Geospatial Assessment of Agricultural Drought Vulnerability Using Integrated Three-Dimensional Model In The Upper Dwarakeshwar River Basin In West Bengal, India

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Abstract

It is essential to measure the degree of agricultural drought vulnerability in an underdeveloped rain-fed agro-based economy at the local, regional, and national level. Agricultural drought has become a major concern in respect to the global food crisis for investigation and development of a sustainable agricultural system that sustains the food security of a country. In this research, delineation of the agricultural drought vulnerability (ADV) status has been carried out by multidimensional mixed-method index approach using remote sensing and geographic information system. An integrated three-dimensional model has been adopted for this study. The three indices of this model are - Exposure Index (EI), Sensitivity Index (SI) and Adaptive Capacity Index (ACI). Exposure Index has been calculated using NDDI, LULC, ADI, DF, ADD and PI. Sensitivity Index has been calculated using satellite-based remote sensing factor VHI, NDWI, EVI, NDVI, VCI, NDWI, LST, and TCI. The ACI has been formed by combining the Environmental Adaptive Capacity (EAC), Social Adaptive Capacity (SAC) and Economical Adaptive Capacity (EcAC) Index. Each index has been computed by assigning the weights based on their relative importance by using the Analytic Hierarchy process (AHP) approach. Final results were classified into five vulnerability zones, e.g., very low, low, moderate, high, and very high covering an area 362.32 km^2, 186.68 km^2, 568.69 km^2, 547.05 km^2 and 266.89 km^2 respectively. Finally, results have been validated with long term Aman paddy yield data (2004 to 2014) through the Yield Anomaly Index (YAI).

Introduction

Drought is a least known complex climatic phenomenon that affects the Earth's environment (Boken et al. 2005; Badamassi et al. 2019; Pandey et al. 2012), that impacts on the economy of people who are directly and indirectly dependents on agriculture and applied activities (Wilhite 2000; Nagarajan 2009). This crisis is gradually increasing due to climate change and global warming (Bates et al. 2008). Recently, population growth and increasing demand of water for domestic use led’s toward water shortage for agriculture all over the world (Dembele and Zwart 2016).

West Bengal (WB) is a predominantly agricultural based state of India. Almost 70% population of WB directly or indirectly depends on agriculture for their livelihood, whereas two-thirds of agricultural land is still dependent on monsoonal rainfall for cultivation (Ghosh 2019). The western parts of WB, mainly Bankura and Purulia districts are prone to this recurring drought phenomenon (Bhunia et al. 2020). So, the agriculture is the worst drought-hit sectors in this region (Palchaudhuri and Biswas 2019). The crop production is disrupted due to insufficient root zone soil moisture availability during the growing period of crops (sowing to maturity). As a result, agricultural drought is one of the serious threats to the agro-based rural economy of WB (Dutta et al. 2015).

Agricultural drought vulnerability is the significant aspects of drought management and monitoring for both short and long-term strategies (Murthy et al. 2015; Karet al. 2018). Drought vulnerability differs from one region to another region due to physio-climatic conditions (Sehgal and Dhakar 2016).

Accurate assessment of agricultural drought vulnerability can reduce the probable threat in agricultural sector. So, vulnerability assessment is essential step to increase economic development and agricultural stability in developing countries like India. There are several authorities like- National Agricultural Drought Assessment and Monitoring System (NADAMS) in collaboration with National Remote Sensing Agency (NRSC), The Mahalanobis National Crop Forecast Centre (MNCFC), Indian Meteorological Department (IMD), and agricultural department of different states are involved to monitor and assessment the drought in India. In recent times, researchers have used various methods to assessment agricultural drought vulnerability and risk delineation, like- Improved Projection Pursuit Model (Pei et al. 2016), Analytical Hierarchy Process (Ekrami et al. 2016; Rahman and Lateh 2016), combination of Analytic Hierarchy process (AHP) and fuzzy comprehensive evaluation (Wijitkosum 2018), Probabilistic Assessment Models (Ramadas and Govindaraju 2015), relationship between time series NDVI and rainfall (Murthy et al. 2010), vegetation condition index (VCI) and the standardized precipitation index (SPI) (Dutta et al. 2013; Dutta et al. 2015). Park et al. (2019) have been used random forest model based on index for drought area prediction. Apart from the aforesaid models, Weighted based (on different factors) method has been used by Kar et al. (2018), Zeng et al. (2019), Kim et al. (2018) to assess agriculture drought vulnerability. GIS-based weighted overlay method has also been used to evaluate drought in Jharkhand (Pandey et al. 2012), Ken River basin (Jain et al. 2014), and Rajasthan (Sehgal and Dhakar 2016) using bio-Ecomonic, climatic and social factors. Sensitivity, exposure, and Adaptive capacity indicators were integrated to assess the agricultural drought

vulnerability (Murthy et al. 2015a; Murthy et al. 2015b; Weis et al. 2016; Fischer and Frazier 2017; Prabnakorn et al. 2019). Although it is noticeable that there is no well accepted universal method is exist to forecast agricultural drought vulnerability. But, recently remote sensing (RS) and Geographical information system (GIS) based work is playing a significant role to monitor agricultural drought forecasting (Chockalingam et al. 2015; Hundera et al. 2016; Sanchez et al. 2018; Trnka et al. 2020). This paper focuses on multi-dimensional holistic index based approach using RS, GIS and AHP techniques constructing integrated Agricultural Drought Vulnerability Index (ADVI) based on three dimensional models in the upper Dwarakeshwar river basin in West Bengal (India) and also to evaluate the geo-spatial distribution of agricultural drought.

Study area:

The upper Dwarakeshwar river basin is situated in the eastern lower part of Chota-Nagpur plateau. The basin comprises a bordering area amidst the two districts (e.g., Bankura and Purulia) which are located in the western province of West Bengal, a state in the eastern part of India. The study area lies between 23°08´58.80 N to 23° 31´55.88 N and 86° 30´52.43 E to 87° 09 ´13.34 E, covering an area of 1934 sq km. The basin is situated in the middle part of the Puruliya district comprising the Kashipur, Puncha, Hura, Santuri, Para and Raghunathpur-I blocks while in Bankura district it covers the Chhatna, Bankura-I, Bankura-II, Indpur, Onda, Gangajalghati and Saltora blocks (Figure.1). The region receives an average annual rainfall about 1528.37 mm. It is also noted that about 80% of the rainfall is recorded due to the influence of south-west monsoon (June to October). Here, Kharif is the main cropping season and the major crops are Aman paddy that is normally cultivated during this time. On other side, Wheat, mustard, till and potato are cultivated in winter season as robi crops.

Materials And Methods

Data used

To perform work, different types of data (e.g., remote sensing, metrological, morphological, soil, drainage, groundwater, and socio-economic status) have been used in calculation of the aforesaid three composite indexes. The detail description of data source and their specifications for Agricultural Drought Vulnerability Index (ADVI) are given below in Table 1.

Table 1 Details of Data sources used for thematic layers preparation

Data	Source
Exposure index	
LANDSAT 8 (spatial resolution 30 m) (LC08_L1TP_139044_20181220_20181227_01_T1)	USGS earth explorer (https://earthexplorer.usgs.gov/)
Rainfall data (Daily basis) from 2003 to 2013	Climate forecast System Reanalysis (https://globalweather.tamu.edu/)
Sensitivity index	
LANDSAT/LC08/C01/T1_8DAY_NDVI (30 meters spatial resolution) in 2016	Google earth engine (https://code.earthengine.google.com/)
LANDSAT/LC08/C01/T1_8DAY_NDWI (30 meters spatial resolution) in 2016	Google earth engine (https://code.earthengine.google.com/)
LANDSAT/LC08/C01/T1_8DAY_EVI(30 meters spatial resolution) in 2016	Google earth engine (https://code.earthengine.google.com/)
LST (MODIS/006/MOD11A1) 1000 meters spatial resolution in 2016	Google earth engine (https://code.earthengine.google.com/)
Adaptive capacity index	
Ground water data	Central Ground Water Board (CGWB), India. (http://cgwb.gov.in/)
SRTM DEM(n23_e086_1arc_v3,n23_e087_1arc_v3)spatial resolution 30 meters	USGS earth explorer (https://earthexplorer.usgs.gov/)
Rainfall data	Indian Meteorological Department (IMD),Pune (http://dsp.imdpune.gov.in/)
Soil depth, texture, and Drainage (Scale – 1: 50,000)	National Bureau of Soil Survey and Land Use planning (NBSS&LUP)
Aquifer systems of India (Scale – 1: 50,000)	Central Ground water Board, Ministry of water Resources, Government of India.
Population, no of agricultural labour and farmer, Literacy relates	Census of India, 2011
Health data, Old-aged Persons, Road(KM), drinking water facility, fertilizer depots, Seed stores, production, livestock, Pisiculture	District Statistical handbook, Bankura and Puruliya, in 2014
Irrigated area	Irrigation and Waterways Directorate, Govt of W.B,

Methodology

Three principal composite indexes these are Sensitivity Index (SI), Exposure Index (EI), and Adaptive Capacity Index (ACI) have been taken for vulnerability assessment. Each composite index has been generated using AHP technique which has the ability to explain complex problems and make the decision where multiple factors are employed. Factors of each individual composite index (e.g., SI, EI and ACI), have been shown in Table 2. Them, multi-dimensional index-based integrated ADVI has also been measured using this formula [ADVI= (EI + SI) – ACI]. The details methodology of this research is shown using flow chart (Pic. 2).

Table 2 Selected parameters for agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Vulnerability component	Thematic layers
Sensitivity	(1) Vegetation Health Index (VHI), (2) Normalized Difference Water Index (NDWI), (3) Enhanced Vegetation Index (EVI), (4) Normalized Difference Vegetation Index (NDVI), (5) Vegetation Condition Index (VCI), (6) Land Surface Temperature (LST), and (7) Temperature Condition Index (TCI)
Exposure	(1) Normalized Difference Drought Index (NDDI), (2) Landuse and Landcover (LULC), (3) Average Drought Intensity (ADI), (4) Drought Frequency (DF), (5) Average Drought Duration (ADD), and (6) Peak Intensity (PI)
Environmental adaptive capacity	(1) Average Groundwater Depth (AGD), (2) Rainfall (RA), (3) Drainage Density (DD), (4) Drainage Buffer (DB), (5) Soil Drainage (SD), (6) Normalized Difference Vegetation Index (NDVI),(7) Aquifer Media (AM), (8) Soil Texture (ST), (9) Soil Depth (SDpt), (10) Relative Relief (RR), (11) Elevation (EL), (12) Slope (SL)
Economic adaptive capacity	(1) Irrigation Area Density (IAD), (2) Crop Production Density (CPD), (3) Agricultural Area Density (AAD), (4) Livestock Density (LD), (5) Drinking Water Facility (DWF), (6) Piscicultural Area Density (PAD), (7) Road Density (RD), (8) Ratio of Seed Stores (RSS), (9) Ratio of Fertilizer Depots (RFD)
Social adaptive capacity	(1) Rural Education (RE), (2) Agricultural Labor Density (ALD), (3) Farmer Density (FD), (4) Population Density (PD) (5) Old-Age Dependency Population (ODP), (6) and Rural Health Facility (RHF),

AHP technique

The Analytical Hierarchy Process (AHP) is a semi-quantitative comprehensive technique that fulfills the objective (Quantitative) and subjective (qualitative) aspect (Sener et al. 2011). It is a Multi Criteria Decision Analysis (MCDA) approach which has been used to judgment of final outcome through the assigned weights of the parameters with the pair-wise comparison matrix (Bera et al. 2019).

Each individual composite index was developed by following formula:

$$\mathbf{nCI} = \sum_{i=1}^{n} \mathbf{Wa} \times \mathbf{Ra}$$

Where, nCI is the three composite index of vulnerability, Wa is the each factor assigned of weight, and Ra is the Relative rating weights of the pair-wise comparison values under a classified factors.

AHP technique is build up by two leading segments. The primary segment is the prime scheme of Normalized pair-wise comparison matrix and was calculated by the weights for each factor. The secondary segment is calculated by the relative rating weights of all the factors into sub-classes by using pair-wise comparison matrix of each factor. To create a matrix of pair-wise comparison, each criterion is assigned against the other criterion by allocating a relative rank on Satty's scale (Saaty 1980), between 1 (minimum significant) to 9 (maximum significant) (Table 3). The relative scales of all these factors are given based on different criteria, relative influences, preferences and importance etc. In the Pair-based comparison matrix, each parameter in the row follows the opposite value and its significance with the other parameters. Weights for every factor ware obtained from pair-wise comparison matrix by normalizing the values and this was determined by dividing each cell with corresponding sum of the column and then averaging the rows of each criterion. The general pair-wise comparison matrix P1 is constructed as follows,

$$P1 = \begin{matrix} 1 & 2 & 3 \ldots\ldots n \\ 1/2 & 1 & 2 \ldots\ldots n \\ 1/3 & 1/2 & 1 \ldots\ldots n \end{matrix}$$

At last, the consistency of the Pair-based comparison matrix is assessed by Consistency Ratio (CR). CR is calculated by the following equation:

Consistency Ratio (CR) = CI/RI

Where,

CI =Consistency Index and

RI =Random Index

If, CR is less than or equal to 0.1, the comparison matrix is considered as consistent, else it will be corrected.

The Random Index (RI) value obtained from the Satty's standard RI table, which is shown in Table 4. The Consistency Index (CI) is applied and it is calculated using the following equation-

Consistency index (CI) = $((\gamma max - n)/(n - 1))$

Where,

λmax = the principle Eigen value of matrix.

n = Number of parameters used in the analysis.

Table 3 The satty's 9-point relative scale

Scale's	1	2	3	4	5	6	7	8	9
Degree of importance	Equal	Weak	Slight	Moderate	Quite	Very strong	Extreme	very strong Extreme	Absolute

Table 4 Random Index (RI) value (Saaty 1990)

n	1	2	3	4	5	6	7	8	9	10	11	12
RI	0.0	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

Here, all the index parameters of normalized weights value shown in Table 5 and sub-classes weights value of all the parameters shown in Table 6 & 7.

Table 5 Normalized weights of Exposure index (EI), Sensitivity index (SI) Environmental Adaptive Capacity (EAC) index, Economic Adaptive Capacity (EcAC) and Social Adaptive Capacity (SAC)

Parameter of EI	weight	Parameter of SI	weights	Parameter of EAC	weights	Parameter of SAC	weights	Parameter of EcAC	weights
NDDI	0.379	VHI	0.338	AGD	0.237	RE	0.379	IAD	0.306
LULC	0.248	NDWI	0.224	RA	0.199	ALD	0.248	CPD	0.218
ADI	0.160	EVI	0.143	DD	0.123	FD	0.160	AAD	0.154
ADD	0.102	NDVI	0.112	DB	0.122	PD	0.102	LD	0.108
DF	0.065	VCI	0.079	SD	0.089	ODP	0.065	DWF	0.076
PI	0.043	LST	0.056	NDVI	0.065	RHF	0.043	PAD	0.053
		TCI	0.045	AM	0.048			RD	0.037
				ST	0.033			RSS	0.025
				SDpt	0.031			RFD	0.018
				RR	0.021				
				EL	0.012				
				SL	0.012				

Table 6 Normalize assign weight values for all subcategories of Exposure Index (EI) and Sensitivity Index (SI).

Parameter	Sub-classes of Exposure Index (EI)	weights	Parameter	Sub-classes of Sensitivity Index (SI)	weights
NDDI	0.61-1	0.419	VHI	76-93	0.344
	0.41-0.60	0.263		61-75	0.344
	0.31-0.40	0.160		56-60	0.177
	0.01-0.3	0.097		46-55	0.088
	-1 - 0	0.062		45-11	0.047
LULC	Agricultural land	0.427	NDWI	0.21-04	0.386
	Natural vegetation	0.260		0.16-0,2	0.246
	Fallow land	0.158		0.11-0.15	0.173
	Settlement	0.096		0.01-0.1	0.120
	Water Body	0.059		-0.1	0.075
ADI	-1.37 to -1.35	0.471	EVI	0.41-0.57	0.471
	-.35 to -1.34	0.268		0.31-0.4	0.268
	-1.33 to -1.35	0.143		0.21-0.3	0.143
	-1.31 to -1.30	0.075		0.11-0.2	0.075
	-1.29 to -1.28	0.044		-0.13	0.044
DD	2.71-2.87	0.445	NDVI	0.301-0.4	0.492
	2.53-2.7	0.262		0.201-0.3	0.270
	2.36-2.52	0.153		0.101-0.2	0.135
	2.18-2.35	0.088		0.001-0.1	0.065
	2-2.17	0.052		-0 -0.0797	0.037
AF	13.69-14.9	0.419	VCI	81-100	0.419
	13.39-13.68	0.263		61-80	0.263
	13.13-13.38	0.160		41-60	0.160
	12.86-13.12	0.097		21-40	0.097
	12.50-12.85	0.062		0-20	0.062
PI	-2.72 to -2.56	0.419	LST	30.28-31.86	0.365
	-2.55 to -2.39	0.263		31.87-32.29	0.275
	-2.38 to -2.22	0.160		32.3-32.7	0.191
	-2.21 to -2.06	0.097		32.71-33.28	0.106

-.05 to -1.89	0.061		33.29-34.39	0.063
		TCI	81-100	0.363
			61-80	0.362
			41-60	0.161
			21-40	0.076
			0-20	0.039

Table 7 Normalize assign weight values for all subcategories of environmental adaptive capacity (EAC) index, Economic Adaptive Capacity (EcAC) and Social Adaptive Capacity (SAC)

Parameter of EAC	Sub-classes	weights	Parameter of SAC	Sub-classes	weights	Parameter of EcAC	Sub-classes	weights
Average groundwater depth	2.13-3.92	0.445	Rural Education	0.8 - 1	0.445	Irrigation area density	0.8 - 1	0.513
	3.93-4.45	0.262		0.6 -0.8	0.262		0.6 -0.8	0.262
	4.46- 4.97	0.153		0.4 - 0.6	0.153		0.4 - 0.6	0.129
	4.98-6.05	0.089		0.2 - 0.4	0.089		0.2 - 0.4	0.063
	6.05-8.82	0.052		0 - 0.2	0.052		0 - 0.2	0.033
Rainfall	1585-1631	0.418	Agricultural Labour Density	0.8 - 1	0.513	Crop production density	0.8 - 1	0.471
	1540-1584	0.263		0.6 -0.8	0.262		0.6 -0.8	0.268
	1499-1539	0.160		0.4 - 0.6	0.130		0.4 - 0.6	0.143
	1454-1498	0.097		0.2 - 0.4	0.063		0.2 - 0.4	0.075
	1398-1453	0.062		0 - 0.2	0.033		0 - 0.2	0.044
Drainage density	2-3.6	0.471	Farmer Density	0.8 - 1	0.471	Agricultural area Density	0.8 - 1	0.419
	1.5-1.9	0.264		0.6 -0.8	0.268		0.6 -0.8	0.263
	1.2-1.4	0.143		0.4 - 0.6	0.143		0.4 - 0.6	0.160
	0.73-1.1	0.078		0.2 - 0.4	0.075		0.2 - 0.4	0.097
	0.0021-0.72	0.044		0 - 0.2	0.043		0 - 0.2	0.062
Drainage buffer	100	0.471	Population Density	0.8 - 1	0.419	Livestock density	0.8 - 1	0.470
	300	0.268		0.6 -0.8	0.263		0.6 -0.8	0.262
	500	0.143		0.4 - 0.6	0.160		0.4 - 0.6	0.144
	1000	0.075		0.2 - 0.4	0.097		0.2 - 0.4	0.079
	1500	0.044		0 - 0.2	0.062		0 - 0.2	0.045
Soil Drainage	Excessive	0.350	Dependent Population	0.8 - 1	0.470	Lack of water facility mouza	0.8 - 1	0.445
	Somewhat Excessive	0.276		0.6 -0.8	0.262		0.6 -0.8	0.262
	Well	0.159		0.4 - 0.6	0.145		0.4 - 0.6	0.152
	Mod. Well	0.096		0.2 - 0.4	0.079		0.2 - 0.4	0.089
	Imperfect Well	0.058		0 - 0.2	0.045		0 - 0.2	0.052

	Imperfect Mod	0.037						
	Imperfect	0.025						
NDVI	-0.134	0.513	Rural Health	0.8 - 1	0.419	Pisicultural density	0.8 - 1	0.470
	0.201-0.387	0.275		0.6 -0.8	0.263		0.6 -0.8	0.262
	0.101- 0.2	0.138		0.4 - 0.6	0.160		0.4 - 0.6	0.144
	0.001- 0.1	0.074		0.2 - 0.4	0.097		0.2 - 0.4	0.079
				0 - 0.2	0.062		0 - 0.2	0.045
Aquifer media	Older Alluvium	0.415						
	Older Alluvium, Sand and Silt	0.255				Road density	0.8 - 1	0.445
	Laterite	0.153					0.6 -0.8	0.262
	Schist	0.089					0.4 - 0.6	0.153
	Banded Gneissic Complex	0.054					0.2 - 0.4	0.088
	Basic Intrusives	0.034					0 - 0.2	0.052
Soil texture	Sandy loamy group	0.427				Ration of seed stores	0.8 - 1	0.418
	Sandy clay group	0.260					0.6 -0.8	0.263
	Loamy group	0.158					0.4 - 0.6	0.160
	Gravelly group	0.096					0.2 - 0.4	0.097
	Clay group	0.058					0 - 0.2	0.061
Soil Depth	Very Deep	0.446				Ratio of fertilizer depots	0.8 - 1	0.419
	Deep	0.262					0.6 -0.8	0.262
	Moderate	0.152					0.4 - 0.6	0.160
	Shallow	0.089					0.2 - 0.4	0.097
	Very Shallow	0.052					0 - 0.2	0.062
Relative Relief	<20	0.471						
	21-25	0.264						
	26-35	0.143						

	36-45	0.078
	>46	0.044
Elevation	69-112	0.419
	113-140	0.263
	141-168	0.160
	169-201	0.097
	202-255	0.062
slope	0-1	0.419
	1.1-3	0.263
	3.1- 5	0.160
	5.1-7	0.097
	>7	0.061

Synthesizing the composite index

Exposure Index (EI)

Exposure index (EI) is the measurement of the degree of disclosure which received by the drought. Exposure means something particularly embarrassing, damaging or harmful. Here, NDDI, LULC, and Standardized precipitation Index (SPI) based Average Drought Intensity (ADI), Drought Frequency (DF), Drought Duration (DD), and Peak Intensity (PI) indicators are considered (Figure 3) to create the exposure index by using GIS based AHP technique. The Parameters of evaluation exposure indexes have been shown in Table 8.

Table 8 Evaluation Exposure Index (EI) for the agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Index thematic layer	Formulating method	Description	Relation with Exposure	Reference
NDDI	NDDI = ((NDVI - NDWI) / (NDVI + NDWI))	NDDI is a satellite-generated and widely known frequently used as agricultural drought indicator. Higher NDDI value indicates higher probability of drought exposure and vice versa.	Positive	Gu et al.2007
LULC	Supervised calcification	LULC is another important factor for assessing exposure of agricultural drought. Agricultural land, fallow land and natural vegetation are higher probability of drought exposure index relatively water bodies and settlement.	Agricultural land is very high exposure, and Water Bodies is very low.	Biazina and Sterk 2013
Average Drought Intensity	ADI= (N_1+N_2+N_3…..+ Nn /Tm)	Higher average drought intensity value indicates higher probability of drought exposure and vice versa.	Positive	Ghosh. 2019
Average Drought Duration	ADD = (D_S/ D)	Higher average drought duration value indicates higher probability of drought exposure and vice versa.	Positive	Ghosh. 2019
Drought Frequency	$DF_{j.10}$ = (Nj / j.n) x 100%	Higher drought frequency value indicates higher probability of drought exposure and vice versa.	Positive	Wang et al.2013
Peak Intensity	Lowest spi value of observational 3-month SPI	Higher peak intensity value indicates higher probability of drought exposure and vice versa.	Positive	Raha and Gayen.2020

Sensitivity Index (SI)

Sensitivity in vulnerability assessment is a measure of how much the local climate will change in vulnerability to during drought. Sensitivity is assessment of the susceptibility of moisture stress or water threads for agricultural drought. Vegetation health and freshness, soil moisture, soil temperature, evaporation, and transpiration are all critical factors for assessing agricultural drought sensitivities. Here the Sensitivity index is created using the satellite based remote sensing factor VHI, NDWI, EVI, NDVI, VCI, NDWI, LST, and TCI (Figure 4) and all thematic layers has been prepared and resampling in 30 m spatial resolution through GIS environment. Parameters of evaluation sensitivity indexes have been shown table 9. In addition, a combination of eight different indicators has been developed using data from various sensors like Landsat and Modis in 2016 to better understand the agricultural drought sensitivity.

Table 9 Evaluation Sensitivity Index (SI) for the agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Index thematic layer	Formulating method	Description	Relation With sensitivity	Reference
VHI	VHI = α × VCI + (1 + α) × TCI	VHI is a combination of VCI and TCI and is a two-dimensional indicator for assessing the incidence of agricultural drought temporarily and spatially. Higher VHI value represents higher probability of drought sensitivity.	Positive	sun et al. 2013
NDWI	NDWI = ((NIR - SWIR)/(NIR + SWIR))	NDWI is primarily designed to describe the spatial characteristics of surface open water condition and it used to monitorvegetation and agricultural droughts. That means Higher NDWI value indicates lower probability of drought sensitivity and vice versa.	Negative	Amalo et al. 2018
EVI	EVI = 2.5 x (NIR - RED)/(NIR + 6 x RED - 7.5 x BLUE +1)	EVI has proven to be an effective way to assess the long-term trend in vegetation “greening”.So, Higher EVI value indicates higher probability of drought sensitivity and vice versa.	Positive	Zhu et al.2016
NDVI	NDVI= (NIR - RED) / (NIR + RED)	The seasonal and inter-annual plant growth in a region and Potential cultivable areas can be identified by NDVI. Higher NDVI value indicates higher probability of drought sensitivity and vice versa.	Positive	Bhavani et al. 2017
VCI	VCI = ((NDVIi – NDVImin) / (NDVImax – NDVImin)) * 100	VCI derived from NDVI isolates short-term weather-related signals from long-term environmental factors and is effective in observing and comparing drought-affected plants across a large area. So Higher VCI value indicates higher probability of drought sensitivity and vice versa.	Positive	Palchaudhuri and Biswas 2019
LST	LSTc = (LST × 0.02) – 273.15	LST is a significant parameter for the study of drought and environment and Higher VCI value indicates higher probability of drought sensitivity and vice versa.	Positive	Arekhi et al. 2019
TCI	TCI = (LSTIi – LSTmin) / (LSTmax – LSTmin)) * 100	TCI is involved in the brightness temperature calculated from LST. Higher VCI value indicates higher probability of drought sensitivity and vice versa.	Positive	Rojas et al. 2011

Adaptive Capacity Index (ACI)

Adaptive capacity elaborates the efficiency of acclimatize power. So, Adaptive capacity provides the ability to reconfigure with minimal loss of resilience, environmental, Ecomonic, and human socio-economic system functions. An adaptive capability includes social and technological skills and strategies that allow multiple individuals or groups to adjust the environmental and socio-economic changes. In the context of the food system, adaptive capacity is usually developed or deployed to maintain livelihoods, food production or food access.

In field of drought vulnerability, Adaptive capacity is the inherent strength of the agricultural area to cope with the reduction of the crop productivity and probable loss in the agricultural drought. Here, The ACI is a composite index of three indices, namely Economic Adaptive capacity (EcAC), Environmental Adaptive Capacity (EAC), and Social Adaptive Capacity (SAC).

The SAC and EcAC data was normalized by using the following equations-

If p has positively related to vulnerability then

pn = (pα - pmin)/(pmax - pmin)

And if p has negatively related to vulnerability then used

pn = (pmax - pα)/(pmax - pmin)

Where, pn is normalized parameters, $p\alpha$ is each individual parameter, and $pmax$ and $pmin$ respectively represent maximum and minimum value of each parameter.

Environmental Adaptive Capacity (EAC)

The environmental elements control the amount of potential damage from a potential hazard or disaster and also build the EAC index. To measures EAC index, average groundwater depth, rainfall, drainage density, drainage buffer, soil drainage, NDVI, aquifer media, soil texture, soil depth, relative relief, elevation, slope factors have been used and it has also been attached by AHP technology. All collected data has been thematically mapped in GIS platform at 30 m spatial resolution (Figure. 5) respectively. Parameters of evaluation EAC has been shown in table 10. Finally, the EAC Index is computed by using the GIS overly analysis method based on the weightage of all the parameters.

Table 10 Evaluation Environmental Adaptive Capacity (EAC) index for the agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Index thematic layer	Formulating method	Description	Relation with EAC
Average groundwater depth	Interpolation (IDW) method	Higher average groundwater depth higher probability of drought adaptive capacity.	Positive
Rainfall	Interpolation (IDW) method	Higher Rainfall indicates higher probability of drought adaptive capacity.	Positive
Drainage density	Drainage length/area	Higher Drainage density indicates higher probability of drought adaptive capacity.	Positive
Drainage buffer	Multiple Buffer	Near the drainage indicates higher probability of drought adaptive capacity.	Positive
Soil drainage	Digitalization	Higher Soil drainage indicates higher probability of drought adaptive capacity.	Positive
NDVI	(Nir - red)/(Nir + red)	Higher value of NDVI indicates higher probability of drought adaptive capacity.	Positive
Aquifer media	Digitalization	Higher replaceable recharge indicates higher probability of drought adaptive capacity.	Positive
Soil texture	Digitalization	Finer the Soil texture indicates higher probability of drought adaptive capacity.	Positive
Soil Depth	Digitalization	Higher Soil Depth indicates higher probability of drought adaptive capacity.	Positive
Relative Relief	From DEM	Higher Relative Relief indicates lower probability of drought adaptive capacity.	Negative
Elevation	From DEM	Higher Elevation indicates lower probability of drought adaptive capacity.	Negative
Slope	From DEM	Higher Slope indicates lower probability of drought adaptive capacity.	Negative

Social Adaptive Capacity (SAC)

The adaptive capacity of a society is created by bringing together the social elements that empower the society from a single disaster. Social adaptive power controls the severity and duration of any kind of catastrophe. Social infrastructures such as education, health, labor force, unity, technology and productivity have the power to control the consequences of any kind of disaster. Here, to diagnose social adaptive capacity, six parameters have been used, such as, agricultural labor density, farmer density, rural literacy rate, old-age dependency population ratio, rural health facility, and population density (Figure.6). Parameters of evaluation SAC has been shown table 11.

The SAC index has been constructed using the GIS overlay method with AHP based assigned weightage on the thematic layers of all the permits based on their normalized value. Thematic layers are farmers, agricultural labor, rural literacy, population density, old age dependency population and health.

Table 11 Evaluation Social Adaptive Capacity (SAC) index for the agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Index thematic layer	Formulating method	Description	Relation with SAC
Rural education	Obtained directly from Rural literacy rate	Higher Rural education indicates higher probability of drought adaptive capacity.	Positive
Agricultural labour density	No of agricultural labour/Area	Higher Agricultural labour density indicates lower probability of drought adaptive capacity.	Negative
Farmer density	No of farmer/Area	Higher Farmer density indicates lower probability of drought adaptive capacity.	Negative
Population density	Total population/Area	Higher Population density indicates lower probability of drought adaptive capacity.	Negative
Old age dependent Population	No of old age dependency population/Total Population	Higher Old age dependant Population indicates lower probability of drought adaptive capacity.	Negative
Rural health	(No of bed/population) x 100	Higher Rural health facility indicates higher probability of drought adaptive capacity.	Positive

Economic Adaptive Capacity (EcAC)

The EcAC Index is formed by the elements that Economically control the ability to adapt any kind of natural phenomena. EcAC index depend on various natural factor which is important index to determine region-based agricultural droughts. These are the road density, drinking water facility, irrigation area, agricultural area, total crop production, ratio of seed stores and livestock for determining the EcAC of agricultural drought in the agro-based upper Dwarakeshwar River Basin which is showing in figure 7. Parameters of evaluation EcAC have been shown in Table. 12.

Table 12 Evaluation Economic Adaptive Capacity (EcAC) index for the agricultural drought vulnerability assessment in the upper Dwarakeshwar river basin.

Index thematic layer	Formulating method	Description	Relation with EcAC
Irrigation area density	Irrigated area/ total area	Higher irrigation density indicates a higher adaptive capacity that means lower vulnerability.	Positive
crop production density	Total crop production/ Total agricultural area	A higher crop production indicates higher probability of drought adaptive capacity.	Positive
Agricultural area Density	Total agricultural area/ total area	A higher Agricultural area indicates lower probability of drought adaptive capacity.	Negative
livestock density	No of livestock/ total area	Livestock is an alternative source of income. So a higher livestock density area indicates higher probability of drought adaptive capacity.	Positive
Drinking water facility	Total mouza – Drinking water facility mouza	A higher water facility block indicates higher probability of drought adaptive capacity.	Positive
Piscicultural Area Density	Piscicultural area/ total area	Pisciculture is an alternative source of income, so higher Piscicultural density areas indicate higher probability of drought adaptive capacity.	Positive
Road density	Length of road / total area	A higher Road density indicates higher probability of drought adaptive capacity.	Positive
Ration of seed stores	No of seed stores/ total area	A higher seed stores density area indicates higher probability of drought adaptive capacity.	Positive
Ratio of fertilizer depots	No of fertilizer depots/total area	A higher ratio of fertilizer depots indicates higher probability of drought adaptive capacity.	Positive

Results

The GIS-based 3 indicators have been used to assess agricultural drought vulnerability. The vulnerability of agricultural drought depends on the regional distribution of these three indicators such as, EI, SI and ACI.

The exposure index (EI) of upper Dwarkeswar river basin has been divided into 5 regions such as, very low (EI value is 0–20), which covering of 52.36 sq km (2.71%) area, low (21–40) : 326.87 sq km (16.9%) area, medium (41–60) : 791.78 sq km (40.94%) area, high (61–80): 641.58 sq km (33.17%) area and very high (81–100) : 121.40 sq km (6.28%) area (Fig. 8). Deep green area is showing the very low exposure index, covering very small part and scattered portion area of the basin. The light green color indicates the low exposure index region; these are mostly in forest areas. The yellow portion is showing moderate exposure index which is covering mainly north-eastern and central parts of the study area. Brown color portion represent high exposure index, and south western part of the study area shows in very high exposure index which indicate in red color.

The Sensitivity Index (SI) is the second most important indicator of agricultural drought vulnerability. This sensitive index is formed by combining the different satellite-based drought indicators with the help of GIS overlay method. According to Sensitivity Index, the study area is divided into five sub classes, namely ‘very high' (81–100), ‘high'(61–80), ‘medium’ (41–60), ‘low’ (21–40) and ‘very poor’ (0–20) covering an area of 54.66, 257.85, 590.52, 869.96 and 171.01 sq km accounting 2.83, 13.33, 30.53, 44.47 and 8.84%, respectively, of the total area (Fig. 9). The Sensitive Index of the Deep Green Region, which is sparsely scattered in the northern and western parts of the study area, is very low, and northern and western region falls within the low sensitivity index. Moderate and high sensitive index has been seen in the middle portion of the study area. Areas with a very high sensitive index are distributed scatterly throughout the study areas which are shown by red color.
Adaptive Capacity Index (ACI) (Fig. 10) these three indices namely EAC, SAC, and EcAC (Fig. 11) have been combined to calculate the Total Adaptive Capacity Index. ACI of the study area is divided into five classes, which are: such as very low (0–20), low (21–40), moderate (41–60), high (61–80), and very high (81–100).These classes have covered 334.05 sq km area (17.29 %), 1090.30 sq km area (56.42 %), 281.50 sq km area (14.57%), 174.16 sq km area (9.01 %), and 52.49 sq km area (2.72%) respectively. Bankura-II block has very high and high adaptive capacity. Some part of Bankura-I is high and some part is shown moderate

adaptive capacity. Santuri and some part of Gangajalghati have moderate adaptive capacity. Indpur, puncha, some portion of Hura, para and Saltora block has very low adaptive capacity. Raghunathpur-I, Kashipur, Chnatna, and some parts of Saltora also has low adaptive capacity.

Finally the Agricultural Drought Vulnerability Zone (ADVZ) map was prepared by using the ArcGIS environment. Combined three indices to assess the spatial distribution of agricultural drought vulnerability in the upper Dwarakeshwer river basin. Shown in Fig. 12.

There are five zones under the vulnerable category namely: very high (266.89 sq km), high (547.05 sq km), moderate (568.69 sq km), low (186.68 sq km), and very low (362.32 sq km). South and southwestern part of the study area has been recognized as very high to high agricultural drought vulnerability, mainly Indpur, puncha, hura and para. Southeastern parts of Bankura-II block showing very low vulnerability. Some portion of Bankura-I and Santuri are noticed with low vulnerability. Remaining areas mainly Chhatna, Gangajolghati. Kasipur, Santuri and Raghunathpur have moderate to high drought vulnerability. Overall 13.82% of the study region is under very high vulnerability, 28.32% area of the study region is under high vulnerability. Moderate vulnerability affected portions cover almost 29.44% of the total area of the region and 9.66% area is under low vulnerability. The remaining portion (18.76% area) has very low agricultural drought vulnerability.

Higher adaptive capacity indicates lower vulnerability. Adaptive capacity can be controlled through environmental and sustainable socio-economic development. Sensitivity can be changed by changing the type of crop. But the exposure is associated with patterns of rainfall. So, it is not possible to control it. However, real time forecasting can be of some benefit.

Validation

There is no universally accepted, accurate, and direct mechanism has not developed for determining the validity of agricultural drought vulnerability (Murthy et al. 2015). Thus, some research papers have not been validated (Dalezios et al. 2012; Pei et al 2016; Kar et al. 2018). But many research papers have tried to determine the validity using some indirect methods such as comparative discussions with drought events of different years. In someresearch papers (He et al.2012) the empirical evidence of crop yield reduction with previous drought events (Zhao et al. 2011), crop yield variability of principal crop (Murthy et al 2015a), Yield Anomaly Index (YAI) (Dutta et al. 2015), Correlation of food grain productivity and HDI with drought events years (Sehgal and Dhakar 2016) are used to validate their respective work. Yield Anomaly Index (YAI) has been to determine the validation of this agricultural drought vulnerability map. YAI is a very reliable technology for determining the deviation of crop yield production in a particular year from long term mean. The following formula is used to calculate YAI:

$$YAI = (Y - Xy)/sd$$

Where,

Y - Crop yield, Xy - long term means yield, and sd - standard deviation.

Long term aman paddy yield data from 2004 to 2014 (Missing data in year 2009) has been used here. YAI of aman paddy of a drought year 2010 and a Normal (wet) year YAI of 2012 are used for comparative discussion (Fig. 13). It can be seen that almost every block has a negative YAI in the dry year of 2010 and a positive YAI in the normal wet year of 2012. The result shows that the entire region is a drought vulnerability region, which validates the prepared ADVZ.

Discussion

The above agricultural drought vulnerability analysis and mapping of the study were revealed for agricultural drought management purposes. This AHP and GIS-based unique methodology was used to reveal the EI, SI, and ACI that determine the basin-scale drought vulnerability. Here, the principal exposure factor is rainfall that can determine the water scarcity due to precipitation deficit. Calculation of drought duration, intensity, and frequency of SPI over the 10 years' time period was done. On the other hand, satellite-based NDDI disclosed the drought condition of the study area. LULC is showing that the region is highly dependent on an agro-based economy. As a result, when drought phenomenon happens, the probability of potential losses of the agricultural sector in this basin is relatively very serious. The sensitivity of this area is mainly dependent on vegetation, soil moisture, and temperature. These are assessed by using remote sensing-based index meanly VHI, NDVI, EVI, NDVI, VCI, and TCI.

TCI materially monitors the surface temperature conditions. NDWI essentially monitors the soil moisture and vegetation index basically monitoring the greenness and health of crop conditions which can assess water stress on the crop over the whole seasons. The total adaptive capacity index demonstrates a region's capability to defend drought vulnerability.

The exposure index and the sensitivity index of region together increases the vulnerability to drought, while the adaptive capacity index builds the capacity of drought tolerance which reduces the drought vulnerability. The agricultural drought vulnerability map showed that Indpur, some part is puncha and para, northern part of Saltora, western part of Onda, middle portion of Chhatana, north western and middle parts of Kashipur block have high vulnerability for agricultural drought due to very low adaptive capacity. Western Hura, south western Kashipur, south eastern Saltora and Gangajalghati, eastern Onda, north eastern Chhatna block has moderate vulnerability for agricultural drought due to low sensitivity, low adaptive capacity, high to moderate exposure index. Bankura-I and Santuri block has under the low vulnerability zone because moderate to high adaptive capacity and moderate to low sensitivity index. Bankura – II block has very low vulnerability due to very high adaptive capacity and low sensitivity index. So assessment of agricultural drought vulnerability adaptive capacity is a principal controlling factor that regulating to decrease the agricultural drought vulnerability. The irrigation area density, rural education and ground water depth, also drainage and soil condition, agricultural labour density, crop production density, agricultural are density are the important regional parameter for agricultural drought vulnerability assessment. According to regional nature of upper Dwarakeshwar river basin that region is under highly agricultural vulnerable when drought occurs. So, 1) To minimization of the ratio of agricultural dependent population, 2) spreading of economic diversification, 3) promotion of drought resistant crop farming and 4) increase investment for replace the traditional irrigation system to modern (sprikel, drip, pipe, infiltration) irrigation system are the main way to reduce the ADV. That is why; diagnostic assessment of three indices-based agricultural drought vulnerability map of agro-based economic region is required for a drought reduction plan.

Conclusion

Drought is a major hidden catastrophe of agricultural production in any region of the world. As a result, due to climate change, agricultural drought risk management is very necessary for maintaining food security. The current study has accepted a three dimensional holistic perception for assessment and spatial distribution of agricultural drought vulnerability map. Agricultural drought vulnerability considers address the multidimensional nature of multiple parameters such as exposure factors like LULC,NDDI and daily rainfall based 3-month SPI(drought duration, intensity, frequency), sensitive factor like NDVI, NDWI, VCI, TCI, VHI, EVI and adaptive capacity factors like Economic, social and environmental adaptive capacity. Different input indicators were selected by studying the various vulnerabilities related to climate and these inputs are managed in a systematic way to diagnose the spatial distribution of agricultural drought vulnerability. Weights were selected based on the ability of the parameters involved in the subjectivity to affect that particular index. Finally, an agricultural drought vulnerability map has been created using those three indices. Ultimatly vulnerability maps will assist in drought management, identifying agricultural areas affected by extreme drought. This will greatly benefit the planners and government officials in formulating government policy for local scale drought management strategy. It also demonstrates the effectiveness of remote sensing and GIS-based three-dimensional methodology for identifying drought-related stresses in the agricultural economy. Thus, by modifying or directly using this methodology, it is possible to assess the agricultural drought in any part of the world and to formulate management policies based on it.

Abbreviations

NDDI, Normalized Difference Drought Index; LULC, Landuse and Landcover; ADI, Average Drought Intensity; DF, Drought Frequency, ADD, Average Drought Duration; PI, Peak Intensity; VHI, Vegetation Health Index; NDWI, Normalized Difference Water Index; EVI, Enhanced Vegetation Index; NDVI, Normalized Difference Vegetation Index; VCI, Vegetation Condition Index; LST, Land Surface Temperature, TCI, Temperature Condition Index;

Declarations

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Author contribution

Conceptualization, Methodology development, Formal analysis and investigation: Ujjal Senapati. Writing—original draft preparation and review and editing: Ujjal Senapati and Tapan Kumar Das.

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Data availability

All the data used for this study are available and provided by the public entities. Data sources are given in Table 1.

Code availability: Not applicable.

Ethics approval: Not applicable.

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Figures

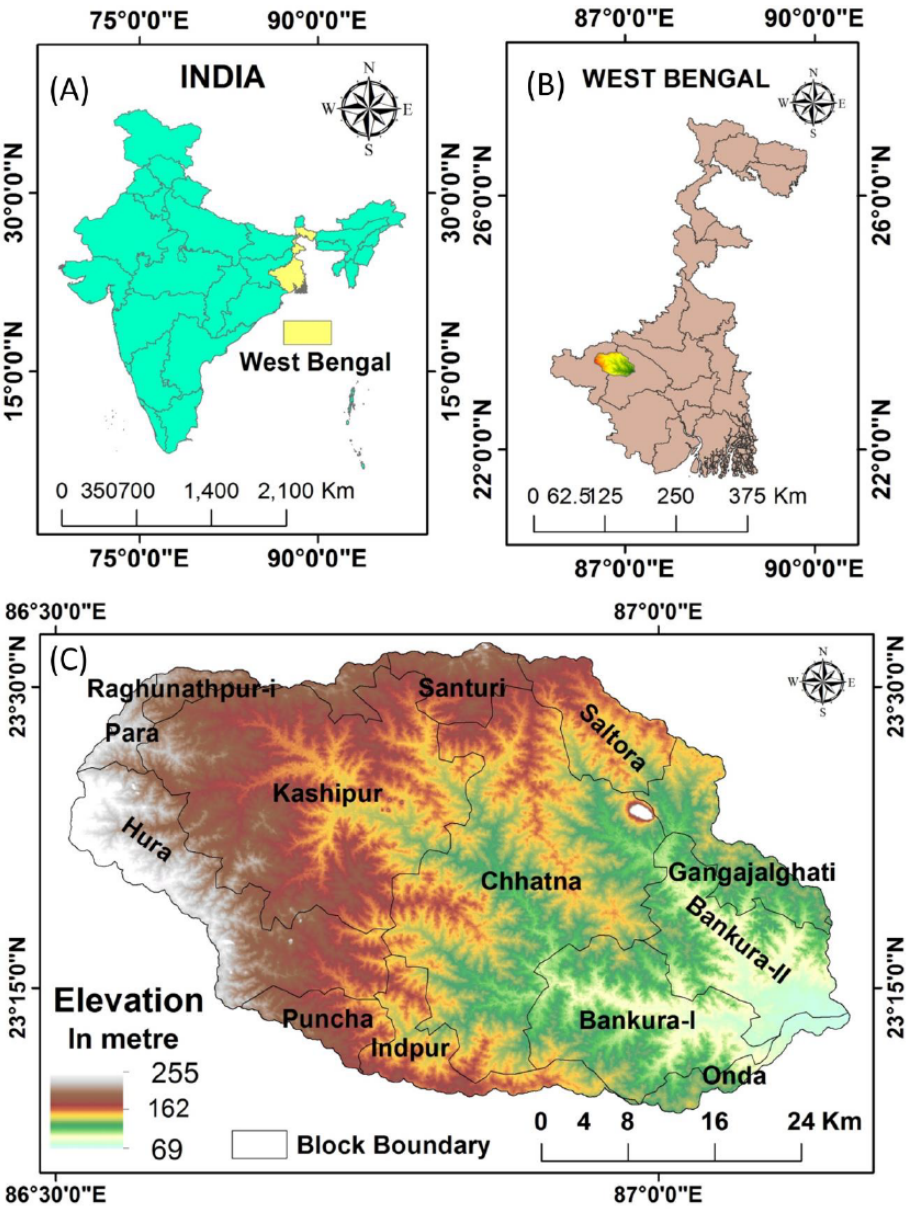

Figure 1

Location map of the study area: (A) India, (B) West Bengal, and (C) Spatial distribution of associated blocks of upper Dwarakeshwar river basin.

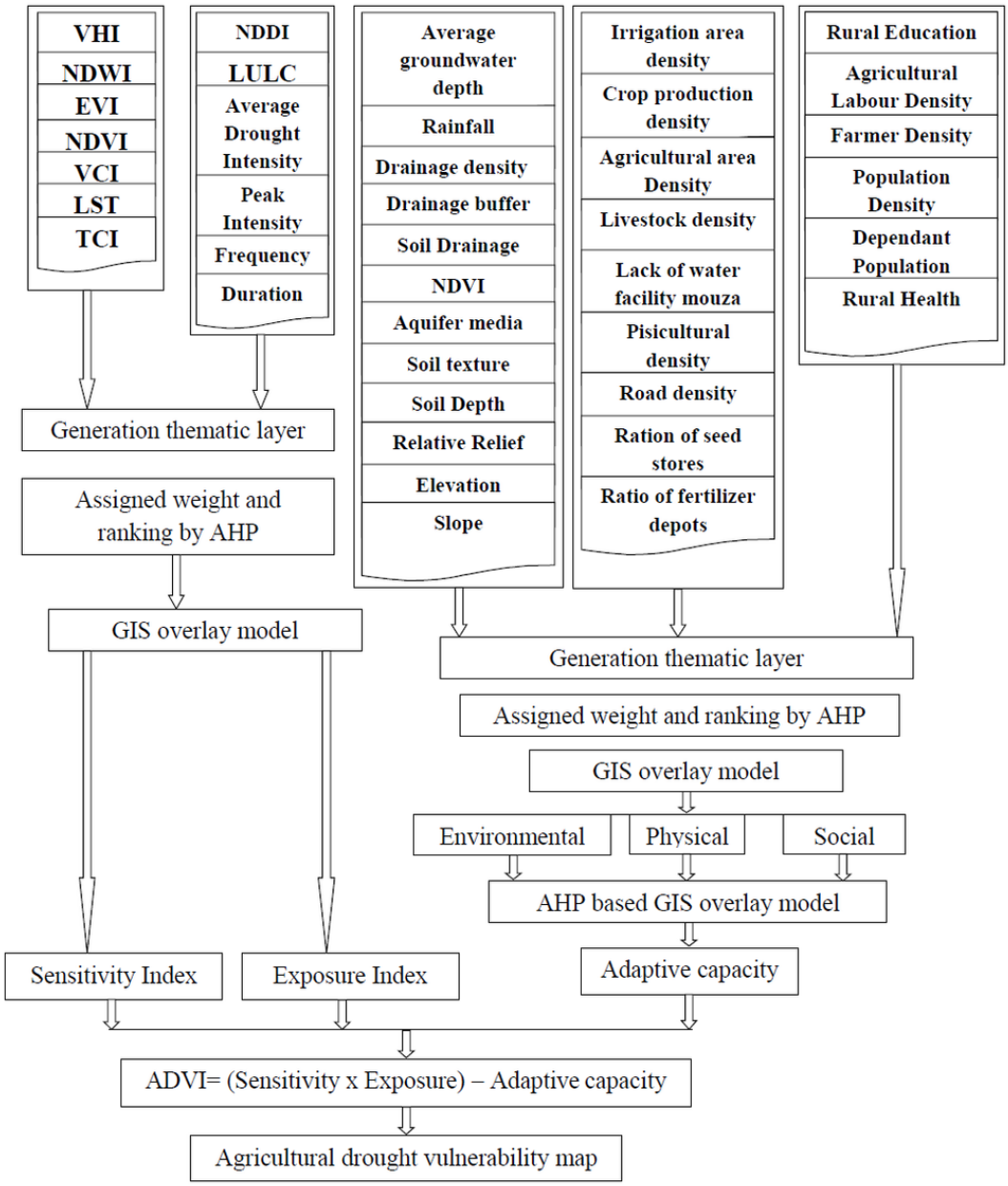

Figure 2

Flowchart of Agricultural drought vulnerability index Zone map methodology.

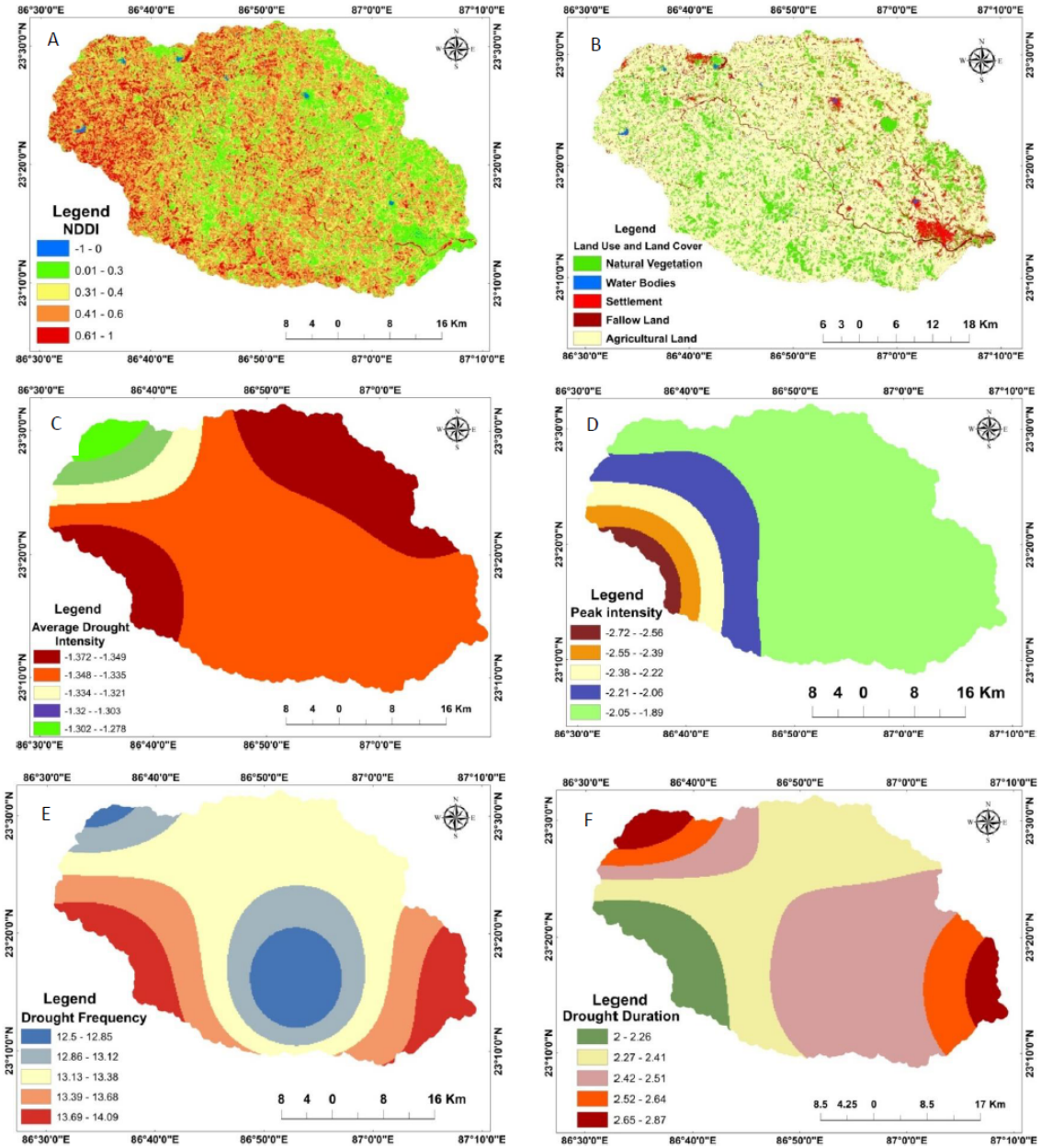

Figure 3

Thematic layers for Exposure index (A) NDDI, (B) Land use and Land cover, (C) Average Drought Intensity, (D) Peak Intensity, (E) Drought Frequency, (F) Drought Duration.

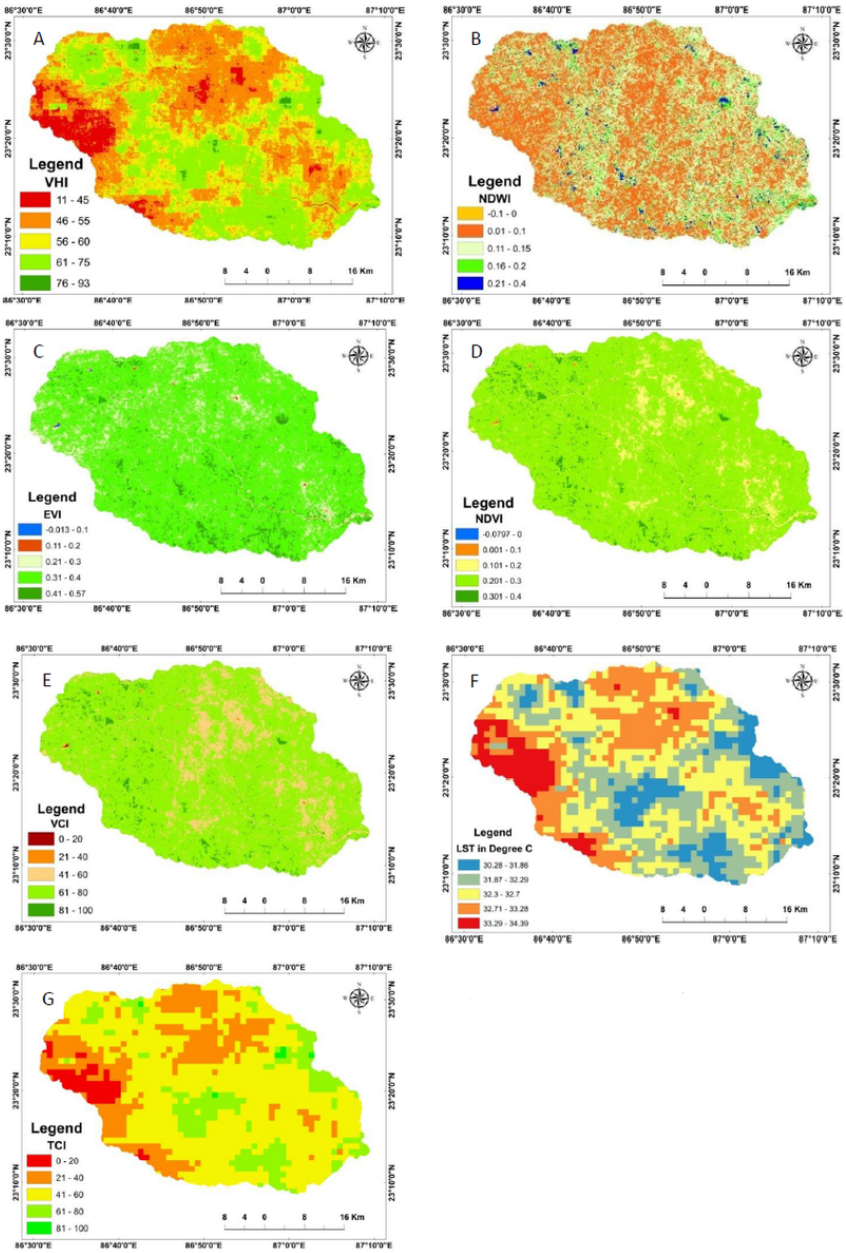

Figure 4

Thematic layers for Sensitivity index (A) VHI, (B) NDWI, (C) EVI, (D) NDVI (E) VCI, (F) LST, (G) TCI

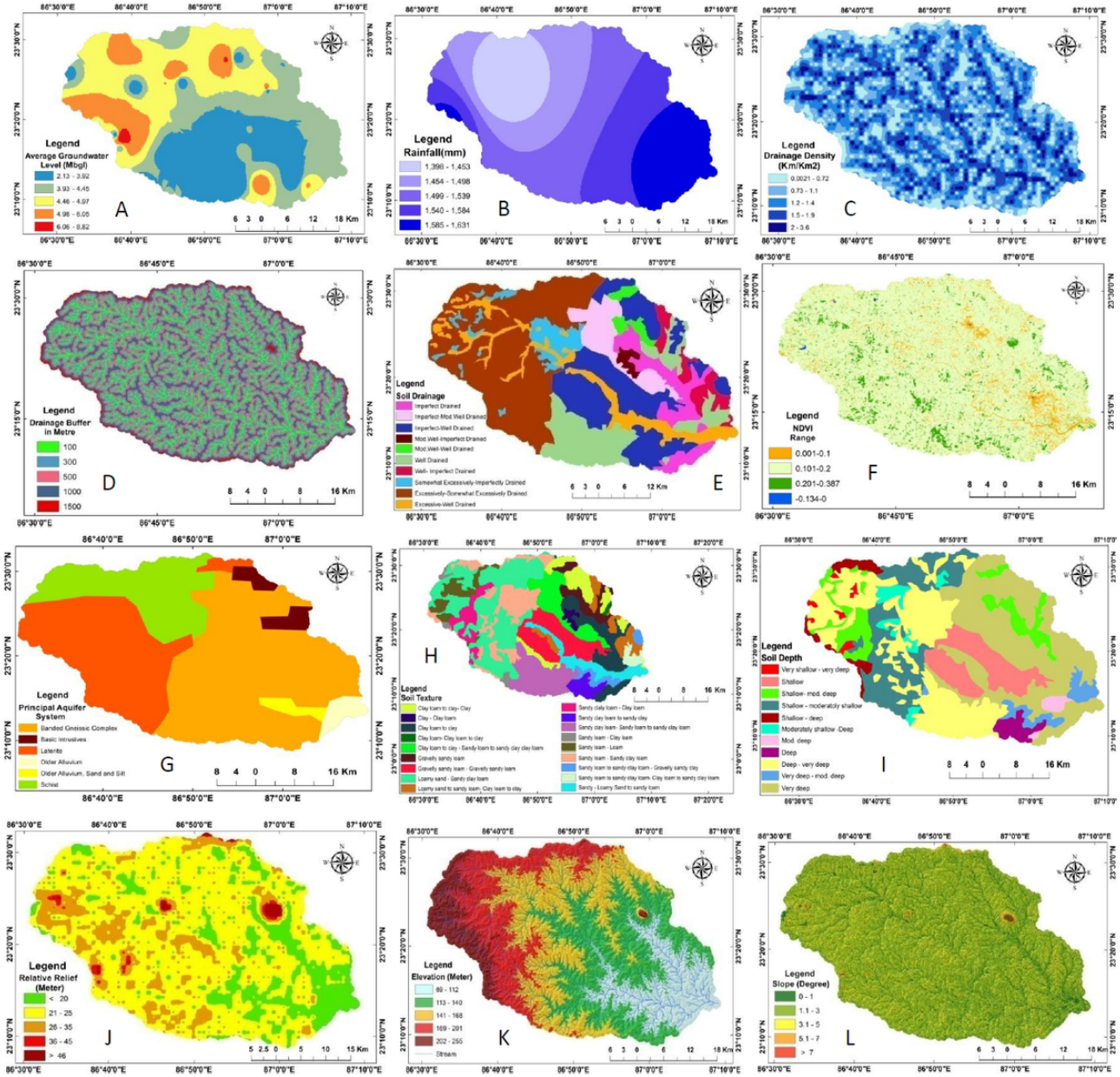

Figure 5

Thematic layers for Environmental Adaptive capacity (A) Average groundwater depths, (B) Rainfall, (C) Drainage density, (D) Drainage buffer, (E) Soil drainage, (F) NDVI, (G) Principal aquifer system, (H) Soil texture, (I) Soil depth, (J) Relative relief, (K) Elevation, (L) Slope.

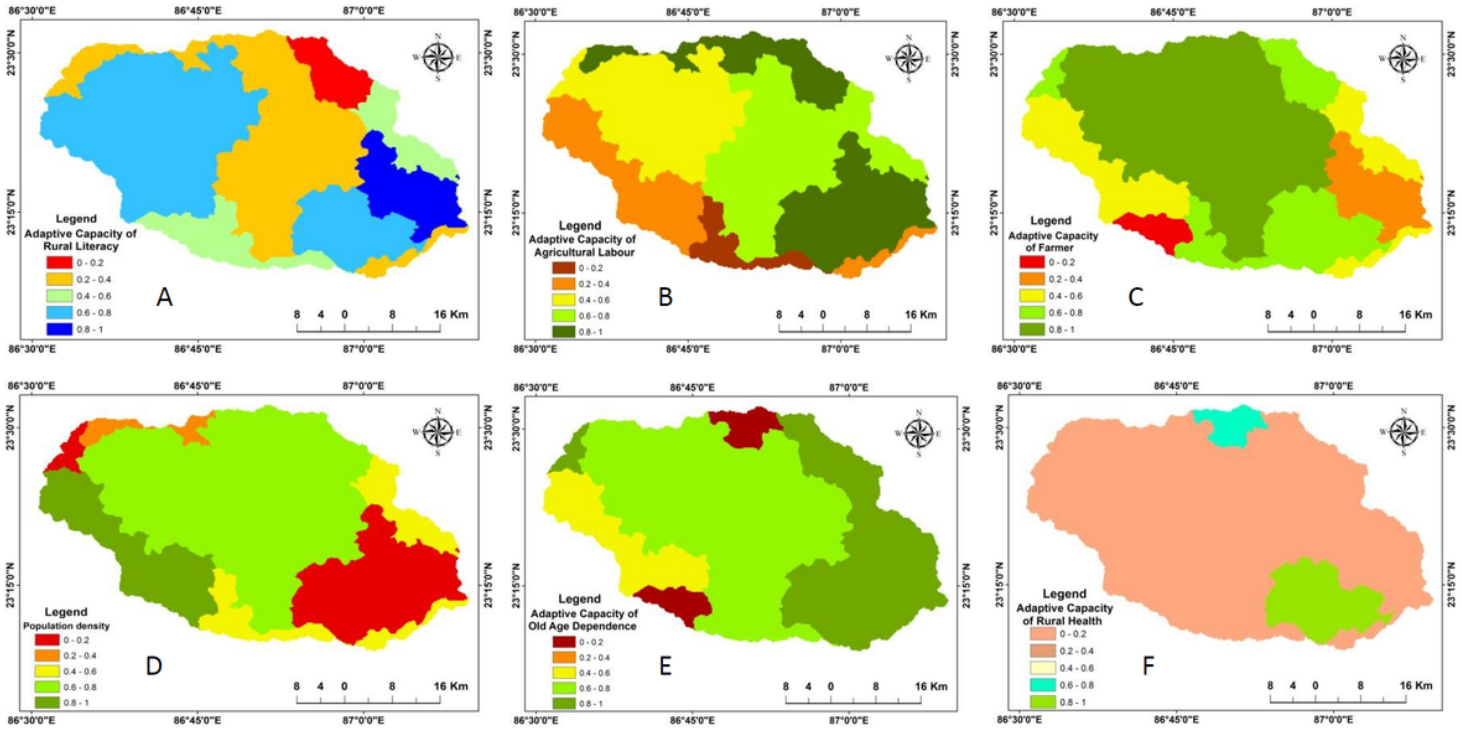

Figure 6

Thematic layers for Social Adaptive capacity (A) Rural literacy, (B) Agricultural Labour, (C) Farmer, (D) Population density, (E) Old age dependence, (F) Rural Health.

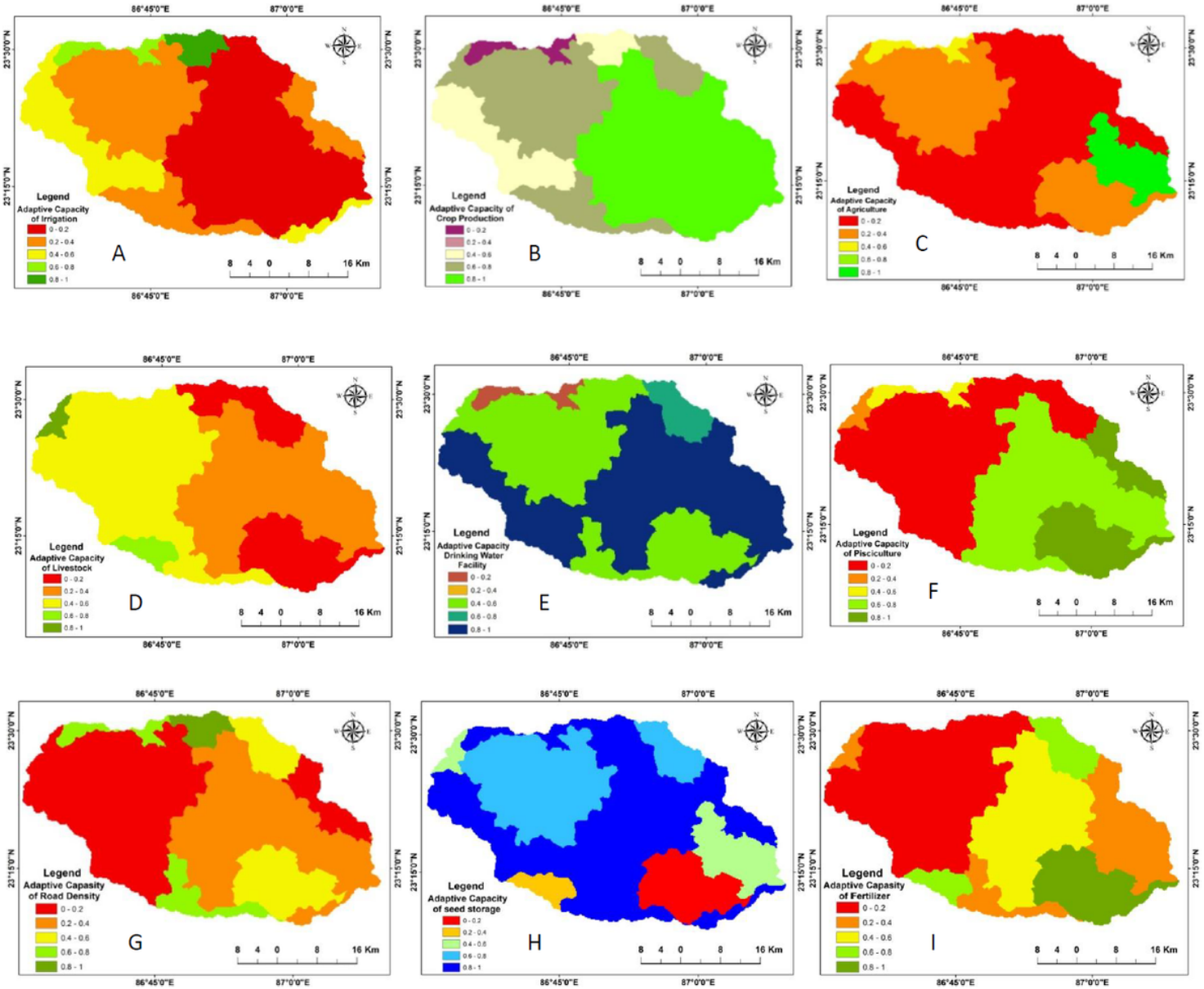

Figure 7

Thematic layers for Physical Adaptive capacity (A) Irrigation, (B) Crop production, (C) Agriculture, (D) Livestock, (E) Drinking water facility, (F) Pisciculture, (G) Road density, (H) Seed storage, (I) Fertilizer.

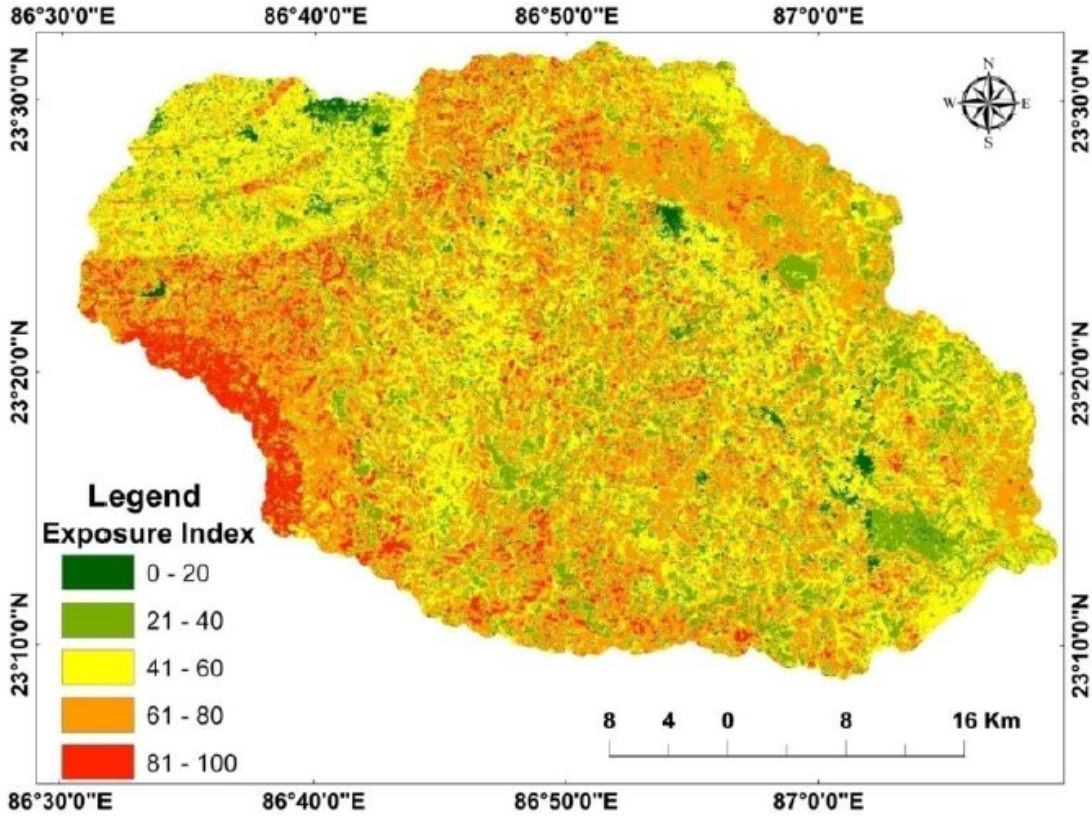

Figure 8

Exposure index

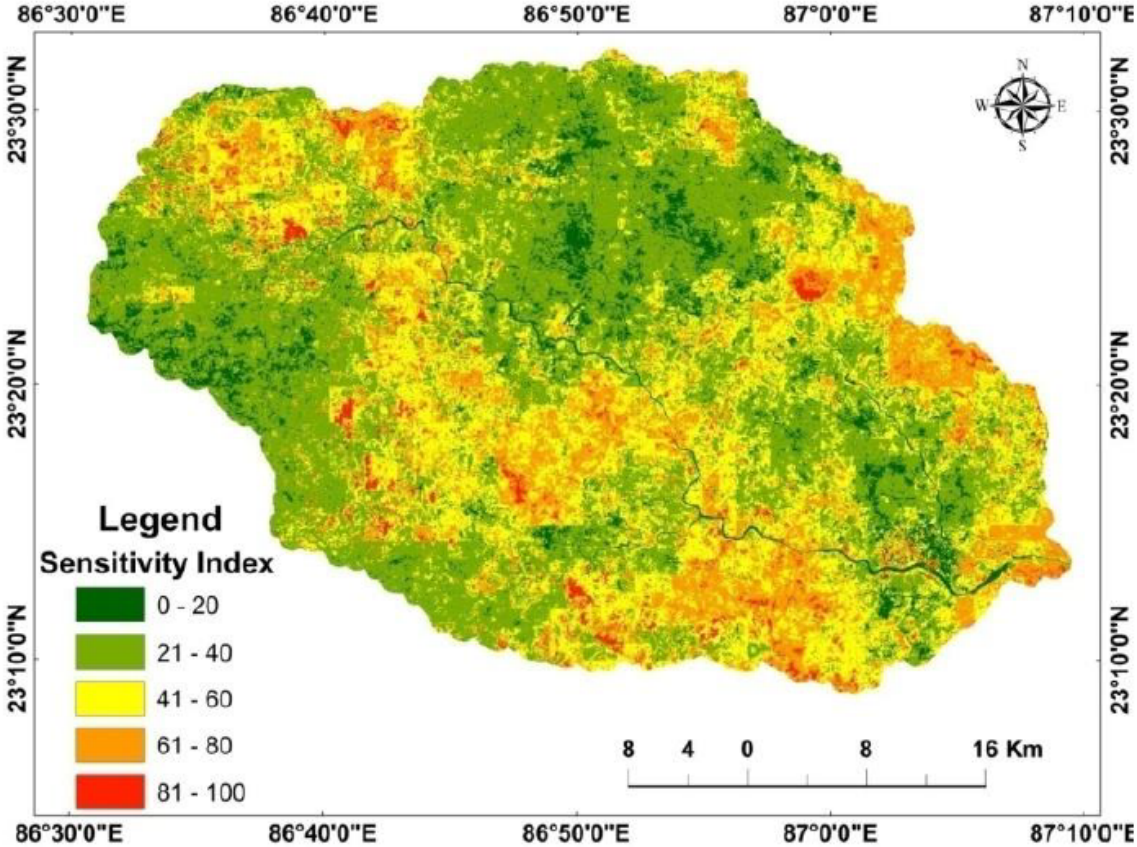

Figure 9

Sensitivity index

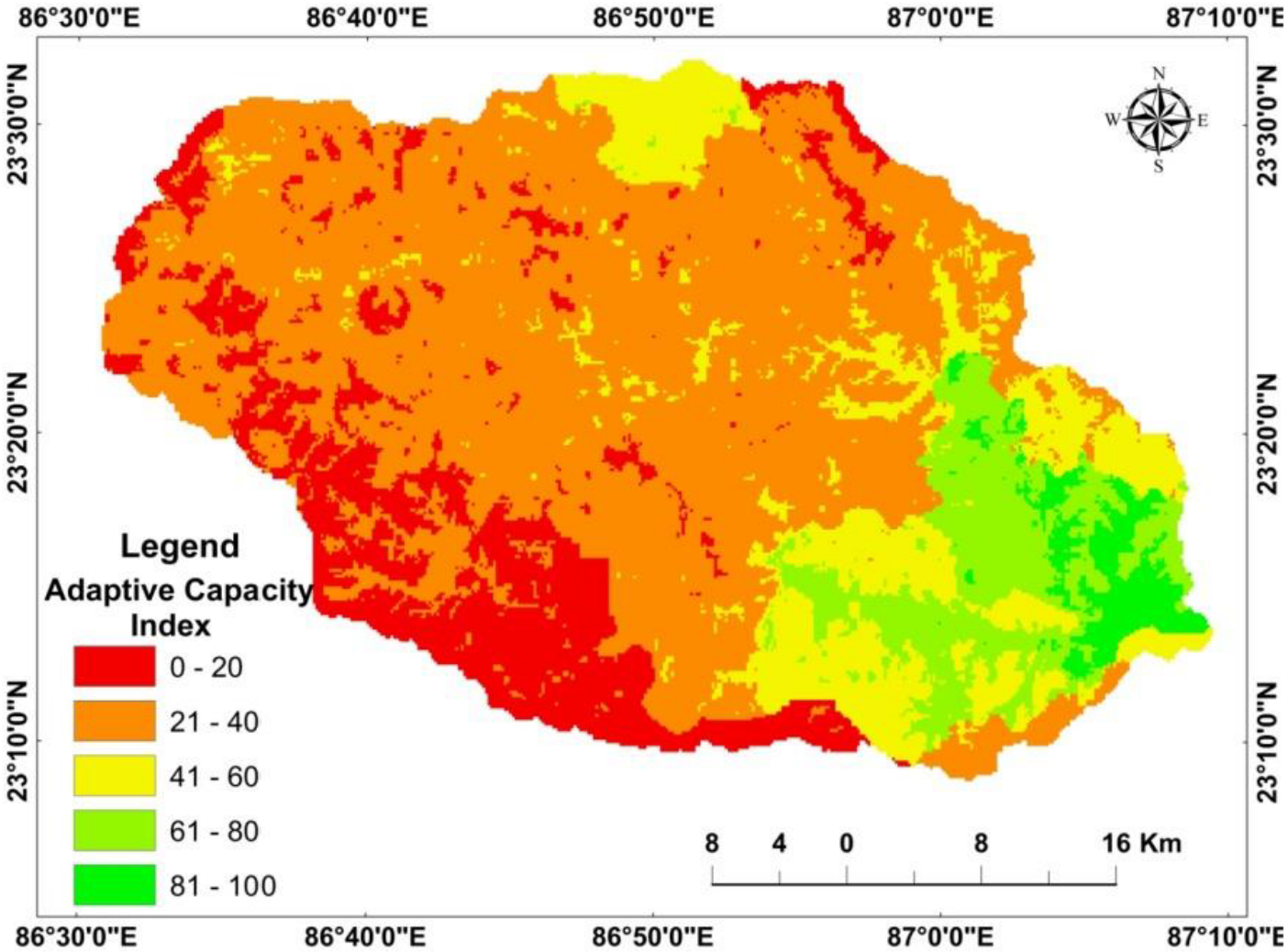

Figure 10

Adaptive capacity index

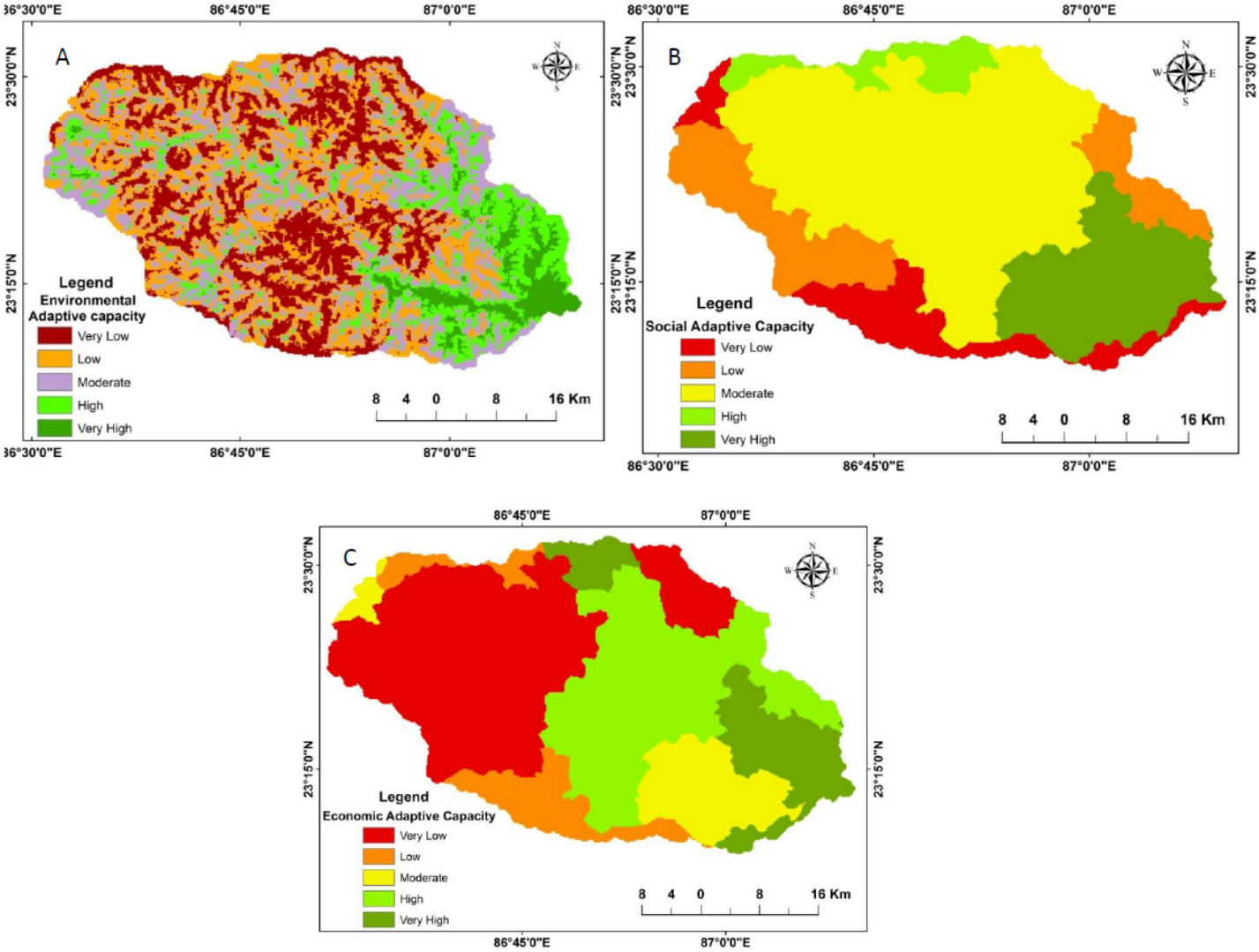

Figure 11

(A) Social adaptive capacity, (B) Environmental adaptive capacity, and (C) Economic adaptive capacity.

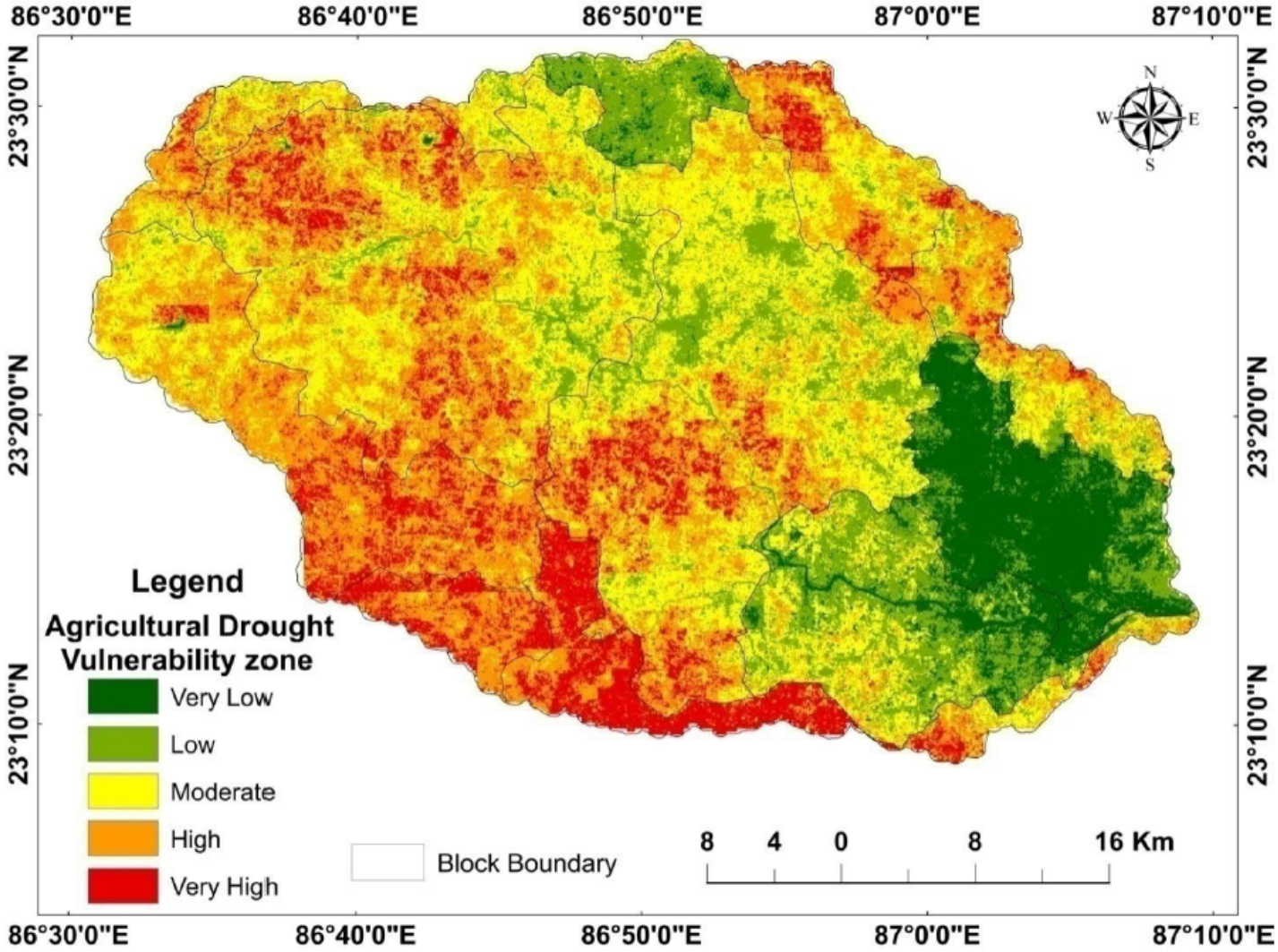

Figure 12

Agricultural drought vulnerability zones.

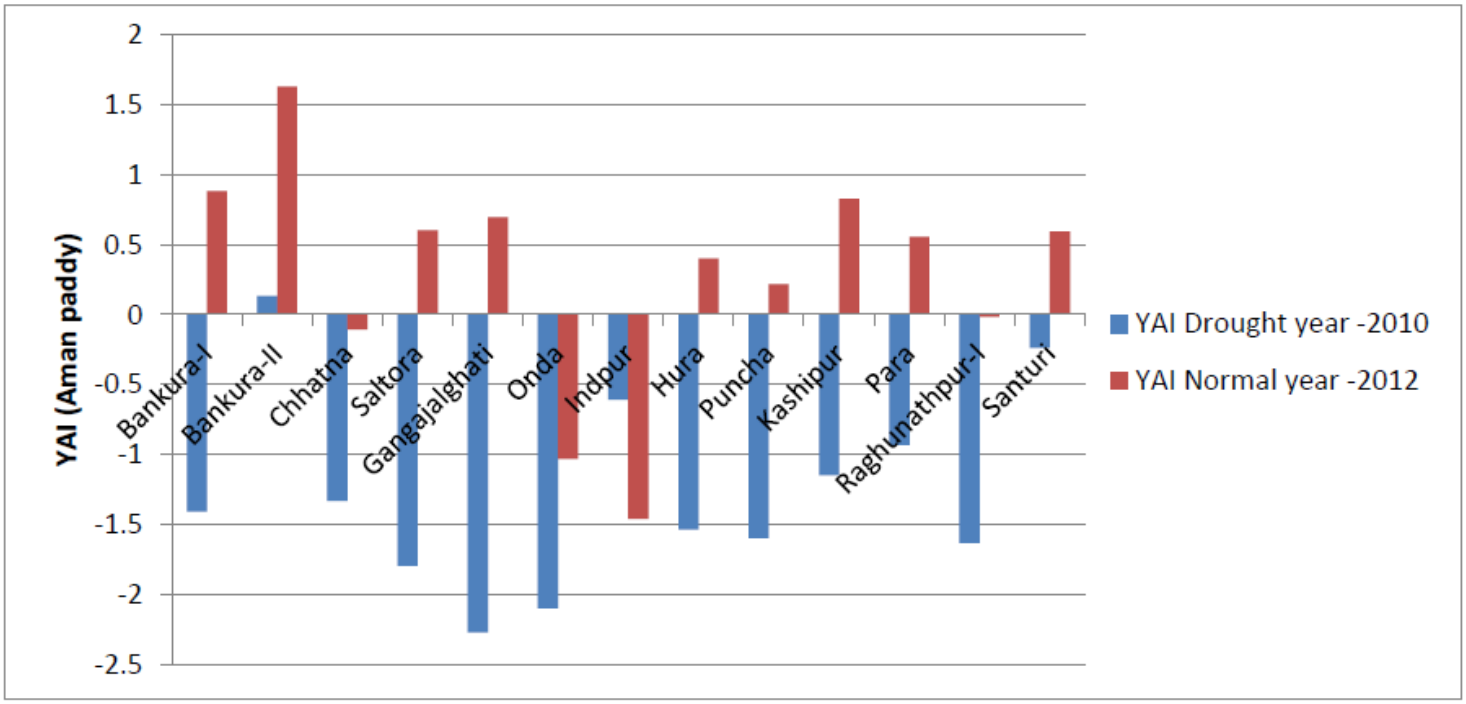

Figure 13

Block wise Yield anomaly index (YAI) of drought year (2010) and normal year (2012).