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RESEARCH ARTICLE

Satellite Remote Sensing for Monitoring Agriculture Growth and Agricultural Drought Vulnerability Using Long-Term (1982–2015) Climate Variability and Socio-economic Data set

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Abstract Climate variability significantly impact the agricultural growth, stress, cropping pattern, phenophase and its vulnerability. Satellite derived indices, climate and socio-economic data sets have been used to study the time series trend of agricultural NDVI and agriculture drought vulnerability for two states of India namely Andhra Pradesh and Telangana. The study uses NOAA AVHRR GIMMS NDVI.3g. v1 (1982–2015) data set. The trend analysis of climate and soil moisture was carried out to understand their impact on the agriculture growth/stress, length of the growing period (LGP) and projected agriculture NDVI for IPCC climate AR5 2050 RCP 2.6 scenario. A novel approach is applied to the integrated data sets i.e. satellite and climate variables including socio-economic to assess the agricultural drought vulnerability at the district level, and at the tehsil level of united Telangana and Andhra Pradesh states for the recent-past. We further projected the vulnerability using IPCC AR5 2050 and 2070 climate RCP 2.6 scenario. The study has revealed that climate and soil moisture have a significant impact on LGP and agriculture condition. The predicted agricultural NDVI are near like normal years (2007 and 2013) indicating climate change signatures are not expected in near future. There is a need to improve the understanding using higher resolution soil moisture data to plan appropriate adaptive and mitigation strategies for the agricultural drought conditions in changing climate scenario.

Keywords GIMMS · Trend · LGP · Climate change · Agricultural drought vulnerability

1 Introduction

In India, 54.6% of population is engaged in agriculture and allied activities (census 2011). Hence, any change in the crop condition/stress is likely to affect the overall economy of the country [1]. At least once in every 3 years, over the last few decades, India has experienced moderate-to-severe drought conditions [1]. Drought is one of the most crippling hazards and its direct impact is generally observable on agriculture. It is influenced by vegetation, land use, water resources, climate related parameters like precipitation, temperature, evapotranspiration, and socio-economic parameters [2].

Variation in crop stress, crop phenophase, cropping pattern, length of crop growing periods etc. are the indicators of the impact of climate change [3]. The climate change is expected to influence the drought condition, which in turn has an impact on agriculture [4, 5].

Phenology metrics are used to distinguish regionally the same crop having differences in sowing date and growth profile [6]. The time series change in phenology profiles is mainly due to the impact of weather conditions, climate change and anthropogenic factors. Length of the growing period (LGP) determined from the phenophase profiles have been studied in India only during the period of *kharif* season [7] and that too specific to agro-ecological zones of erstwhile Andhra Pradesh State [8]. LGP for any given region represents the number of days when plant growth takes place.

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Agricultural drought, caused by reduced soil moisture availability to crops would lead to considerable economic loss worldwide. Agriculture is one of the most sensitive and vulnerable to climate change among all the sectors [4]. Therefore, study of vulnerability is important as it enables the identification of areas or resources at risk, and the loss of such resources that could threaten future adaptation and sustainable development [9]. There are three widely used approaches to assess the vulnerability, namely (i) socio-economic approach, (ii) biophysical approach and (iii) integrated assessment approach. A few studies have been carried out in India to assess the drought vulnerability. For example, Chandrasekar et al. [10] have adopted Multi Criteria Analysis (MCA) for assessing agricultural drought vulnerability in Tamil Nadu State; Kaushalya et al. [2] computed the vulnerability using satellite and climatic data sets in Agro-ecological sub-division (ASER) of India; and Murthy et al. [11]. adopted IPCC composite index approach using remote sensing data during *Kharif* crop (August-October) in various states. Studies were also carried out without spatial data, considering bio-physical and socio-economic parameters with climate change during *Kharif* season in Indo-Gangetic plains using integrated approaches [12]. However, most of the studies have ignored the impact of monsoon on winter/*rabi* and summer/*zaid* cropping season. Bhavani et al. [13] have shown that monsoon rains would also have an impact on rabi and zaid cropping periods. Therefore, agriculture stress of three cropping seasons with respect to climate can be used to study the agriculture drought vulnerability in three seasons.

Satellite NOAA Advanced Very High Resolution Radiometer (AVHRR) GIMMS NDVI 3g.v1(1982–2015) continuous time series data is used for time series trend analysis of agriculture NDVI and LGP, whereas for agricultural drought vulnerability assessment, satellite indices derived from GIMMS and MODIS ($NDVI_{Dev}$, VCI, % Ratio of crop fluctuation) adopted from Bhavani et al. [13], climate (1982–2015), and socio-economic data sets are used. The data sets are described in detail in Sect. 2.2.

The specific objectives of the study are

1. to examine long-term variations (33 years) of NDVI and LGP with climate and soil moisture using GIMMS NDVI3g.v1 data for the two states under consideration viz., Telangana (TS) and Andhra Pradesh (AP), and projection of future agriculture NDVI using IPCC AR5 RCP 2.6 climate scenario;
2. to compute and assess the current status of agriculture drought vulnerability in TS and AP states at district and tehsil levels using integrated data sets i.e. satellite derived indices (adopted from Bhavani et al. [13]), climate, socio-economic and Institutional data; and
3. to assess the future agricultural drought vulnerability (only at district level using the projected climate scenarios (RCPs 2.6, 4.5, 6.0 and 8.5) during three cropping seasons (June–September, October-January and February-May).

2 Materials and Methods

2.1 Study Area

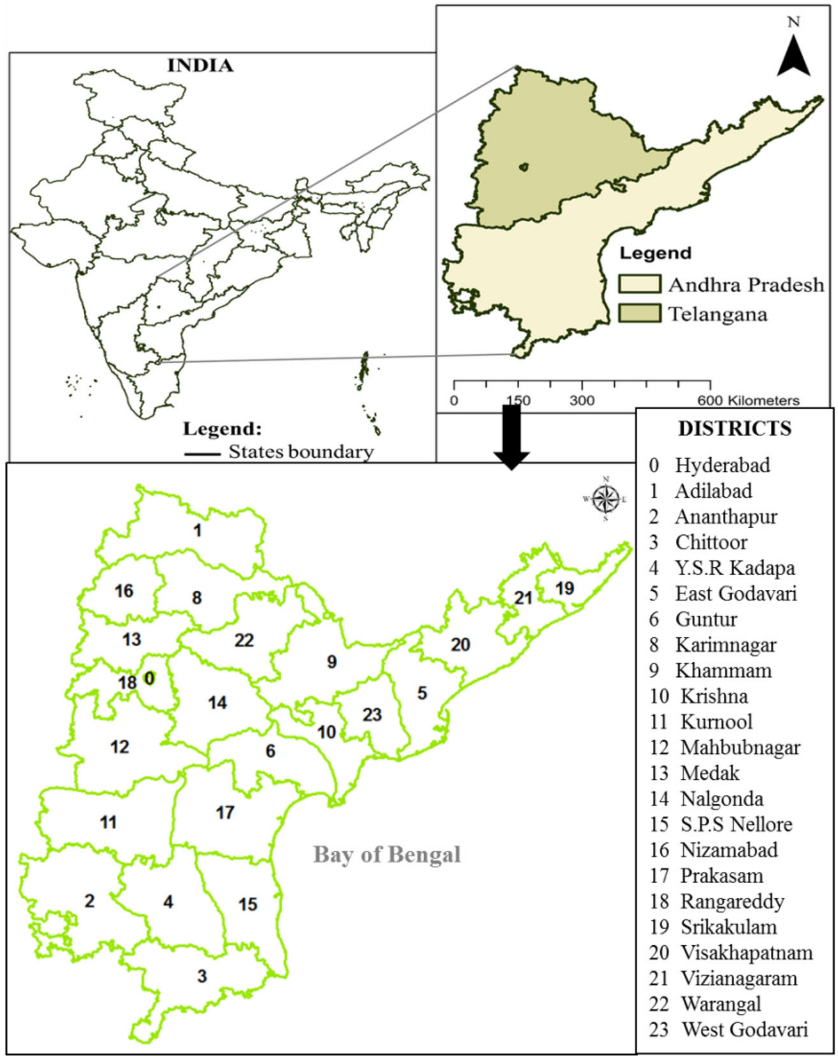
The study area encompasses two states namely Telangana (TS) and Andhra Pradesh (AP). Hyderabad district falling in TS is excluded from the present study because it has no significant agricultural area [14]. The former undivided AP state lies in the tropical region between the latitudes 12°14′N and 19°54′N and longitudes 76°46′E and 85°40′E. The area falls in the semi-arid region of peninsular India was bifurcated into two states in 2014, namely, Andhra Pradesh (comprising of 13 districts) and Telangana (10 districts), as shown in Fig. 1. The three distinct seasons of former AP are the *kharif* or summer monsoon (June–September), winter or *rabi* (October–January) and summer or *zaid* (February-May). The annual maximum temperature of the state is ~ 20 °C, and the minimum is around 10–12 °C [15]. The coastal plains experience relatively warm summer with temperatures often exceeding ~ 38 °C at places. The southwest monsoon contributes to almost two-thirds of the annual rainfall, which, however varies widely across the state. Some coastal areas receive 1400 mm of rain, whereas the northern and western parts of the plateau receive about 500 mm. Most of the cultivation (about 68.27%) takes place during the monsoon/rainy period from June to September. Other irrigation sources and the residual soil moisture are used for cultivation in winter (*rabi*) and summer season (*zaid*). The moisture stress modulates the crop growth and gets reflected in the NDVI. The sowing pattern is also dependent on the precipitation and available soil moisture.

2.2 Data

2.2.1 Satellite Data

2.2.1.1 NOAA AVHRR GIMMS NDVI NOAA (AVHRR) GIMMS NDVI3g.v1 (third generation version 1) bimonthly products with spatial resolution of 8 km × 8 km was downloaded from https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/00FILE-LIST.txt during July 1981 to December 2015. These NDVI data sets have been corrected for calibration, viewing geometry, volcanic aerosols and other effects that are not related to vegetation change. The data

Fig. 1 Location map of study area



contain global geographical projections (Geographic, WGS 1984). The GIMMS products are at 8 km resolution, 16-day maximum value composite (MVC) bimonthly global NDVI product generated from AVHRR data. The data sets are in GEO TIFF and NetCDF format. Satellite indices ($NDVI_{Dev}$, VCI, %RCF) derived from-NDVI product were adopted from our previous study [17] to assess the agriculture drought vulnerability, whereas GIMMS NDVI 3g.v1 continuous data over the time period from 1982 to 2015 was used to assess the long-term trend of agriculture growth/stress and to calculate LGP and their relationship with climate and soil moisture.

2.2.2 Soil Moisture and Soil Maps

Soil moisture plays an important role in agriculture process, drought and run off generation. The soil moisture data (available in NetCDF format) have been downloaded from European Space Agency (ESA) Climate Change Initiative (CCI) daily merged passive and active sensor at $0.25° \times 0.25°$ for the period 1982–2013 (http://esa-soilmoisture-cci.org/node/139). Soil maps have been downloaded from National Bureau of Soil Survey and Land use Planning (NBSSLUP). These maps consist of the following parameters; surface form, soil depth, parent material, particle size class, mineralogy, calcareousness, soil temperature regime, soil reaction (pH), Slope, soil drainage, erosion, surface texture, salinity, acidity, organic carbon (OC), surface stoniness, cation exchange capacity (CEC), and flooding. In this study, soil depth and soil texture have been used to generate the available water holding capacity (AWHC).

2.2.3 Climate Data sets

The daily rainfall and temperature data sets available at $0.25° \times 0.25°$ and $0.5° \times 0.5°$ from the India Meteorological Department (IMD) for the period 1982–2015 were used in this study [16]. These variables are used to assess Exposure (E). Further, project AR5 climate parameters (rainfall and temperature) were also used to project/assess future agricultural drought vulnerability. Future projected data are available from the IPCC AR5 climate projections from global climate models (GCMs) for four representative concentration pathways (RCPs) [17]. The GCM output was downscaled and calibrated (bias corrected) using World Clim 1.4 as baseline 'current' climate.

AR5 global gridded climate data with a spatial resolution of 30 s (1 km $\times$ 1 km) have been downloaded from World Clim- Global Climate data (http://www.worldclim.org/). The monthly climate data i.e. minimum and maximum temperature, precipitation generated from Hadley Centre Global Environment Model version 2-Earth System (HadGEM-ES) available for the periods 2050 and 2070 have been used in this study.

2.2.4 Socio-economic Data

Socio-economic data sets are used as indicators for assessing vulnerability. The digital form of socio-economic data (Census of India) is available only for 2001 and 2011. The socio-economic data set of 2011 comprising of population density, literacy rate, migrant rural persons and livestock are downloaded from Census of India as one the parameters of Sensitivity (S) or Adaptive Capacity (AC) to assess present Agricultural Drought Vulnerability Index (ADVI). The data sets viz., population density, literacy rate, livestock available from 1966 to 2011 were downloaded from ICRISAT VDSA to project socio-economic parameters for the year 2030. These projected parameters are used as one the parameters of S or AC to assess future ADVI.

2.2.5 Agricultural Field Data

The historic data sets from 1966 pertaining to agricultural labors, agriculture wages and gross irrigated data are downloaded from ICRISAT VDSA to project the data for the year 2030. The present (2011) field data i.e. agricultural labors (main and marginal), agriculture wages and agriculture consumption are downloaded from census of India. The Gross Irrigated Area (GIS), Extent of Gross Irrigated Area (Ex. GIr), Surface Water (SW), Ground Water (GW) and the Net Irrigated Area (NIA) statistics of the state for the period 2011–2012 were downloaded from the International Crop Research Institute for Semi-Arid Tropics (ICRISAT), and Village Dynamics in South Asia (http://vdsa.icrisat.ac.in/).

2.2.6 Institutional Data

The institutional data sets such as agricultural credit society, commercial banks, and agricultural marketing society and road networks for the year 2011 are downloaded from Census of India at tehsil level.

2.3 Data Processing

2.3.1 Methodology

2.3.1.1 NOAA GIMMS NDVI3g.v1 Processing The downloaded NOAA AVHRR GIMMS NDVI products were multiplied by a scale factor before the study area was subset. For time series analysis bimonthly NDVI has been used and for seasonal assessment bimonthly NDVI products from 1982 to 2015 are used.

2.3.1.2 Time Series Trend Analysis For continuous trend analysis of agricultural NDVI; phenophase metrics; its relation to climate (precipitation and maximum temperature) and soil moisture; and projection of agricultural NDVI for 2050 IPCC AR5 RCP 2.6 scenario, GIMMS NDVI 3g.v1 bimonthly pre-processed data have been used in addition to statistically computed data at the state level (TS and AP). For grid wise projection of agricultural NDVI at three cropping seasons, raster bimonthly agricultural NDVI is converted to seasonal data for 1982–2015. The daily gridded rainfall, temperature and soil moisture data sets have been converted to mean bimonthly, similar to that of GIMMS NDVI 3g.v1, and subset to area of interest (AOI).

2.3.1.3 Computing the Length of Growing Period from Phenophase Events The bimonthly agricultural NDVI data starting from June to January each year (1982–2015) was considered, as June to January period (summer monsoon and winter cropping seasons) covers both *kharif* and *rabi* cropping seasons. Double Logistic (DL) Kolsertman-model [18] was fitted to time series agricultural NDVI to extract the phenological events i.e. start of the season (SOS), peak of the season (POS) and end of the season (EOS) based on pheno first derivative method [19]. SOS and EOS are the points where the NDVI profile crosses the threshold value in upward and downward directions respectively. The extracted pheno events for each year are mentioned in Supplementary Table 1 (SM1). The performance of fitting DL model, smoothing and extraction of phenophase are done in R language phenoix package [19]. LGP is computed from aggregated days from SOS to EOS obtained events (Eq. 1). Similar procedure is repeated for each year during 1982–2015. Summation of bimonthly rainfall and soil moisture data sets have also been done with similar NDVI pheno events i.e. SOS to EOS, whereas for maximum temperature, mean value is generated. The impact of climate and soil moisture on LGP is calculated using the following equation

Table 1 Description of data used in the study

Variables		Measurements	Sources
Satellite (1982–2015 and 2000–2015)			
GIMMS/MODIS NDVI	Drought frequency (June–September, October–January and February–May)	It is generated from frequency of deviation of NDVI. It is used to assess the drought prone level	LPDAAC
		$DevNDVI = (NDVIi - NDVImean)$	http://reverb.echo.nasa.gov/reverb
	VCI (June–September, October–January and February–May)	It can estimate the status of vegetation according to best and worst vigour over a time period. It is derived from NDVI time series product. It has a negative relation with vulnerability $\frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$	Kogan [20]
MODIS NDVI	% Ratio of crop fluctuation (June–September, October–January and February–May)	It is used to capture the percentage crop variation during 15 years period	Bhavani et al. [13]
Climate data (1982–2014)			
Rainfall	Present (June–September, October–January and February–May)	33 years three separate cropping calendar (June–September, October–January and February–May) mean precipitation. Good monsoon controls the effect of drought. Thus it is negatively related to vulnerability	IMD
	Future (June–September, October–January and February–May)	AR5 RCP 2.6 Scenarios	World climate data
Temperature	Maximum Minimum	33 years three separate cropping calendar (June–September, October–January and February–May) mean of maximum temperature and also minimum temperature. Temperature has an impact on agriculture. It is negatively related to vulnerability	IMD
	Future (Maximum and min temperature)	AR5 RCP 2.6 Scenarios	World climate data
Socio-economic	% Migrants rural persons	It is the percentage of migrant rural population to that of total migrant's population. It has a positive relation with vulnerability	Census data
	Total agriculture rural labors	The sum of main and marginal agriculture labor. It has a positive relation with vulnerability	
	Population density	It is the ratio of total population to that of total geographical area. Population density is positively related to vulnerability	
	%Total literacy	It is the percentage of total literacy person to that of total population person. It is negatively related to vulnerability, more the literate results more awareness to adapt about the climate change and agriculture vulnerability	
	%Rural literacy	It is the percentage of total rural literacy person to that of total rural population person. It is negatively related to vulnerability, more the literate results more awareness to adapt about the climate change and agriculture vulnerability	

Table 1 continued

Variables		Measurements	Sources
	Live stock	It supports agriculture through animal power and manure and also as farmer's alternate source of income. Thus, have negative relation with vulnerability	ICRISAT
	%Net cropped Areas	Total area sown at least once in particular year. It has a positive relation with vulnerability	Agricultural statistic glance
	%Gross cropped area	Total area sown more than one time in particular year. It also has a positive relation with vulnerability	
	Extent of gross irrigated areas	Total area irrigated only once in a year. Irrigation facility is adapted to overcome moisture stress require for the crop productions. Have a negative relation	
	Gross irrigated areas	Total area irrigated more than once in a year. Irrigation facility is adapted to overcome moisture stress require for the crop productions. It is negatively related to vulnerability	
	Agriculture power consumption	It has a impact on various dimension i.e. improvement of education, health, standard living, demand Irrigation is adapted by supply of electricity. It is negatively related with vulnerability	
Field	Soil erosion	Soil degradation leads to reduction in soil fertility which impact on agriculture. Positive relation with vulnerability	National Bureau of Soil Survey and Land Use Planning (NBSSLUP)
	% Non-cropped area	The total % of Barren and Un-cultivable land area and % of Cultivable waste land area	Census data
	Available water holding capacity	It is computed using soil texture with standard water holding capacity values for particular textures. Negative relation with vulnerability	NBSSLUP, Department of Agriculture Bulletin (DAB) (1960)
Institutional data	Agriculture credit society Commercial banks	Enable the farmers to adopt modern technology and improve agricultural practices for increasing agricultural production and productivity. Thus, has a negative impact on vulnerability	Census data
	Road networks	Agrarian communities are highly dependent on a reliable transport system. Thus has a negative relation with vulnerability	
	Agriculture marketing society	These societies provide marketing facilities and make arrangements for the supply of agricultural necessities and consumer articles in the rural area. Thus has a negative relation with vulnerability	

$$LGP = \sum SOS\ to\ EOS \tag{1}$$

and shown in scatter plots along with the trend lines

2.3.1.4 Long-Term Trend of Agricultural NDVI to the Climate and Soil Moisture The pre-processed agricultural NDVI of GIMMS and temperature have been rescaled to 0.25 degree, to make them consistent with the rainfall-gridded data set of IMD. The converted bimonthly rainfall, maximum temperature, soil moisture and agricultural NDVI are extracted at state level for 1982–2015, staring from June 1982 to May 2015. A decompose function is applied to these data sets using R statistical software to obtain trend component, seasonal component and irregular component. The relation of NDVI with climate variables and soil moisture for both the states is then studied using the graphical plots of time series trends.

2.3.1.5 Projection of Agricultural NDVI for AR5 2050RCP 2.6 Scenario Grid wise projection of agricultural NDVI has been carried out using multiple linear regression model based on the relationship of recent-past long-term (1982–2015) multiple variables i.e., agricultural NDVI and climate data (rainfall and maximum temperature). Bimonthly multiple data sets have been converted into three seasons, namely the Kharif/summer monsoon (June–September), Rabi/winter (October–February) and Zaid/summer (February–May). Each season consists of 32 layers (years). Three raster data sets i.e., seasonal agricultural NDVI, rainfall and maximum temperature are stacked per year, each one consists in 32 raster layers. The parameters i.e. slope, intercept, coefficient of determination (R^2) and significance level (p-values) were extracted at grid level and plotted. R^2 values are used to examine the relationship between agricultural NDVI and climate data sets.

The estimated parameters i.e. slope and intercept from regression model along with IPCC projected AR5 climate data (i.e. rainfall and maximum temperature) for the year 2050 have been used to predict the 2050 seasonal agricultural NDVI at pixel level based on the equation

$$Y = a + b_1\beta_1 + b_2\beta_2 \tag{2}$$

where, Y is predicted agricultural NDVI at each grid; a is Y intercept; b1and b_2 are slopes of two independent variables (rainfall and maximum temperature) and $\beta_1\&\beta_2$ are observed/projected AR5 independent climate variables (rainfall and maximum temperature). The spatial distribution of seasonal agricultural NDVI during the recent years with drought, normal and best years along with projected 2050 seasonal agricultural NDVI are discussed in Sect. 3.2

2.3.1.6 Agriculture Drought Vulnerability IPCC defines vulnerability (V) as the composite index of exposure (E), sensitivity (S) and adaptive capacityindex (AC). In the context of climate change, exposure is defined as "the nature and degree to which a system is exposed to significant climatic variation"; sensitivity of the system to climate change is defined as "degree to which a system is affected, either adversely or beneficially, by climate variability or change"; and adaptive capacity is defined as "the ability (or potential) of a system to adjust successfully to climate change" The study uses agricultural drought vulnerability index (ADVI) at district and tehsil level based on IPCC [7] work frame. Table 1 summarizes the description of data used in the ADVI assessment.

Agriculture drought vulnerability index was calculated based on four steps i.e. identification of indicators, normalization, ranking, weighting of indicators using Analytical Hierarchy Process (AHP).

Identification of indicators of each component (E, S, and AC) for vulnerability analysis is based on the previous studies [11, 21, 22]. Redundancy analysis was carried out to finalize the list of indicators to improve the vulnerability analysis at district and Tehsil levels. This has helped to reduce the dimensionality of parameters for vulnerability assessment. The variables are categorized into broad groups based on the source of the data set listed in Table 2. The socio-economic and agricultural parameters i.e. population, literacy rate, agricultural labors, and gross irrigated available for every decadal years (1966–2011) are computed using Eq. 3a in each case. The decadal percentage growth rate during 1966–2011 is averaged and used for computing the future value for respective parameter using Eq. 3b. The population of AP was considered to be stabilized in 2030. Thus the projections of parameters were done only up to 2030. Since each component has different units and scales the normalization was carried out using the following equations (Eq. 4a, 4b).

$$PR = \frac{\frac{(V_{present} - V_{past})}{(V_{past})} * 100}{N} \tag{3a}$$

$$Future = \left(\frac{Nth\ year * i}{100}\right) * V_{present} \tag{3b}$$

where, PR is Percent Rate; $V_{Present}$ is Present; V_{Past} is Past value; N is number of years; Nth year is the future year to be predicted and i is the average growth rate of past decadal years.

$$Y_{ij} = \frac{(X_{ij} - Min(X_{ij}))}{(Max(X_{ij}) - Min(X_{ij}))} \tag{4a}$$

$$Y_{ij} = \frac{(Max(X_{ij}) - X_{ij})}{(Max(X_{ij}) - Min(X_{ij}))} \tag{4b}$$

Table 2 Recent-past and future indicators finalized in each component

Indicators	Parameter		District wise		Tehsils Level	Source
			Present period 1982–2015	Future		
Sensitivity	GCA		2011	≈	N/D	Census of India
	Drought Frequency		Generated from GIMMS and MODIS Deviation of NDVI	≈	N/D	Bhavani et al. [13]
	VCI		Derived from NDVI 1982–2015	≈	E*	Kogan [20]
	% Ratio of crop fluctuation		N/D	≈	E*	Bhavani et al. [13]
	S.Er		Vector Soil map available 2005	≈	E*	NBSSLUP
	AWHC		Generated using soil texture	≈	E*	NBSSLUP and DAB (1960)
	Pop. D		2011	**	2011	Census of India
	T-AgL		2011	**	2011	Census of India
	% MgR		2011	≈	N/D	Census of India
	% NCA		N/D	N/D	2011	Census of India
	NSA		N/D	N/D	2011	Census of India
Adaptive capacity	%LiT		2011	**	–	Census of India
	%LiR		2011	**	2011	Census of India
	AgP		2011	≈	2011	Agricultural Statistical glance and Census of India
	AgW		2011	**	N/D	Census of India
	L/S		2011	**	N/D	ICRISAT VDSA
	ExG-Ir		2011	≈	N/D	Agricultural Statistical glance
	G-Ir		2011	**	2011	ICRISAT VDSA
	Ag-CrSo		N/D	N/D	2011	Census of India
	CoB		N/D	N/D	2011	Census of India
	RN		N/D	N/D	2011	Census of India
	Ag-Mr-So		N/D	N/D	2011	Census of India
Exposure	Rainfall		1982–2014 (0.25° × 0.25°)	AR5, RCP Scenarios	E*	India Meteorology Department and World Climate
	Temp	Max	1982–2013 (0.5° × 0.5°)		E*	
		Min				

No. DF no of drought frequency, *%RCF* percentage ratio of crop fluctuation, *VCI* vegetation condition index, *GCA* gross cropped area, *S. Er* soil erosion, *AWHC* available water holding capacity, *Pop. D* population density, *T-AgL* total agriculture labour, *% MgR* percentage of migrants rural, *% NCA* % non cropped area, *%NSA* percentage of net sown area, *%LiT* percentage of total literacy, *%LiR* percentage of rural literacy, *AgP* agriculture power consumption, *AgW* agriculture wages, *L/S* live stock, *ExG-Ir* extent of gross irrigated area, *G-Ir* gross irrigated area, *Ag-CrSo* agriculture credit society, *CoB* commercial banks, *RN* road networks, *Ag-MrSo* agriculture marketing society, *Min Temp* minimum temperature, *Max Temp* maximum temperature, *RCP* representative concentration pathway

≈ Same (1982–2015) present data

** Generated 2030 using past 50 years data

E* Extracted the data for Tehsils study area; and N/D: no data

where, X_{ij} represents the actual value of the indicator i for the district j, where i and j can vary from i = 1,2, 3…, n; j = 1,2,3…, m. $MIN(X_{ij})$ and $MAX(X_{ij})$ are the minimum and maximum value of the indicator i. If the indicator has a positive relationship with vulnerability, Eq. 4a was used for the normalization and in case of a negative relationship Eq. 4b was used. An approach for ADVI in Present and Future climate is presented in the Table 3.

After normalization, weights for each component of indicators are determined using the AHP method [23] adopted from Cheng [24] and Miura [25] for vulnerability analysis. The AHP priority and weights used for the district/tehsil level are provided in Tables 4 and 5. The consistency ratio was checked for all the components. Using the respective weights, E, S and AC indices are computed and scaled/categorized into 5 classes. Finally, ADVI is generated using Eq. 5.

Table 3 Approach for agricultural drought vulnerability index in present and future climate (adopted and modified Shukla et al. [5])

Parameters used for agricultural drought vulnerability analysis						
Exposure			Sensitivity		Adaptive capacity	
Current	Future (2050 and 2070)		District 1982–2015	Tehsils	District	Tehsils
1. Long term mean precipitation 2. Long term mean maximum temperature 3. Long term mean minimum temperature	RCP 2.6 RCP 4.5 RCP 6.0 RCP 8.5	1. Annual maximum and minimum temperature 2. Annual mean precipitation	1. GCA 2. No. DF 3. VCI 4. So.Er 5. AWHC 6. Pop.D 7. T-AgL %MgR	1. NSA 2. % RCAF 3. VCI 4. % NCA 5. So.Er 6. AWHC 7. Pop.D 8. T AgL	1. G-Ir 2. Ex G-Ir 3. AgW 4. AgP 5. L/S 6. %LiR 7. % LiT	1. TIA 2. AgP 3. AgCrSo 4. ComB 5. %Li 6. RN 7. Ag.MgSo
Analysis		Extraction of pre-processing indicators Normalisation of indicators Weights of indicators using AHP method				
GIS analysis		Agricultural drought vulnerability index for all climate scenarios ADVI = ([E + S]-AC) Overlay of district boundary to find the highest vulnerable zones Generate vulnerability map				

Abbreviation mentioned below Table 2

Table 4 District and Tehsils level scales/priority of indicators for each component

District						Tehsils					
Adaptive capacity		Sensitivity		Exposure		Adaptive capacity		Sensitivity		Exposure	
Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale	Indicators	Scale
%Li	1	%MR	1	Min Temp	1	Ag_MgSo	1	TAgL	1	MinTemp	1
%LiRu	2	T_AgL	2	Max Temp	3	RN	2	Pop_D	2	Max Temp	3
L/S	3	Pop.D	3	Precipitation	9	%Li	3	AWHC	3	Precipitation	9
AgW	5	AWHC	4			Com.B	5	So_Er	4		
AgP	6	So. Er	5			Ag_CrSo	6	% NCA	5		
Ex-GIA	7	% RCF	6			AgP	7	VCI	6		
GIA	9	No. DF	8			TIA	9	% RCF	7		
		GCA	9					NSA	8		

Abbreviations as mentioned in Table 2

$$ADVI = f((E + S) - AC) \quad (5)$$

where, E, S, AC are exposure, sensitivity and adaptive capacity, respectively.

The E, S, AC and ADVI maps at district and tehsil levels (June–September; October- January and February- May) were prepared using ArcGIS software. Similar procedure is carried out to assess future ADVI for IPCC AR5 (2050 and 2070) climate scenarios as an exposure indicator of vulnerability.

Overall representation of methodology is illustrated in Fig. 2.

3 Results and Discussion

Agriculture yield mainly depends on the water, soil, nutrition and management practices. However, in many cases the proportions of these inputs vary, depending upon the amount of precipitation the region has received, the availability of irrigation facilities and the management of the nutrition and other cultural practices [26]. Socio-economic factors are also responsible for climate change [17], hence, these factors would also influence the agriculture. The present study supports the results of agriculture stress conditions reported in our previous studies [13]. The

Table 5 Pair wise priority weights of indicators of components sensitivity, adaptive capacity and exposure

Indicators	Parameter		District wise	Tehsils level
Sensitivity	% MgR		0.023	N/D
	T-AgL		0.034	0.019
	Pop. D		0.049	0.026
	AWHC		0.073	0.037
	S. Er		0.107	0.053
	% NCA		N/D	0.076
	%RCF		0.156	0.109
	VCI		0.230	0.154
	GCA		0.329	0.218
	NSA		N/D	0.307
Adaptive Capacity	AgMrSo		N/D	0.027
	RN		N/D	0.041
	% LiT		0.027	0.066
	%LiR		0.041	N/D
	L/S		0.066	N/D
	CoB		N/D	0.105
	Ag.Cr.So		N/D	0.163
	AgP		0.105	0.241
	AgW		0.163	N/D
	TIA		N/A	0.358
	ExG-Ir		0.241	N/D
	G-Ir		0.358	N/D
Exposure	Rainfall		0.597 (59.7%)	0.597
	Temp	Max	0.276 (27.6%)	0.276
		Min	0.128 (12.8%)	0.128

Abbreviations as mentioned in Table 2

N/D no data

impact of climate and soil moisture on agriculture and LGP, over the last 3 decades using satellite and climate data (1982–2015), have been captured by time-series analysis. The systematic analysis of agriculture stress and long-term impact of climatic parameters have been further studied to assess the quantity/state of agriculture vulnerability, additionally in considering socio-economic data.

3.1 Long-Term Response of Length of the Growing Period and NDVI with Rainfall and Soil Moisture

Phenological events determine the length of cropping growth cycle. The time period of the agriculture crop growth (i.e. SOS to EOS events) is dependent upon many climatic parameters, soil moisture and irrigation sources. This time period is referred to as LGP. It is a crucial parameter to understand the variation of vegetation/plant growth, start and end of crop seasons events in each year and impact of rainfall and temperature variability on crop [27, 28]. The present study considers two cropping season's i.e. June–January (*Kharif*/summer monsoon and *Rabi*/winter season) bimonthly data sets. The relation of LGP with rainfall, maximum temperature and soil moisture during 1982–2015 for the both the states (AP and TS) is illustrated in scattered plots Fig. 3a, b. An increasing trend is observed in LGP to that of rainfall and soil moisture in both states and vice versa with temperature; hence decision making in sowing, growth pattern, crop calendar, cropping pattern and all crop husbandry practices should be made cautiously. A good coefficient of determination ($R^2 = 0.67$ for TS and $R^2 = 0.57$ for AP) was observed between LGP and rainfall.

To understand the climatic and biophysical influence on the agricultural NDVI condition, long term response of NDVI with climate and soil moisture is studied. It has been observed that crop growth pattern/change in NDVI are influenced by climate and bio-physical distribution [29, 30]. Due to large inter-annual variability, spatial patterns of NDVI and their driving parameters vary significantly in different areas when different study periods are selected [30]. Thus, long term fortnightly NDVI and rainfall time series data provide basis for crop progression during the different years of the study. The impact of climate and soil moisture on agricultural NDVI during 1982–2015 for AP and TS is illustrated in Fig. 4a, b. With the increase in rainfall and soil moisture, agriculture NDVI also increases and vice versa. Reverse effect is observed with maximum temperature in the both the states. Thus, it proves that these parameters are essential to assess the agriculture vulnerability and risk.

3.2 Projection of Agricultural NDVI Using Satellite and Climate Data sets

As discussed above, a long-term trend of agriculture NDVI and LGP have a strong impact of climate and its variables. With this evidence, we have further simulated the future agricultural NDVI spatial pattern over the study region using coefficients determined from model and IPCC AR5 projected climate for RCP 2.6 scenario. The model significance ($p < 0.05$) at each grid is illustrated in Fig. 5. The spatial distribution of seasonal projected 2050 agriculture NDVI along with extreme stress, normal and best agricultural NDVI years are adopted from the previous study [13] in Fig. 6. The projected agricultural NDVI has been observed quite similar to normal agricultural years during all the seasons. However, the decline in agricultural NDVI has been observed during summer

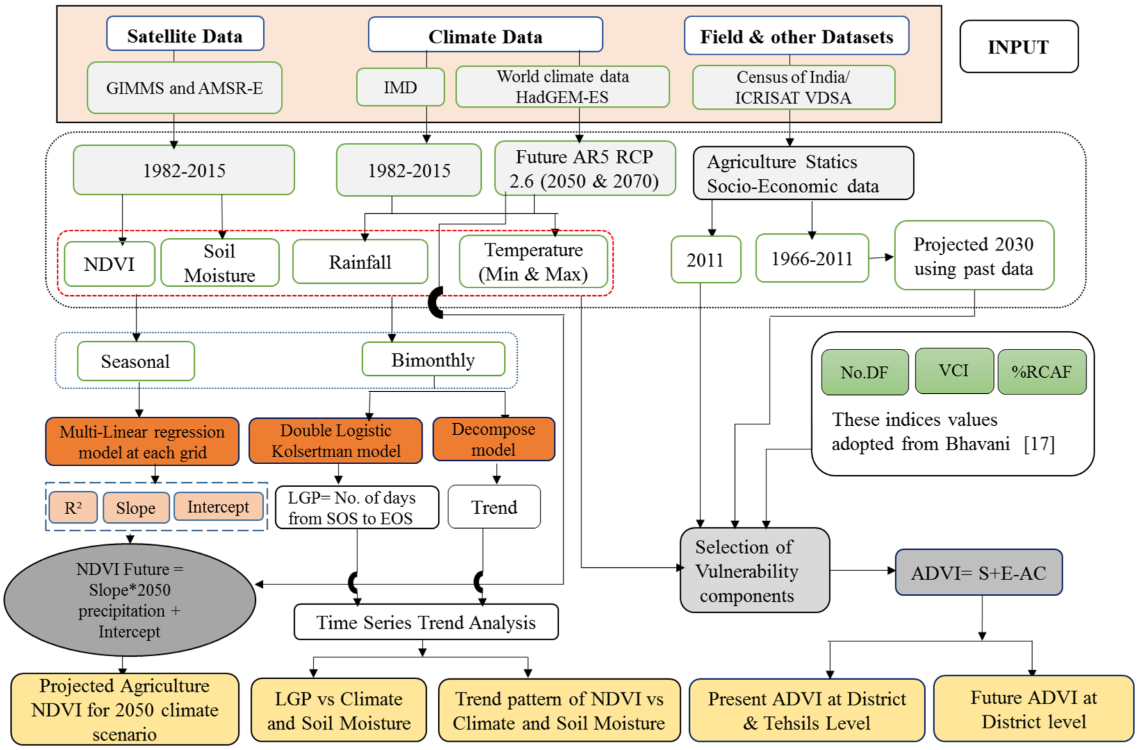


Fig. 2 Flow chart representation of Methodology

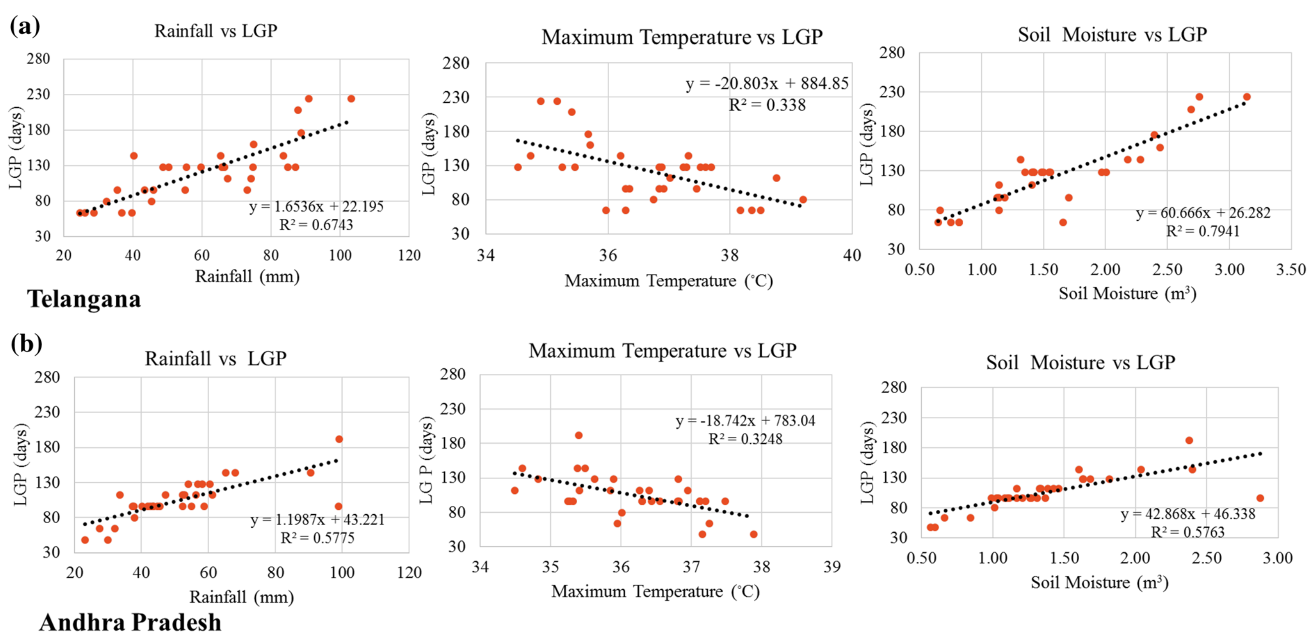


Fig. 3 Trend of LGP with rainfall, maximum temperature and soil moisture for **a** Telangana and **b** Andhra Pradesh states

monsoon and winter season, especially in the coastal area of AP state. This result would help the farmers, insurance policy, and agriculture credit society etc. to improve the agriculture condition at the coastal area by adaptation, mitigation and sustainable agriculture development. Further studies are needed to assess the magnitude and spatial variability of agricultural NDVI under drought/agriculture stress conditions in combination with other additional environmental and climatic parameters in projected climatic conditions.

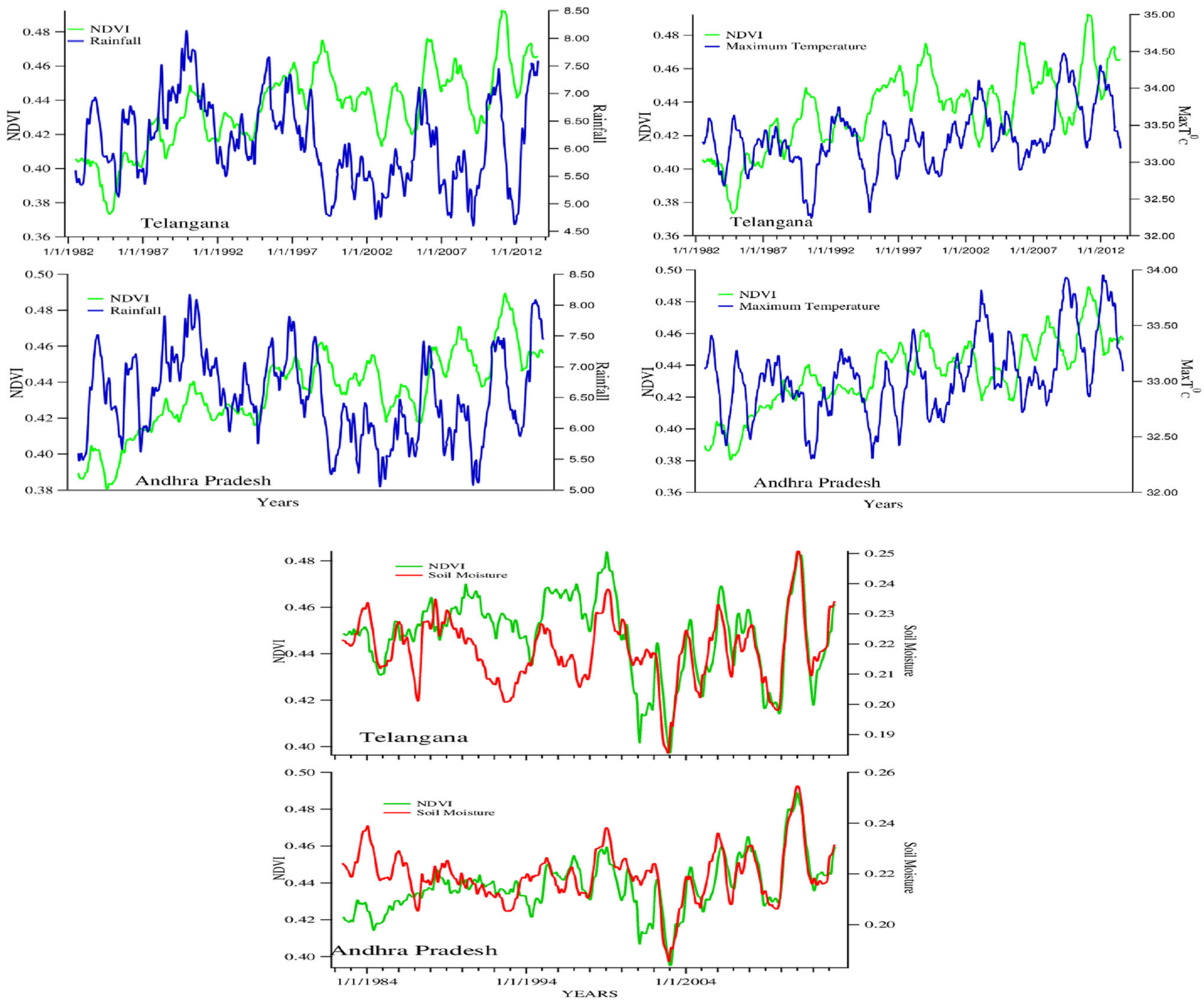


Fig. 4 Trend pattern of agriculture NDVI with rainfall, maximum temperature and soil moisture during 1982–2015 for TS and AP

3.3 Agricultural Drought Vulnerability

3.3.1 Current Status

ADVI is computed using integrated data sets i.e. satellite derived indices, climate and socio-economic data for (1982–2015) at district as well as at Tehsil levels for 2000–2015.

District level: District-wise spatial distributions of S, AC, E and resultant V for three cropping seasons are shown in Fig. 7a–c. Among 22 districts, 13 districts (covering 59% of the total geographical area) have very low AC. Karimnagar (covering 10% of total geographical area of TS) and West Godavari (covering 5% of total geographical area of AP) are the only districts, which show high AC due to large irrigated area. In three cropping seasons, Mahbubnagar district is found to be highly vulnerable due to less adaptive capacity and very high sensitivity. Ananthapur and Kurnool districts are highly vulnerable during the first two cropping periods (summer monsoon and winter), as vegetation indices are highly sensitive to climate change and exposed to frequent climate variability. Y.S.R. Kadapa, Prakasam (covering 52.8% of total geographical area of AP) districts showed high vulnerability during the summer monsoon. During summer/*zaid* season, out of eight districts considered in TS, 5 districts (approximately 77.5% of total geographical area of TS) showed high to extreme vulnerability. In AP state, approximately 44% of total geographical area comes under moderate to highly vulnerable. It is also observed that due to less adaptive capacity and higher climate variability, TS is more vulnerable during winter and summer cropping seasons, whereas AP state during summer monsoon cropping.

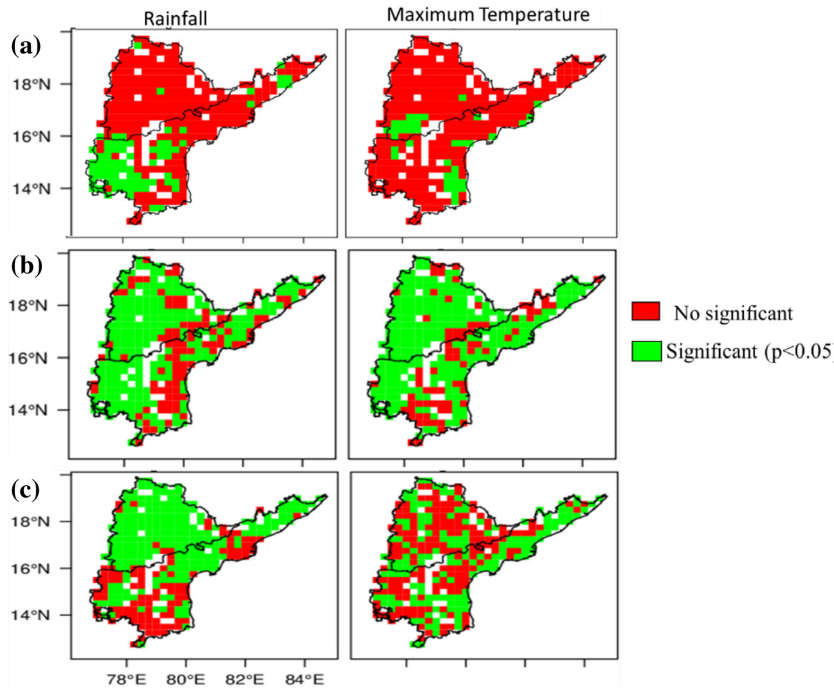


Fig. 5 Significance level of pixels for rainfall and maximum temperature ($p < 0.05$) using multiple regression model. **a** SummerMonsoon/Kharif; **b** winter/Rabi; **c** summer season/Zaid

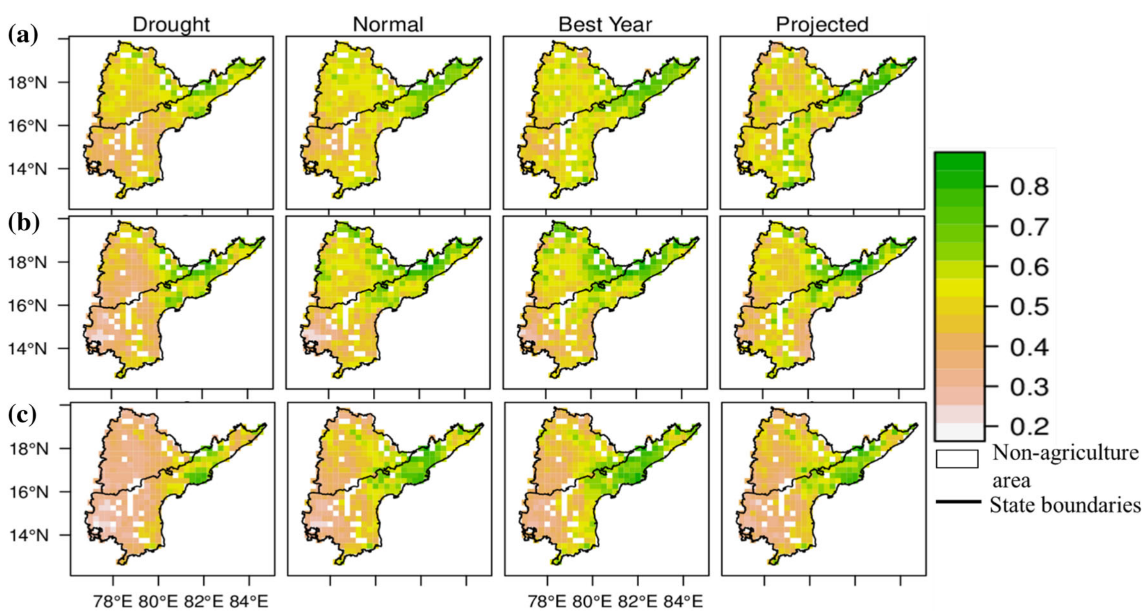


Fig. 6 Spatial distribution of agriculture NDVI for drought, normal, best years of 2000–2015 and projected agriculture NDVI for 2050 RCP 2.6 scenario for three seasons **a** summer monsoon/Kharif; **b** winter/Rabi; **c** summer season/Zaid

Tehsil level: The spatial pattern of AC, E, S and V of the Tehsils of TS and AP are shown in Fig. 8a–c. Less than 20% of tehsils under Adilabad, Ananthapur, Chittoor, and Mahbubnagar districts show moderate to very high AC. During summer monsoon more than 90% tehsils under Krishna and Adilabad districts are exposed to climate. During winter season more than 90% of tehsils under Krishna, Kurnool, and Prakasam districts, followed by Adilabad, Mahbubnagar, Warangal and West Godavari are exposed to climate. During summer season Khammam and Warangal districts (more than 50% of tehsil) show moderate to very high sensitivity. Moderate to very high exposure are noticed in the districts of Guntur and Warangal (more than 80% of tehsils), followed by Mahbubnagar.

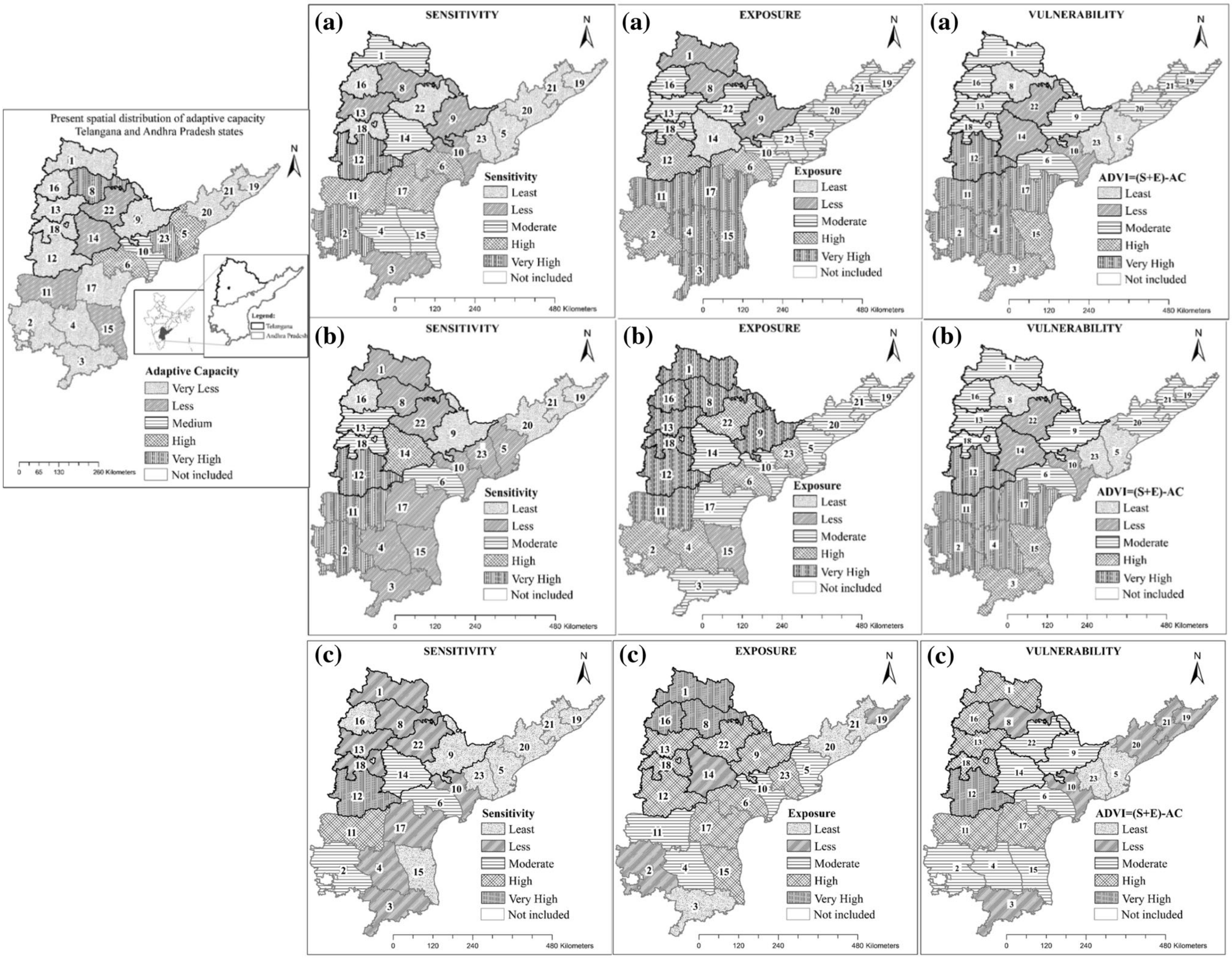


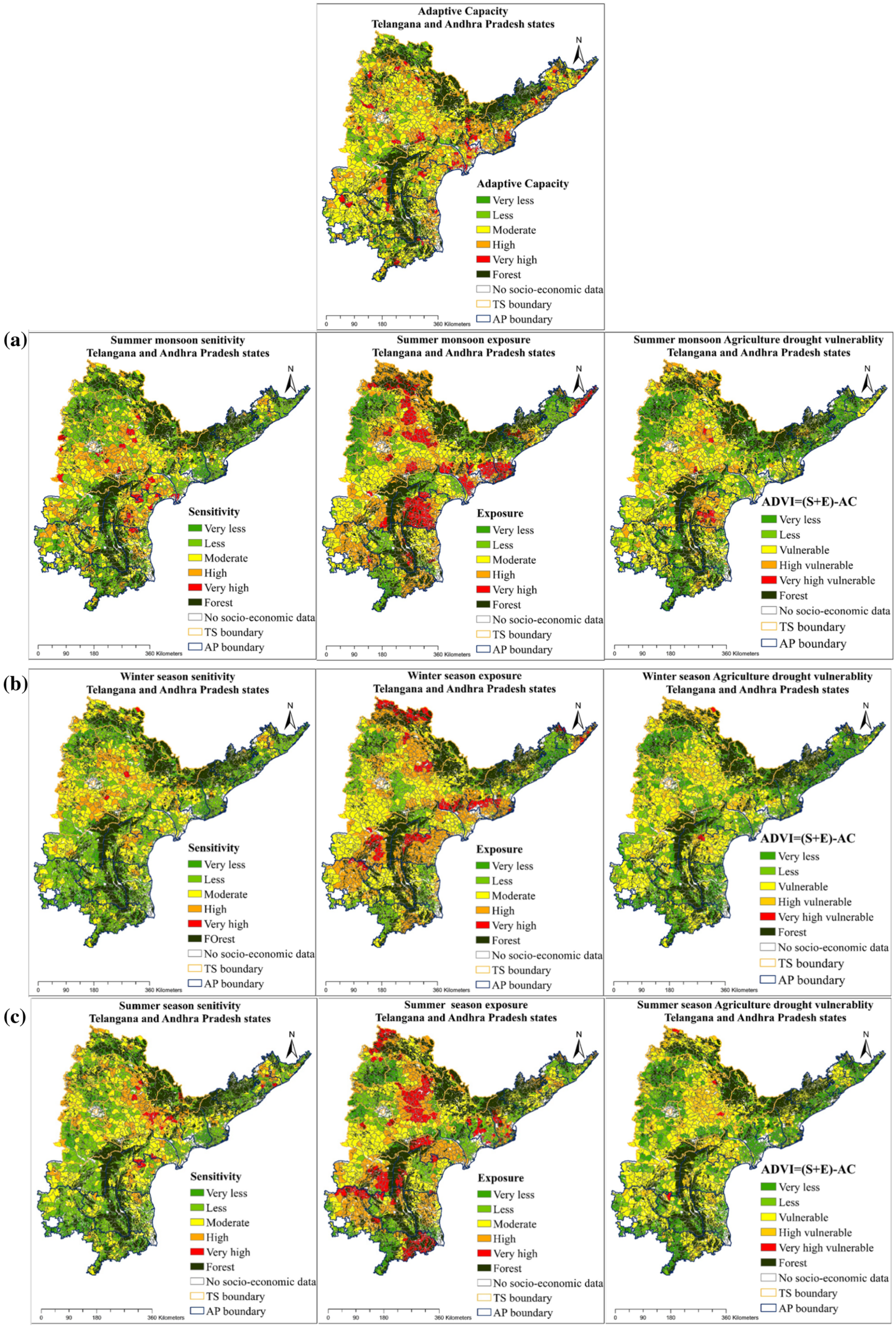
Fig. 7 District wise spatial distribution of adaptive capacity (AC), sensitivity (S), exposure (E), and Vulnerability (V) map during 1982–2015 **a** summer monsoon/June–September; **b** winter season/October–January; and **c** summer season/February–May

During summer monsoon, more than 90% of tehsils under Adilabad district are in moderate to very high vulnerability, due to high exposure followed by Ananthapur, Warangal and Prakasam districts (more than 80% of Tehsils), due to moderate to very high sensitivity. During winter season, Mahbubnagar district (more that 90% of tehsils) is in moderate to very high vulnerability. Whereas in summer season, Guntur district observes 74% of tehsils are in moderate to very high vulnerable range. This is due to high to very high exposure and sensitivity.

3.3.2 Future Status

The future agricultural drought vulnerability has been assessed using AR5 RCPs for climate E indicator and projected S and AC indicators. The ADVI for 2070 behaves almost similar to 2050 RCP 2.6 scenario (Fig. 9a–c. Hence, spatial distribution of E indicator and projected S and AC indicators for the years 2050 (Fig. 10a–c) are explained briefly as follows. Majority of the districts show similar distribution of E and vulnerability during three cropping periods. The AC index shows high values in Karimnagar and Khammam, followed by West Godavari district (5%). Among 22 districts, 5 districts show low AC (21%). The predicted years viz., 2050 and 2070 (all four RCP's) annual ADVI shows a similar pattern in most of the districts of AP and TS except, Ananthapur, Chittoor, East Godavari, Guntur, Nalgonda and Krishna. The districts of AP state viz., Ananthapur, Y.S.R. Kadapa, Nellore and Prakasam show very high E, followed by Kurnool, Chittoor and Guntur. It is observed that the districts in AP state

Fig. 8 Tehsillevel spatial distribution of adaptive capacity (AC), sensitivity (S), exposure (E) and Vulnerability (V) during 2000–2015 **a** summer monsoon/June–September; **b** winter season/October–January; and **c** summer season/February–May ▶


Adaptive Capacity
Telangana and Andhra Pradesh states
Adaptive Capacity
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
0 90 180 360 Kilometers
(a)
Summer monsoon senitivity
Telangana and Andhra Pradesh states
Sensitivity
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Summer monsoon exposure
Telangana and Andhra Pradesh states
Exposure
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Summer monsoon Agriculture drought vulnerablity
Telangana and Andhra Pradesh states
ADVI=(S+E)-AC
Very less
Less
Vulnerable
High vulnerable
Very high vulnerable
Forest
No socio-economic data
TS boundary
AP boundary
(b)
Winter season senitivity
Telangana and Andhra Pradesh states
Sensitivity
Very less
Less
Moderate
High
Very high
FOrest
No socio-economic data
TS boundary
AP boundary
Winter season exposure
Telangana and Andhra Pradesh states
Exposure
Very less
Less
Moderate
High
Very high
Forest
No socio-economic data
TS boundary
AP boundary
Winter season Agriculture drought vulnerablity
Telangana and Andhra Pradesh states
ADVI=(S+E)-AC
Very less
Less
Vulnerable
High vulnerable
Very high vulnerable
Forest
No socio-economic data
TS boundary
AP boundary
(c)
Summer season senitivity
Telangana and Andhra Pradesh states
Sensitivity
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namely Ananthapur, Prakasam, Chittoor and Nellore exhibit very high to high vulnerability representing 41% geographical area. The vulnerability in TS (16%) is less compared to AP state.

The vulnerability is found to be very high in Ananthapur, Kurnool and Mahbubnagar districts during October-January. Almost all (9) districts of TS are found to have high exposure in all scenarios. Whereas, in AP state, Kurnool, Ananthapur and Y.S.R. Kadapa districts show very high to high exposure. Mahbubnagar district was found to be highly vulnerable due to high sensitivity(driven parameters are GCA, %RCF, %TAg.L, %Mig.R) during summer season. Nalgonda district shows the highest rise in intensity/degree of vulnerability in future ADVI during summer monsoon and summer season due to influence of climate variability (decrease in rainfall). Thus, the present and projected future vulnerability status independently for three periods is important because it captures vulnerability of districts of the respective/corresponding cropping seasons.

Figure 11 illustrates current and projected/future vulnerability comparison at state level during the three cropping seasons. The extent of vulnerability decreases in TS and AP due to increase in adaptive coping parameters (Ag.W and GIr) and climate variation (increase in rainfall) during June–September. It is observed that in winter and summer seasons, total geographical area of TS (141.62 km^2) is vulnerable in recent-past and future. The increase in vulnerable area in TS and AP is likely due to the impact of climate (increase in minimum temperature).

4 Conclusions

India, in the past few decades, has been experiencing failure of crops due to variability in the climate, commercialization of agriculture, shortage of labor and urbanization among others. There have been efforts to enhance the irrigated area in India. For example, 33.5% of irrigation growth has been taken place in India since 2011. The states of Telangana and Andhra Pradesh being major contributors of agricultural production in India have been experiencing frequent crop failure due to drought. The state irrigation has grown from 2.90 million hectares in 1960–1961 to 4.21 million hectares in 2009–2010 (SCR 2009-10). Although, drought stress prevails, crop growth and vulnerability of drought remains quite significant for these states. Our results clearly demonstrate the change in climate and soil moisture has impacted the length of growing period as well as agriculture growth/stress, which may further affect the total crop production. Seasonal future agricultural NDVI for IPCC projected AR5 2050 RCP 2.6 climate scenario behaves similar to that of a normal year, and that the major decline in agricultural performance was observed during summer and winter seasons, particularly in coastal regions of AP state. This information is of vital significance while addressing climate change within a vulnerability planning framework and pathways of impact on the natural resources. An integrated impact assessment approach provides an evaluative framework to elucidate these linkages and identify sources of uncertainty. Sector based

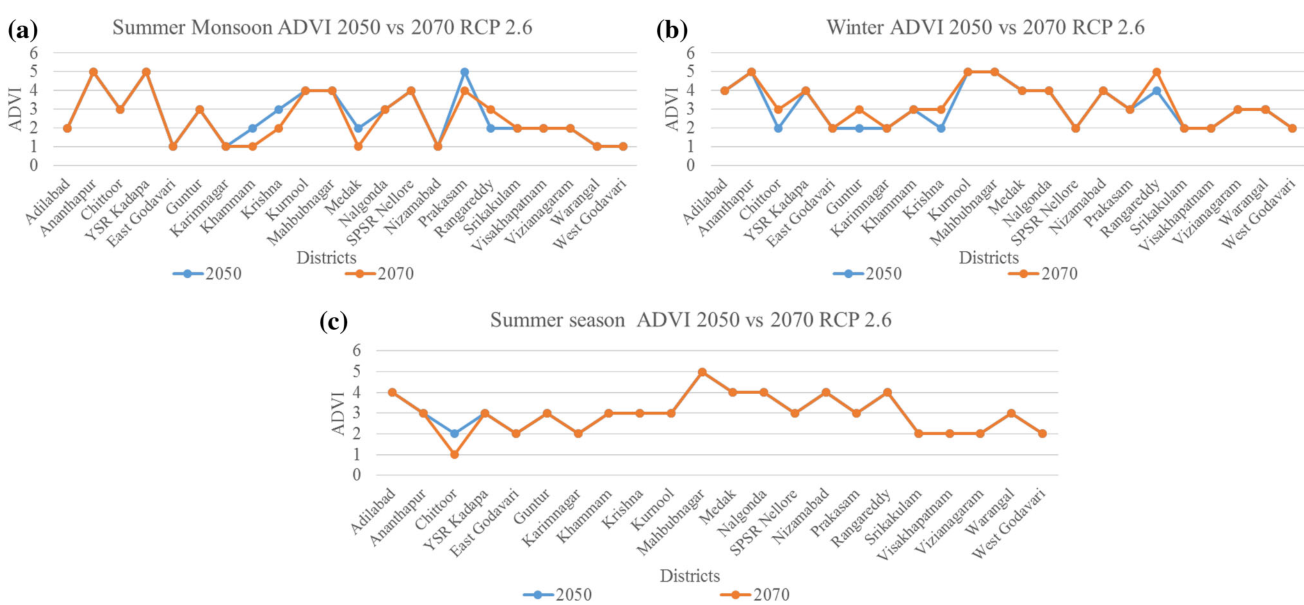


Fig. 9 Comparison of projected ADVI for IPCC AR5 2050 and 2070 2.6 scenario **a** summer monsoon/June–September; **b** winter season/October–January; and **c** summer season/February–May at district wise

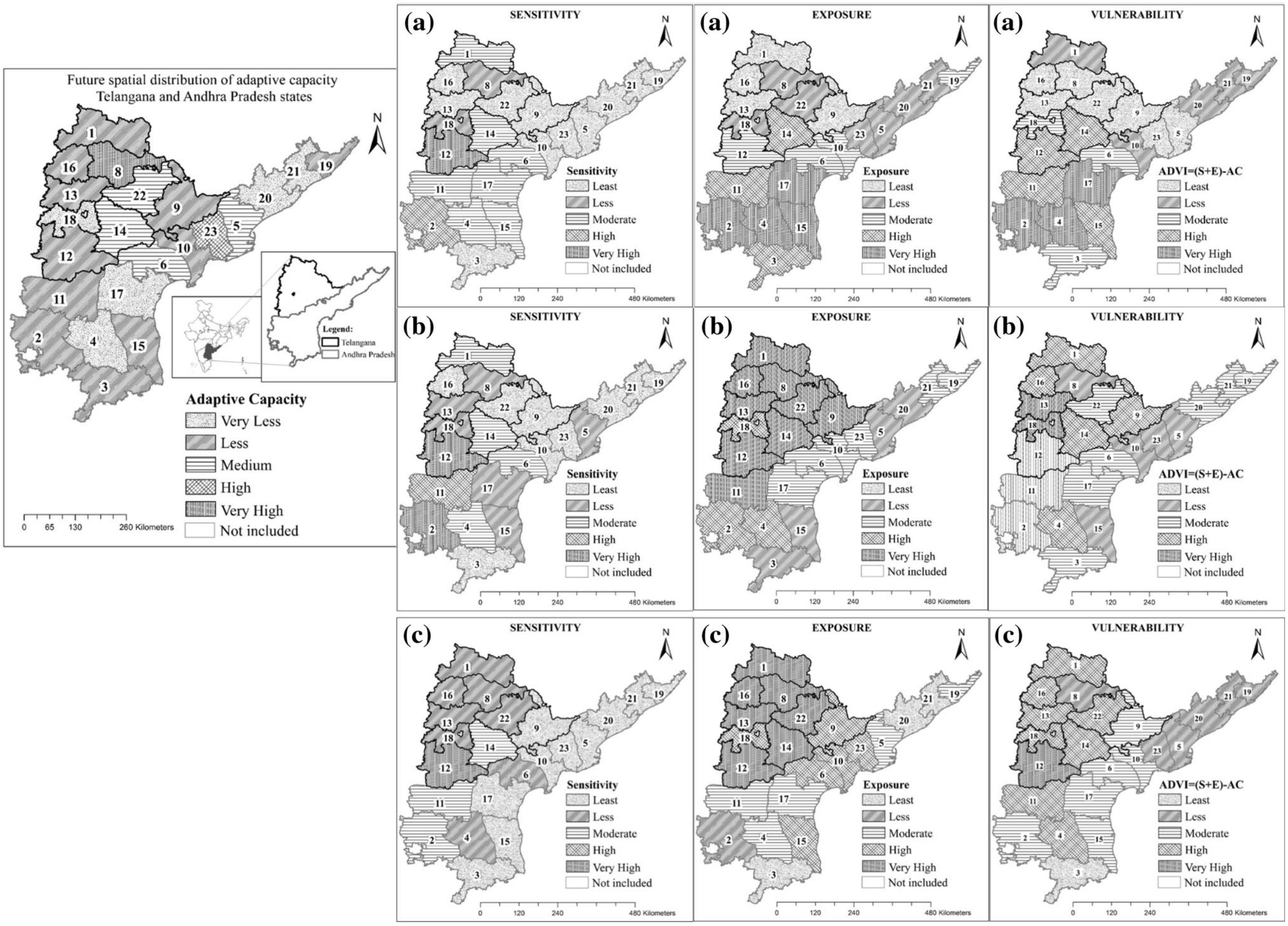
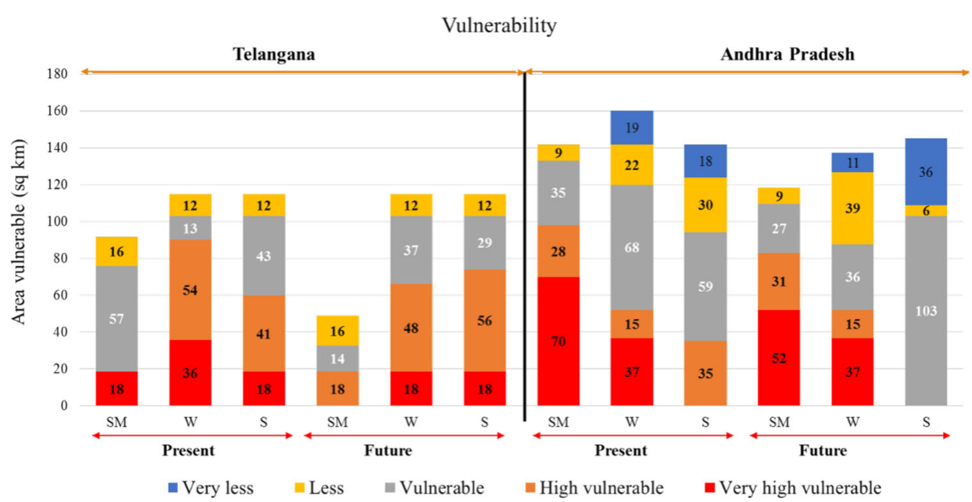


Fig. 10 Future 2050 RCP 2.6 scenario spatial distribution of adaptive capacity (AC), sensitivity (S), exposure (E), and Vulnerability (V) map **a** summer monsoon/June–September; **b** winter season/October–January; and **c** summer season/February–May at district wise

Fig. 11 Present and projected vulnerability comparison at state level during three cropping seasons



vulnerability assessments provide a foundation for integrating multi-dimensional attributes from variety of sources. This study illustrates a process for integrating information obtained from vulnerability assessments into a conceptual modelling process to identify and rank administrative units likely to be vulnerable to the impacts of changing climate.

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