI Crop Moisture Index

CSA Central Statistics Agency

eMODIS Enhanced/expedited/expandable MODIS data

ENVI Environment for Visualizing Image

ERDAS Earth Resource Data Analysis System

EROS Earth Resource Observation and Science

GIS Geographic Information System

GPS Global Positioning System

IDW Inverse Distance Weight

LULC Land Use Land Cover

MODIS Moderate Resolution Imaging Spectro radiometrer

NDVI Normalized Difference Vegetation Index

NGO Non-Governmental Organization

NIR Near Infrared band,

SPEI Standard Precipitation and Evapotranspiration Index

SPI Standard Precipitation Index

SWSI Surface Water Supply Index

TCI Temperature Condition Index

UNISDR United Nations Secretariat of the International Strategy for Disaster Reduction

UNOCHA United Nations Office for The Coordination Of Humanitarian Affairs

USGS United States Geological Survey

UTM Universal Transverse Mercator

VCI Vegetation Condition Index

VHI Vegetation Health Index

WGS World Geodetic System

WZLFRD Waghimra Zone Livestock and Fisheries Resource Department

Declarations

Authors' contributions: The research idea was conceived by **AS**. He actively participated in the design of the study, carried out the data collection, and undertook the GIS and Remote sensing-based data analysis. More importantly, he conducted the full write-up of the research report and organized the manuscript for publication. **SA** read, edit and approve the manuscript for publication.

Availability of data and materials

The dataset and material used during analysis area available from the first author on reasonable request.

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Competing interest

Authors declares that they have no competing interests

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

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References

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*. https://doi.org/10.3390/rs9070669
2. Edossa, D. C., Babel, M. S., & Gupta, A. Das. (2010). Drought analysis in the Awash River Basin, Ethiopia. *Water Resources Management*. https://doi.org/10.1007/s11269-009-9508-0
3. El Kenawy, A. M., McCabe, M. F., Vicente-Serrano, S. M., López-Moreno, J. I., & Robaa, S. M. (2016). Cambios en la frecuencia y severidad en las sequías hidrológicas de Etiopía entre 1960 y 2013. *Cuadernos de Investigacion Geografica*, *42*(1), 145–166. https://doi.org/10.18172/cig.2931
4. FAO (2014).Understanding the drought impact of El Niño on the global agricultural areas: an assessment using FAO's Agricultural Stress Index (ASI), ISBN 978-92-5-108671-1.
5. Gebrehiwot, T., van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*. https://doi.org/10.1016/j.jag.2010.12.002
6. Jiemba E, Singh R, Arrighi J. (2017) Extreme drought in Ethiopia stretches drought management systems
7. Kogan, F. N. (1995). Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. *Bulletin - American Meteorological Society*. https://doi.org/10.1175/1520-0477(1995)076<0655:DOTLIT>2.0.CO;2
8. Kogan, Felix N. (1997). Global Drought Watch from Space. *Bulletin of the American Meteorological Society*. https://doi.org/10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2
9. Legesse, G., & Suryabhagavan, K. V. (2014). *Remote sensing and GIS based agricultural drought assessment in East Shewa Remote sensing and GIS based agricultural drought assessment in East Shewa Zone , Ethiopia*. *April*.
10. Lemma, G.(1996).Climate classification of Ethiopia. Metrological research report series. National metrological services agency of Ethiopia Addis Ababa
11. McKee, T. B., Nolan, J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Preprints, Eighth Conf. on Applied Climatology, Amer. Meteor, Soc.*
12. Mekonen, A. A., Berlie, A. B., & Ferede, M. B. (2020). Spatial and temporal drought incidence analysis in the northeastern highlands of Ethiopia. *Geoenvironmental Disasters*, *7*(1). https://doi.org/10.1186/s40677-020-0146-4
13. *Project on Air Pollution in the context of Ethiopia based on Kaizen philosophy Forwarded Message ––– Berhanu Tadesse Taye*. (2015). *December 2012*, 1–51.
14. Quiring, S. M., & Papakryiakou, T. N. (2003). An evaluation of agricultural drought indices for the Canadian prairies. *Agricultural and Forest Meteorology*. https://doi.org/10.1016/S0168-1923(03)00072-8

15. Rojas, O., Vrieling, A., & Rembold, F. (2011). Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote Sensing of Environment*. https://doi.org/10.1016/j.rse.2010.09.006
16. Tadesse, T., Demisse, G. B., Zaitchik, B., & Dinku, T. (2014). Satellite-based hybrid drought monitoring tool for prediction of vegetation condition in Eastern Africa: A case study for Ethiopia. *Water Resources Research*. https://doi.org/10.1002/2013WR014281
17. Tesfaye, K., & Walker, S. (2004). Matching of crop and environment for optimal water use: The case of Ethiopia. *Physics and Chemistry of the Earth*. https://doi.org/10.1016/j.pce.2004.09.024
18. Thenkabail, P. S., Gamage, M. S. D. N., & Smakhtin, V. U. (2004). The use of remote sensing data for drought assessment and monitoring in southwest Asia. In *IWMI Research Report 085*. https://doi.org/10.3910/2009.086
19. United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) (2015). El Niño: Snapshot of Impact and Projected Humanitarian Needs.
20. Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J. J., López-Moreno, J. I., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., & Sanchez-Lorenzo, A. (2012). Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interactions*. https://doi.org/10.1175/2012EI000434.1
21. Viste, E., Korecha, D., & Sorteberg, A. (2013). Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology*. https://doi.org/10.1007/s00704-012-0746-3
22. Zhu, J., Miller, A. E., Lindsay, C., Broderson, D., Heinrichs, T., & Martyn, P. (2013). *Modis Ndvi Products and Metrics*.
23. Zhumanova, M., Mönnig, C., Hergarten, C., Darr, D., & Wrage-Mönnig, N. (2018). Assessment of vegetation degradation in mountainous pastures of the Western Tien-Shan, Kyrgyzstan, using eMODIS NDVI. *Ecological Indicators*. https://doi.org/10.1016/j.ecolind.2018.07.060

Figures

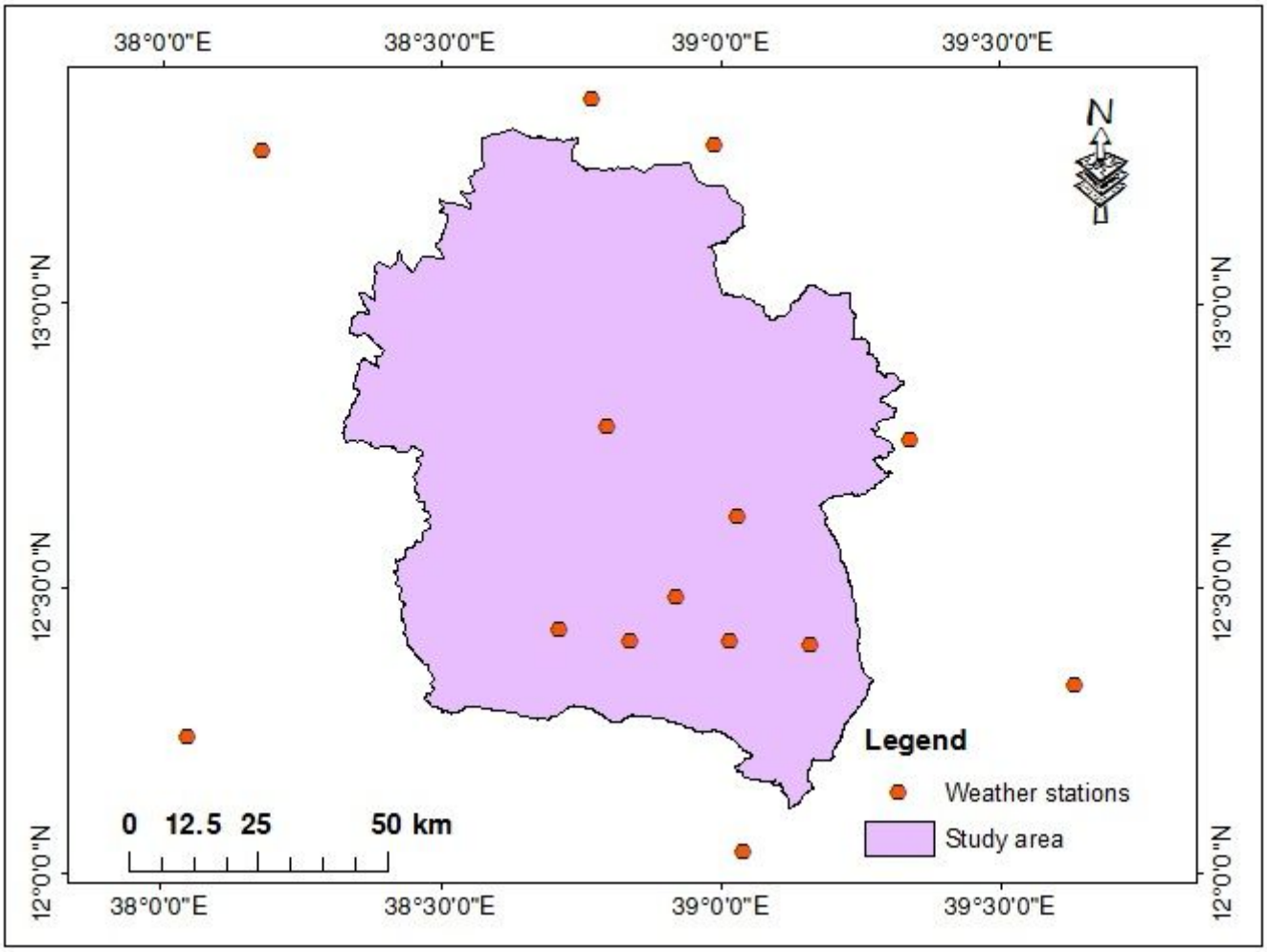

Figure 1

Location map of the study area

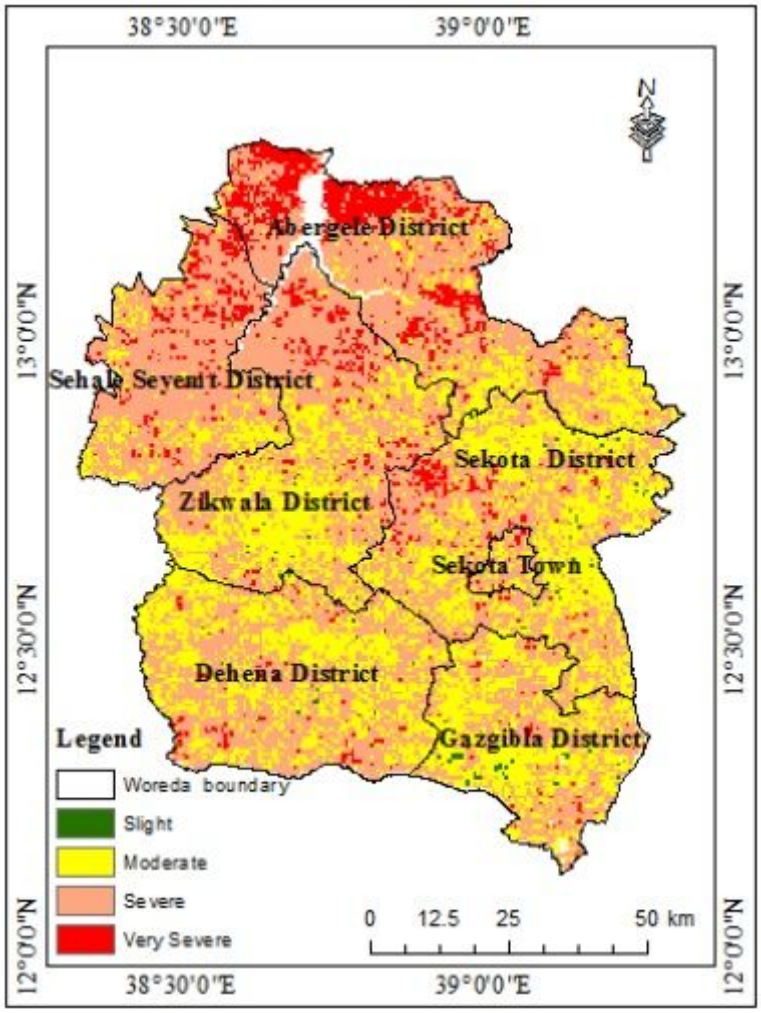

Figure 2

Location of weather station in Waghimra Zone Ethiopia

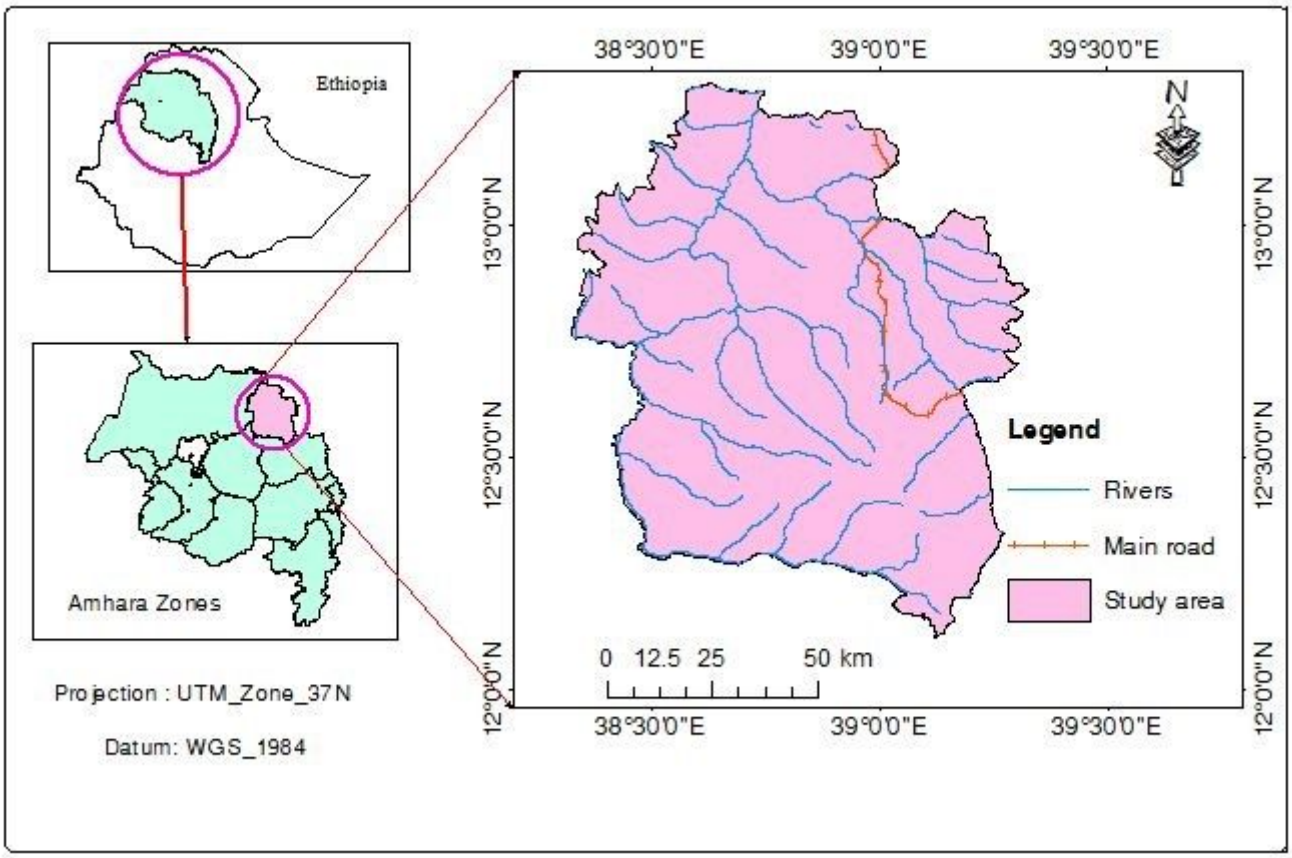

Figure 3

A schematic presentation of the methodology

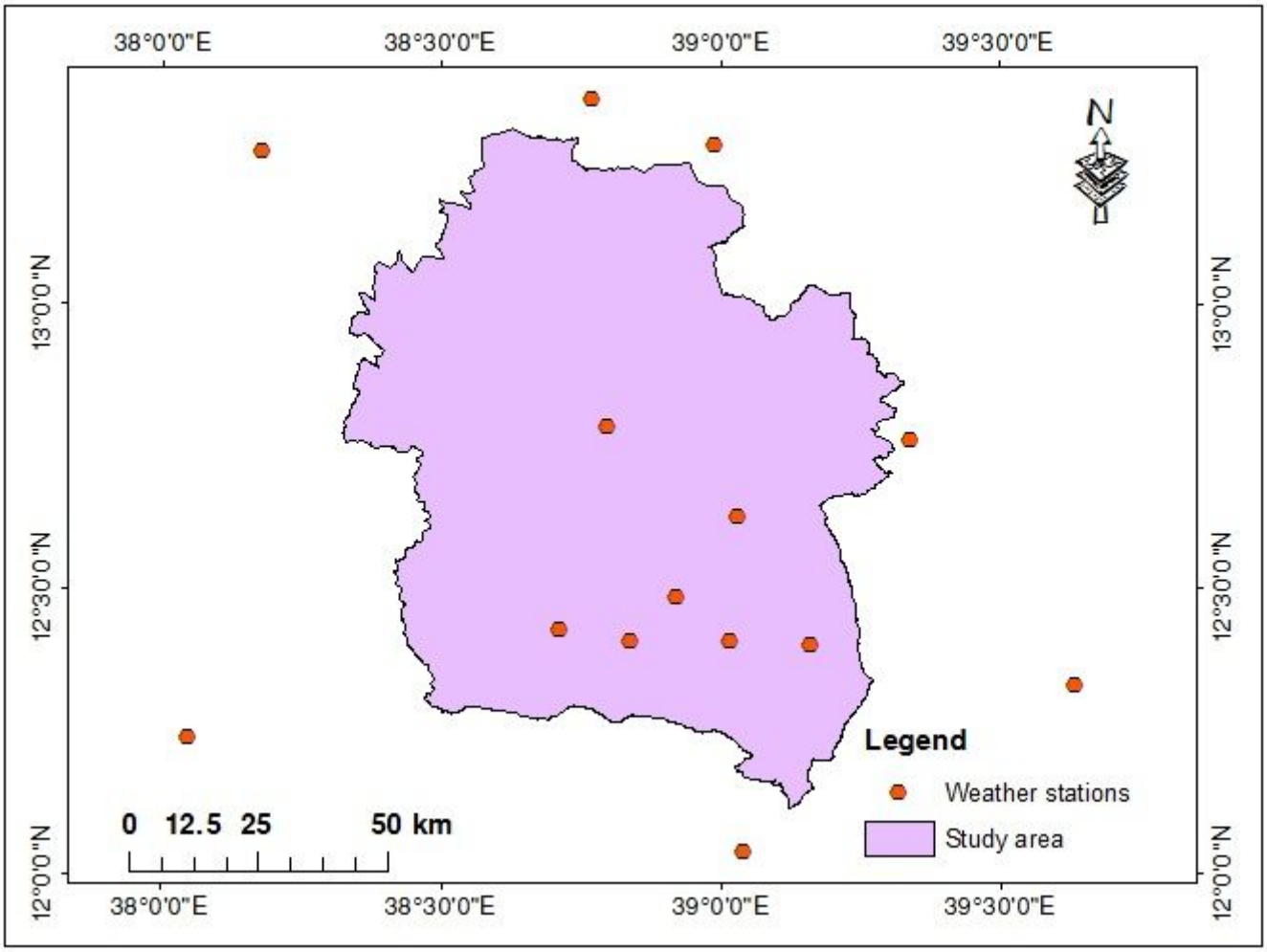

Figure 4

Seasonal (June to September) pattern of rainfall and NDVI (2000 to 2016)

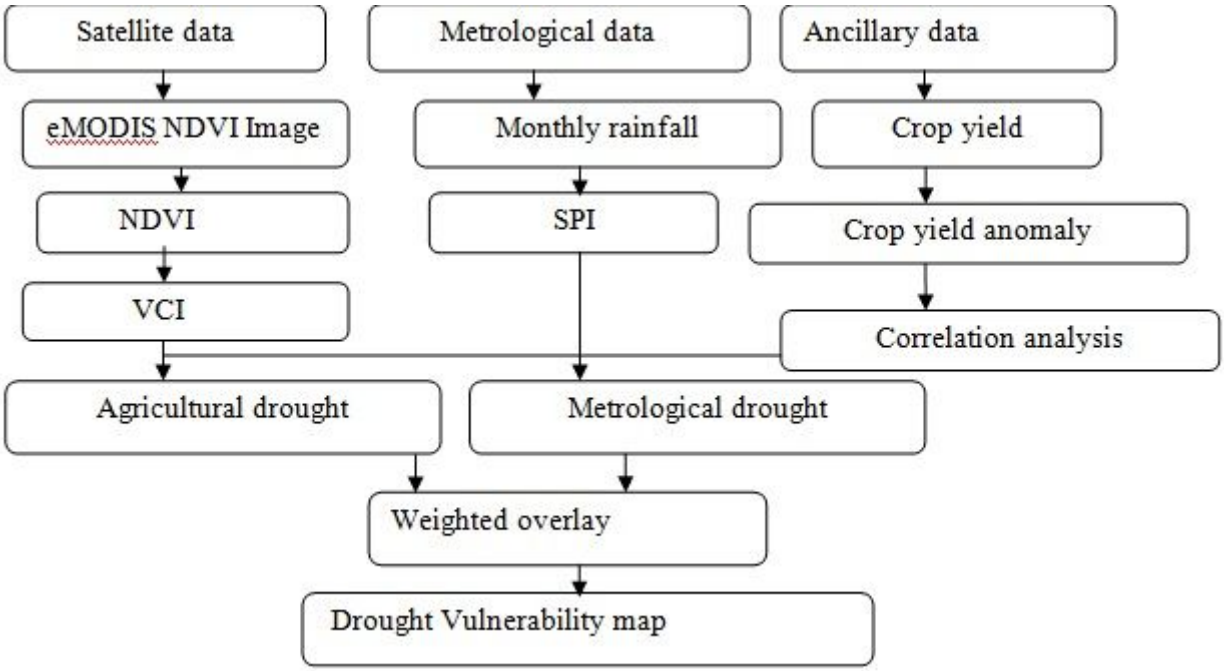

Figure 5

Temporal trend of seasonal Rainfall and NDVI (2000 to 2016)

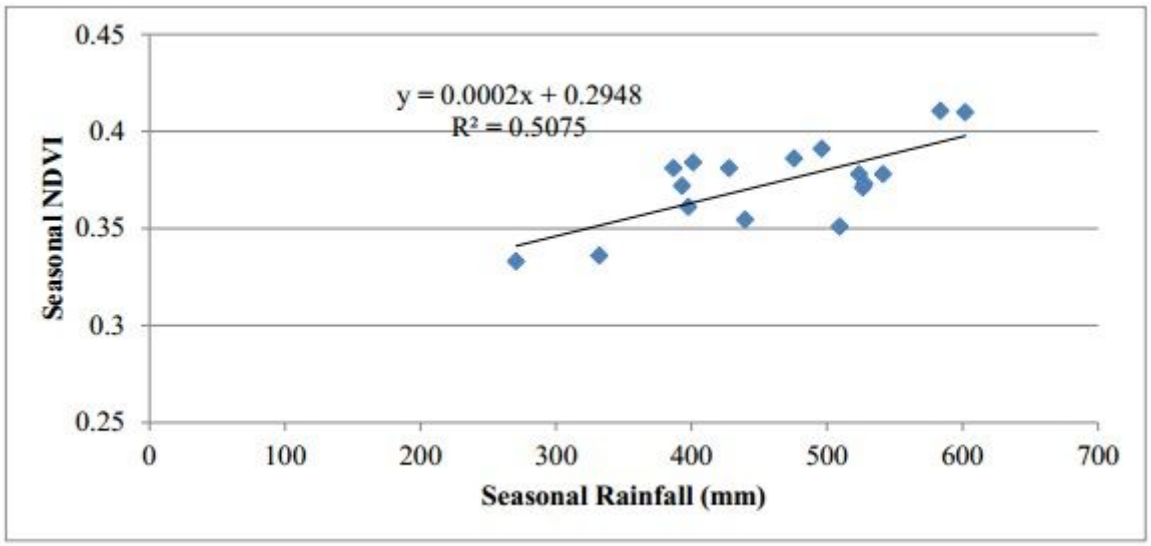

Figure 6

Spatial pattern of agricultural drought expressed by Vegetation condition index during drought year 2009 and 2015

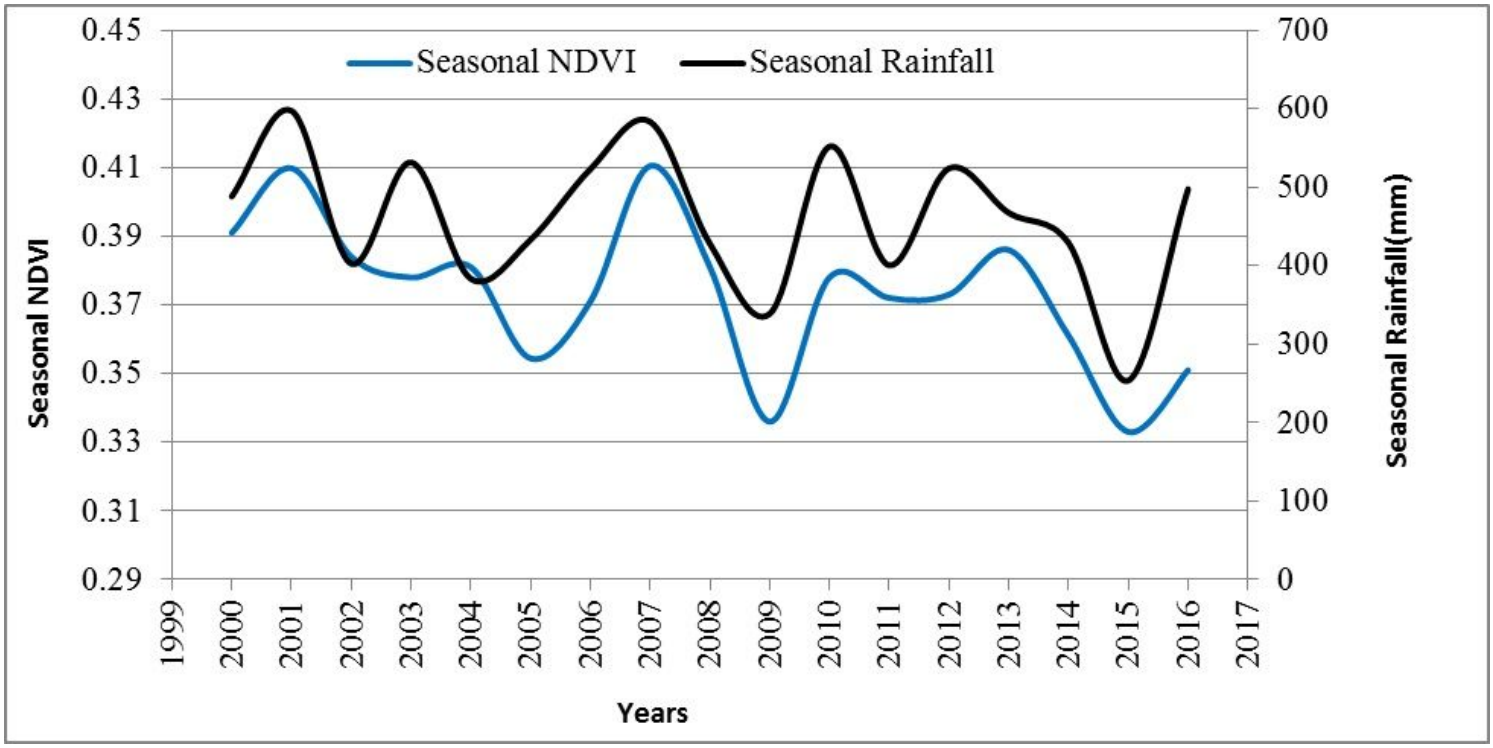

Figure 7

Spatial pattern of agricultural drought expressed as VCI during wet year 2001and 2007

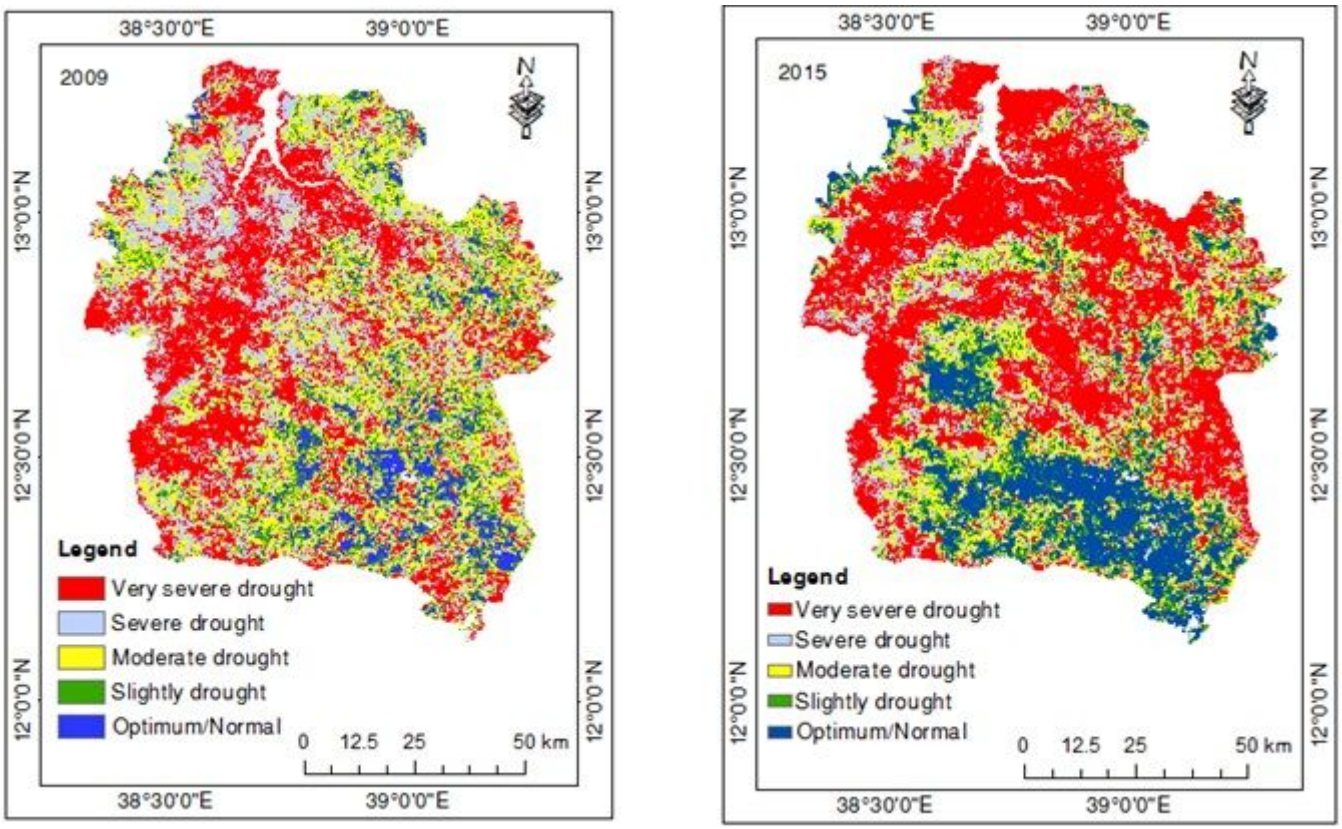

Figure 8

Relation between VCI and crop yield anomaly

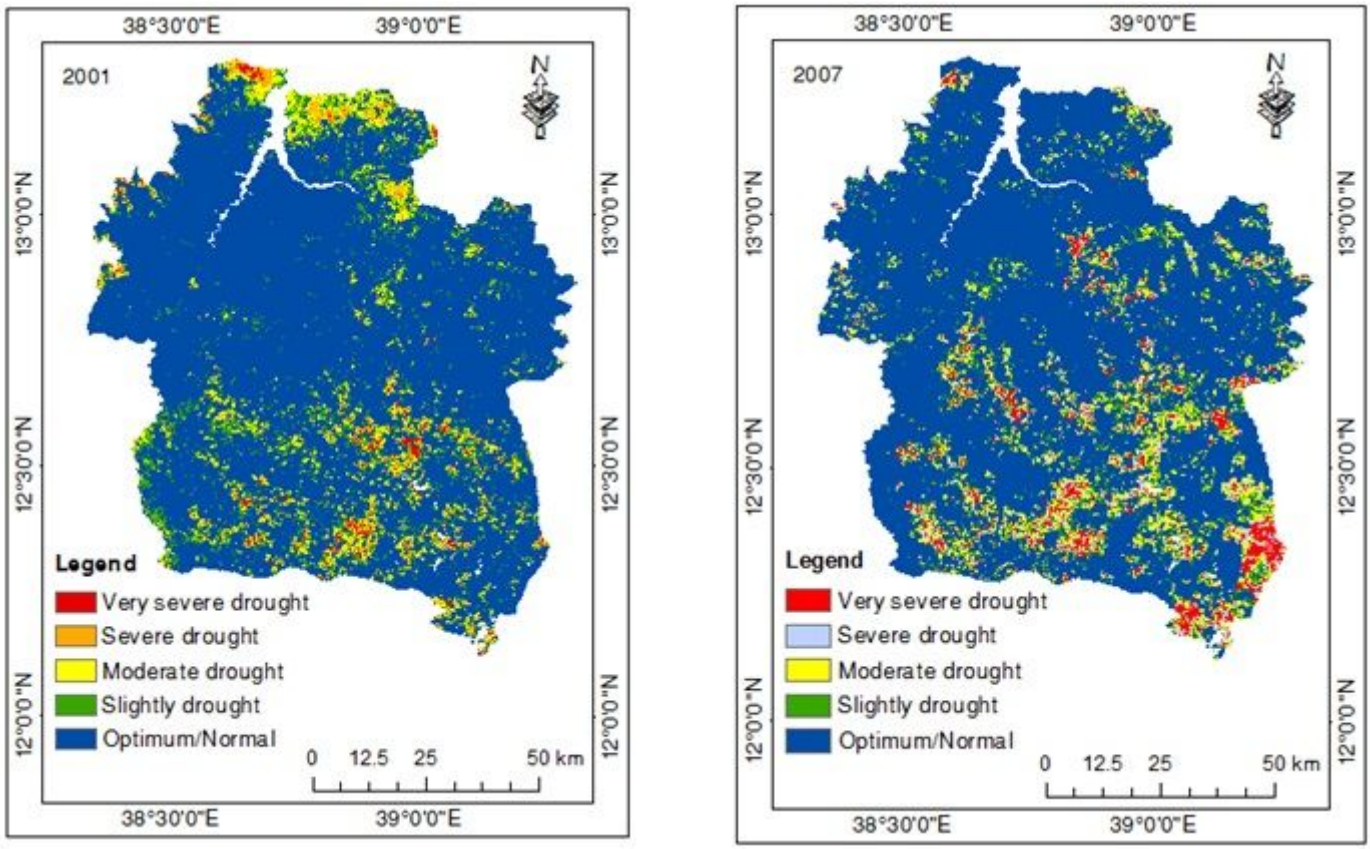

Figure 9

Temporal trend of Standard Precipitation Index (2000 to 2016)

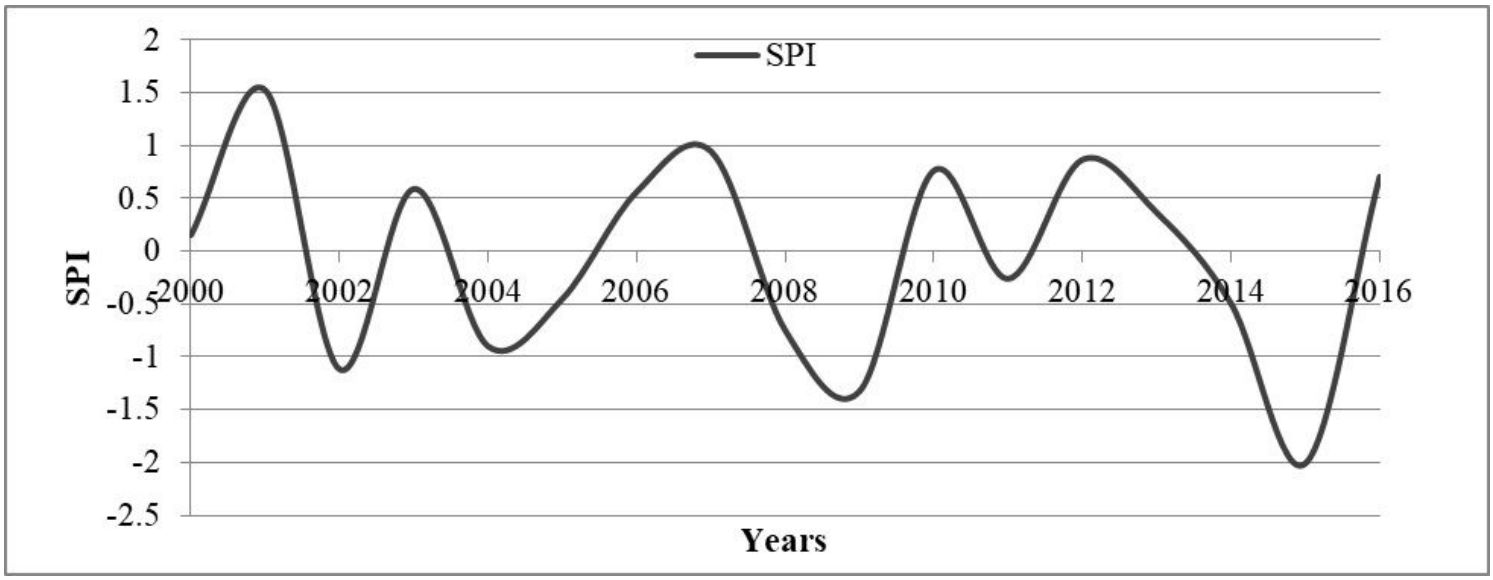

Figure 10

Standard Precipitation Index for drought year 2009 and 2015

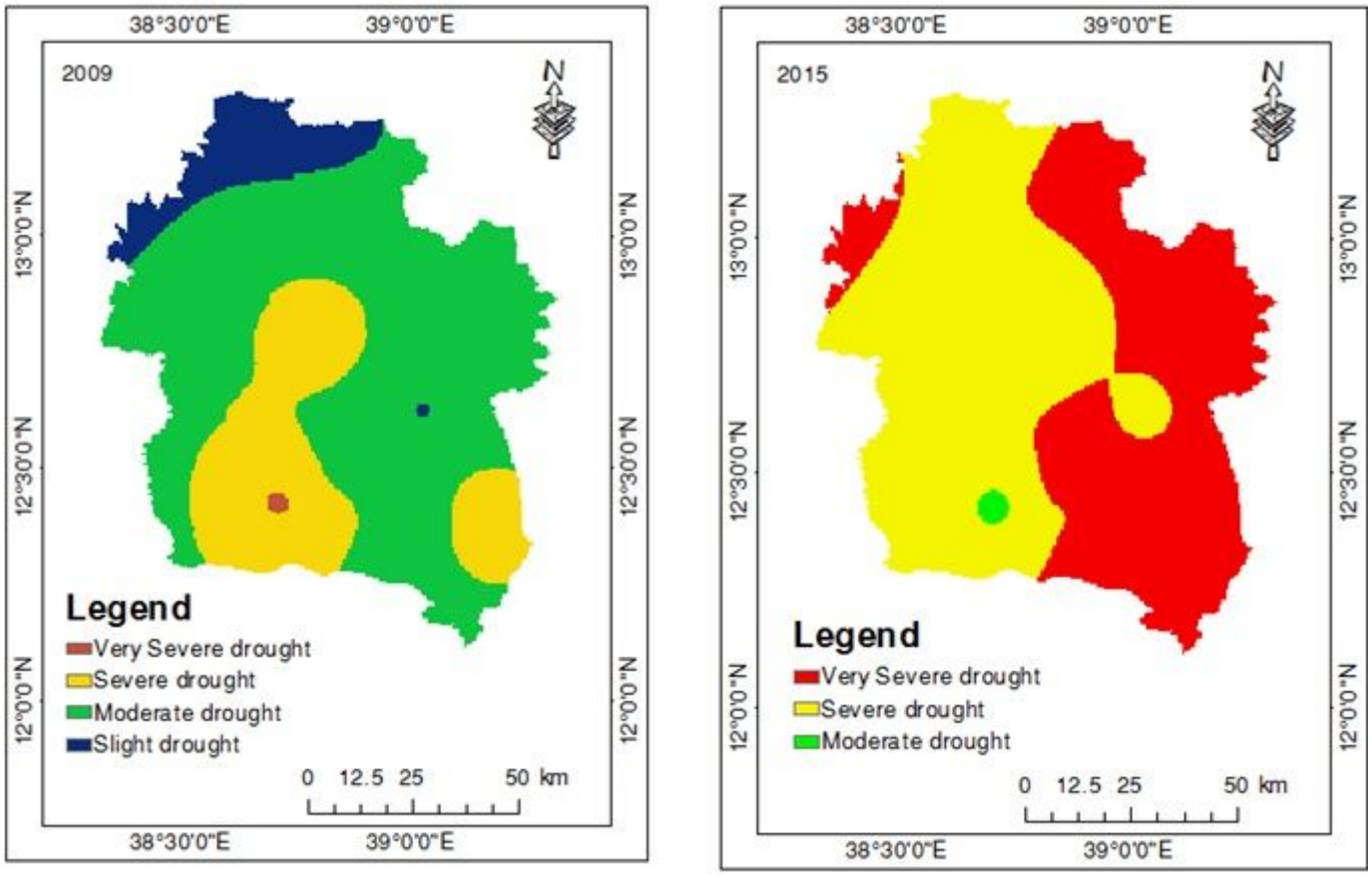

Figure 11

Standard Precipitation Index for wet year 2001and 2007

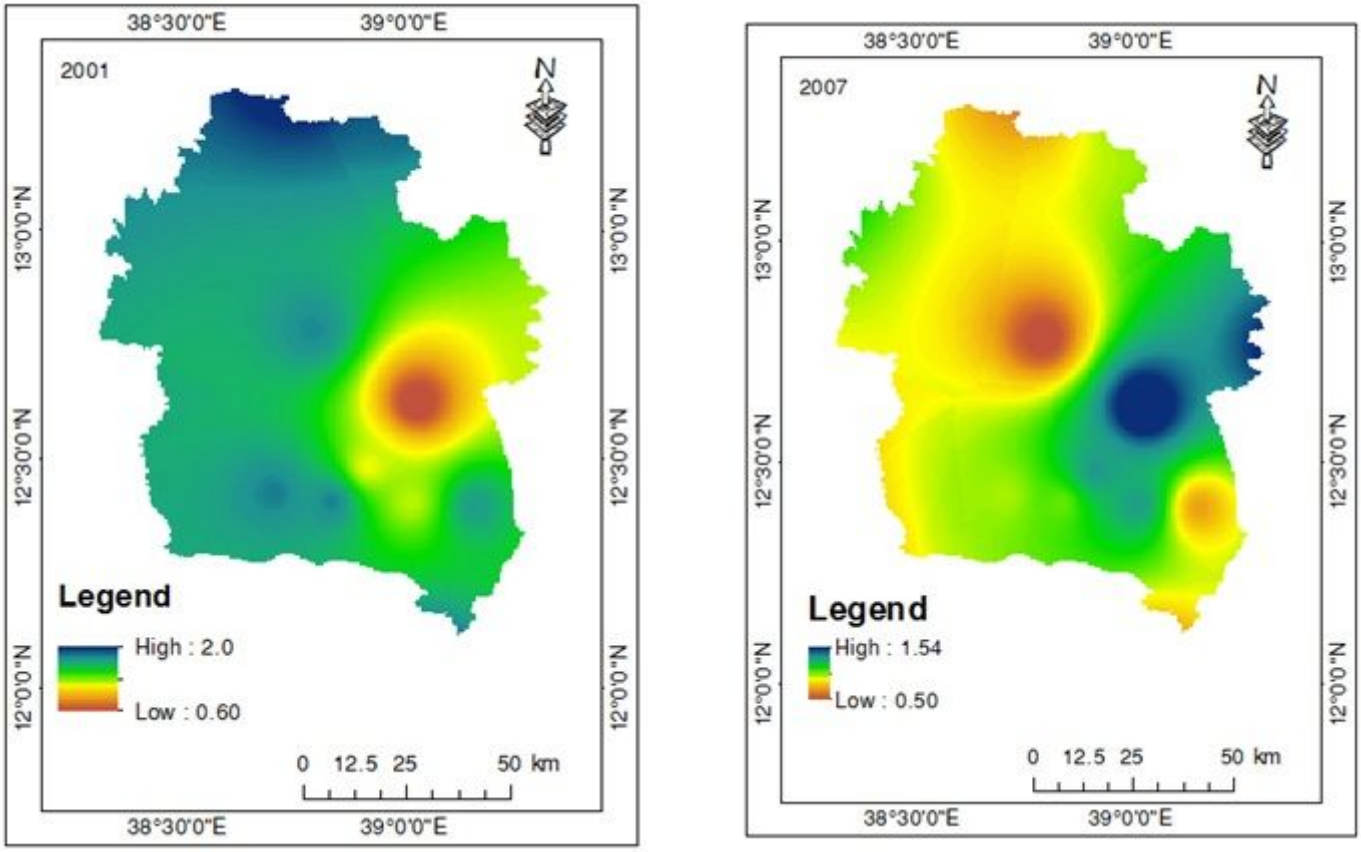

Figure 12

Relation between SPI and Crop yield anomaly

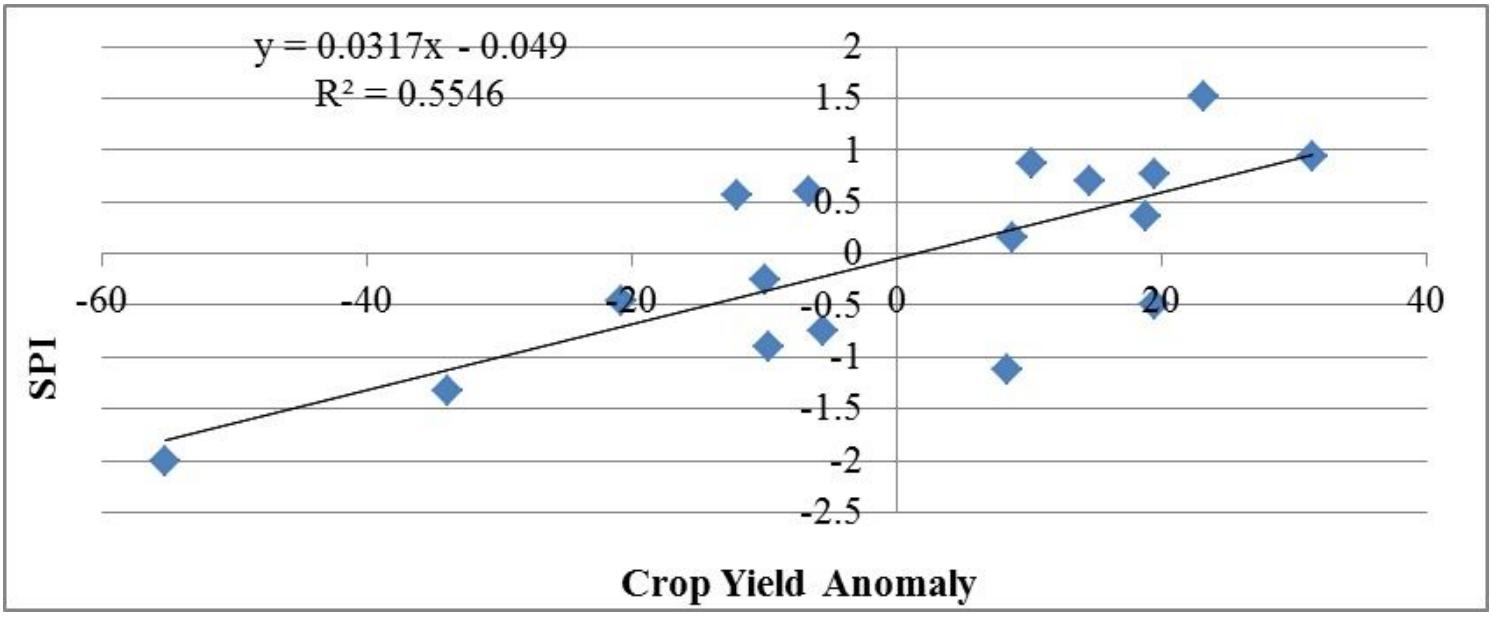

Figure 13

Frequency of Agricultural drought risk in four different severity classes: (a) very severe (b) severe (c) moderate and (d) slight

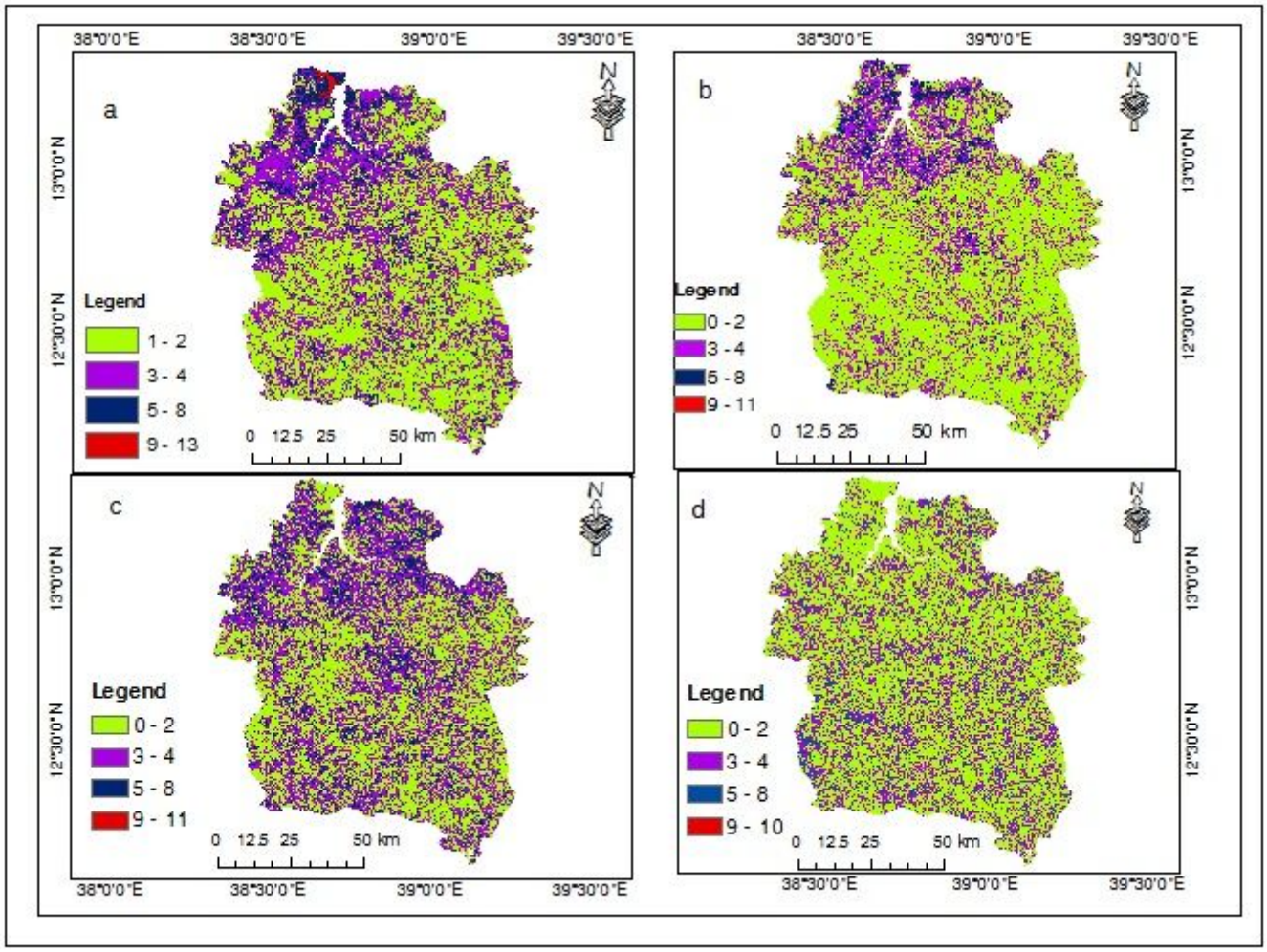

Figure 14

Frequency (year) of metrological drought risk in four different severity classes: (a) very severe (b) severe (c) moderate and (d) slight

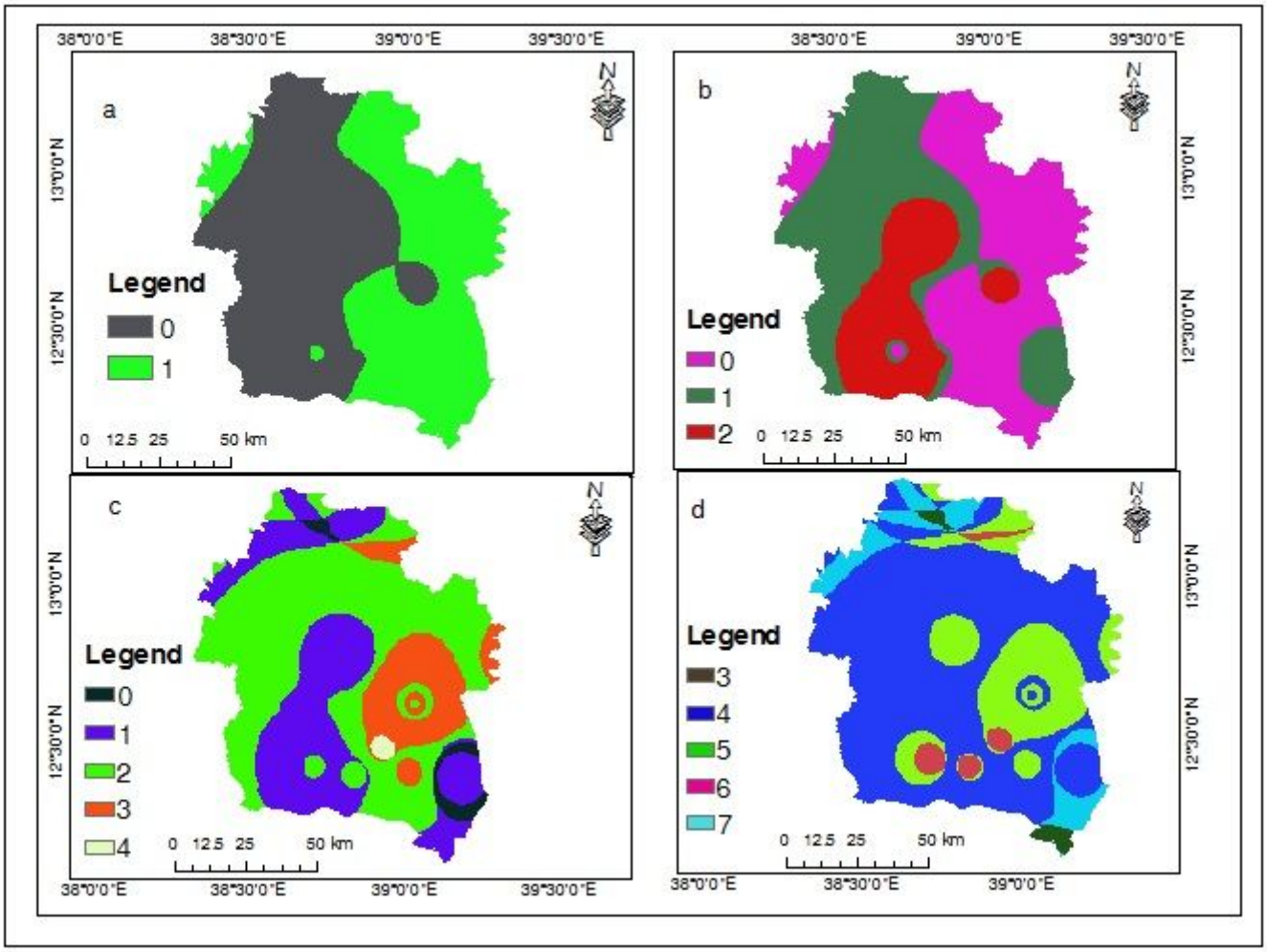

Figure 15

Frequency of agricultural (a) and metrological (b) drought risk map

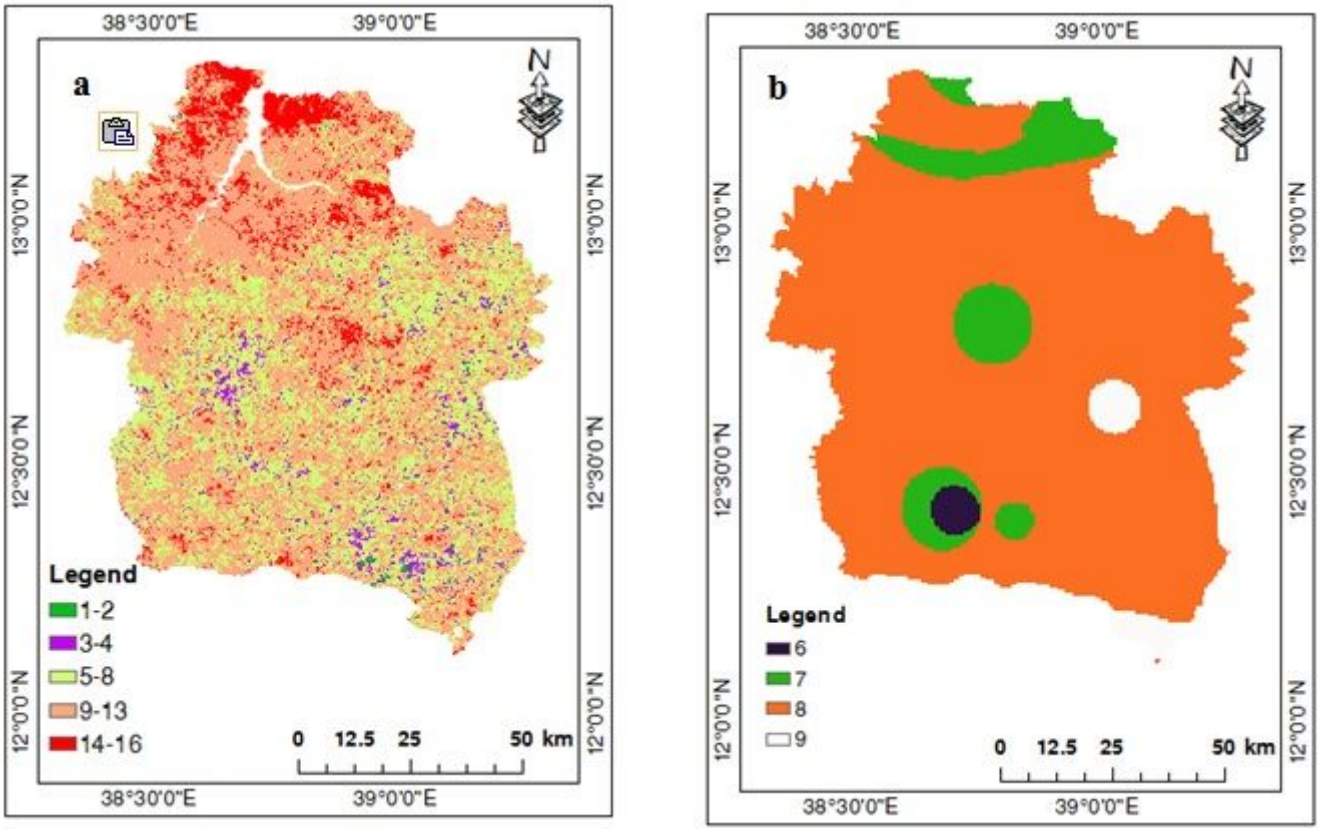

Figure 16

Combined Drought risk map of study area