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RESEARCH ARTICLE

Assessment of vulnerability of Indian agriculture to rainfall variability – Use of NOAA-AVHRR (8 km) and MODIS (250 m) time-series NDVI data products

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Abstract Advanced Very High Resolution Radiometer (AVHRR) (8 km) Normalized Differential Vegetation Index (NDVI) data and Moderate Resolution Imaging Spectroradiometer (MODIS) (16-day, 250m) NDVI data products were considered to analyze vulnerability of Indian agriculture to rainfall variability under climate change impact studies. Predicted higher temperature and altered rainfall patterns accompanied by extreme weather events would impact vegetation growth in natural forest, open scrub, agricultural land and plantations. NDVI derived from 2-band information (Red and Near-infra Red) of multi-spectral imagery of AVHRR (1982 to 2006) and from MODIS (2000-2010) were analysed to understand spatial and temporal variability. Coefficient of Variation (CV) of maximum NDVI from 15-day composites for the total length of the study period was used to assess vulnerability of rain-fed agriculture and results were corroborated with the Standard Precipitation Index (SPI) rather than actual rainfall received during the study period. AVHRR time-series data helped to identify vulnerable areas at regional-scale, i.e., agro-ecological sub-regions (AESR) due to coarser ground resolution while MODIS data products with 250m pixel resolution helped identify vulnerability at the district level. It was estimated that over 241 Mha areas in the country may not be vulnerable to rainfall variability-induced climate change, whereas over 81.3 Mha in arid, semi-arid and dry sub-humid regions in the country may be vulnerable to extreme weather events. Study indicated that over 12.1 and 1.81 Mha of *Kharif* cropland would be mildly and severely vulnerable, whereas 6.86 and 0.5 Mha of *Rabi* cropland may be adversely affected in a similar manner. Of the remaining agricultural lands, 29.93 and 5.24 Mha would also be vulnerable to climate change in a similar manner. Studies also indicated a decrease in length of *Kharif* and *Rabi* seasons and a delay in the start of *Kharif* season based on preliminary findings.

Keywords MODIS, AVHRR, NDVI, AESR, Rain-fed agriculture, Vulnerability, Climate Change

Introduction

Climate Change research has come to occupy centre stage in the last three decades due to the increasing occurrence of extreme climatic events with impacts felt by millions across the world. The general perception among the scientific community that anthropogenic causes such as increasing GHG emissions are behind growing weather aberrations has been underlined by the IPCC report (2008) and prompt real-time media reporting of the impact of extreme climate events, such as drought, heat-wave, flood, frost, cold-wave, gale, cyclones, tornadoes and hurricanes, have made the population alert to variations in weather conditions that may purport climate change.

To scientifically investigate the impacts of aforesaid weather aberrations on the bio-physical mantel of the earth, such as the vegetation, techniques and tools of remote sensing have been used for more than three decades now and have supplied interesting insights on the issue. Studies on the changes in Land Use/Land Cover (LCCS) and on the state and vigour of vegetation (Normalized Difference Vegetation Index – NDVI) can greatly help in understanding these two processes. Use of precipitation and temperature data help in further understanding the genesis and impact of extreme weather events and their impact on LULC and NDVI. To study the impact of variations in weather and its impact on agriculture, a temporal analysis of NDVI data products obtained from NOAA-AVHRR (8 km resolution)

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data and NASA-MODIS (250 m)-based NDVI data products was used. Time-series NDVI datasets from NOAA-AVHRR and MODIS-TERRA were downloaded from their respective websites and used for assessing agricultural vulnerability in India. Global Inventory Modelling and Mapping Studies (GIMMS) dataset of NOAA-AVHRR with 8 km resolution was used to analyse agricultural vulnerability across the country at state- and agro-eco-sub-region (AESR) levels during the 1982–2006 period, whereas MODIS (16-day, 250 m resolution) NDVI data products were used to understand agricultural vulnerability trends at the district level in the country during the period 2001–2011. SPI instead of actual rainfall (Saikia and Kumar, 2011) was used to corroborate extreme weather events with variations in NDVI. In fact, readily available NDVI data products dictated the length of temporal analysis undertaken and reported in this paper.

Study Area

India is a vast country, with reported total geographical area of 328 Mha, extending from tropical climate in the Andaman & Nicobar Islands and the southern tip of mainland India to temperate climate in Jammu & Kashmir in the north, and from per-humid climate in the Brahmaputra valley with over 10,000 mm annual rainfall in the east, to arid desert in Jaisalmer with <100mm annual rainfall in Rajasthan in the west. For the present study, we undertook to analyse Land Use & Land Cover Change (LCCS) and impact of weather variability in the whole of India. According to Land Use – Land Cover (LULC) Atlas of India available at the NRSC (ISRO) web portal http://bhuvan-noeda.nrsc.gov.in (NRSC, 2011), the net sown area under agriculture in 2010–2011 was 144.33 Mha, out of which 52.6 Mha was under double crop, 4.8 Mha under triple crop and 7.3 Mha under plantation. Area under *Kharif* cultivation extended to over 54.1 Mha and for *Rabi* over 24 Mha. The statistics provided by NRSC is based on NDVI and digital interpretation of satellite data. Figure 1 indicates the extent of various LULC classes in 1986 and in 2011 in the country. Current and Long Fallow accounted for 36.7 Mha, whereas forests and plantations covered 61.29 Mha and scrub-forest occupied 9.32 Mha. According to the Ministry of Agriculture, Govt. of India, where land utilization data is generated based on traditional

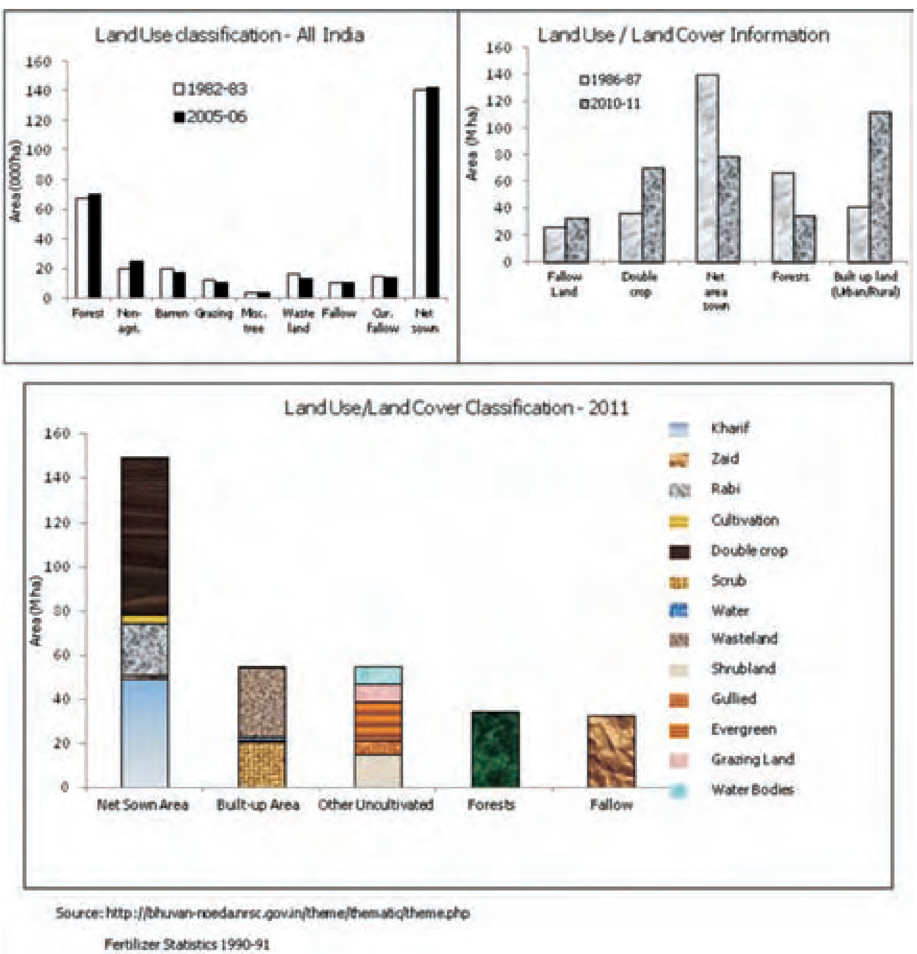

Figure 1 Land use – Land cover pattern in India

enumeration methods, the net sown area in 2006 was reported as 141.364 Mha, which included 63.196 Mha under irrigated cultivation and 78.168 Mha under rain-fed agriculture. Rainfall variability impacts all these types of vegetation in the various agro-climatic zones in India especially in the arid, semi-arid and sub-humid regions and also in other zones that may experience change as reported by Rajeevan et al (2008) and Rupa Kumar et al (2006) in their studies on rainfall trends in India. Use of sensor-based data such as NOAA-AVHRR 8 km NDVI data and MODIS 16-day 250 m NDVI data product has enabled an objective analysis of the vulnerability of vegetation cover across India owing to variations in rainfall.

Material and Methods

Satellite-based NDVI Data Products

Time-series NDVI data products of AVHRR space-borne sensor of NOAA polar-orbiting satellites were used. The first two bands out of the five, i.e., Red (0.58–0.68 μm) and Near-Infrared (0.75–1.1μm) that are useful for mapping clouds, land surface and delineate surface water bodies, respectively, when combined, were found useful for monitoring vegetation (Tucker *et al*., 2004, 2005) and was hence used in the present study to assess agricultural vulnerability in the country. AVHRR NDVI data product is a part of Global Inventory Modelling and Mapping Studies (GIMMS) dataset and was obtained from the AVHRR instrument on board NOAA satellite series 7, 9, 11, 14, 16 and 17 for the period 1981 till 2006. The data was corrected for calibration, view geometry, volcanic aerosols and other effects not related to vegetation change and was made available for download from the Global Land Cover Facility (GLCF) website at www.landcover.org (http://www.glcf.umd.edu/data/gimms/ at 15-day Maximum-Value Composite).

In addition, NASA-operated sensor Moderate Resolution Imaging Spectroradiometer (MODIS) on board TERRA and AQUA earth observation research satellites with a sweeping swath of 2330 km and covering the earth in 1–2 days in 36 discreet spectral bands supplemented earth observation seamlessly with a higher-resolution NDVI dataset (http://terra.nasa.gov/). MODIS data has been found to be ideal for monitoring large-scale changes in the biosphere and was hence deemed useful for assessing agricultural vulnerability at a relatively higher scale like district within the country. MODIS – 250 m NDVI composite products are freely available from the *Land Processes – Distributed Active Archive Centre (LPDAAC)* website of USGS <http://mrtweb.cr.usgs.gov/>. The Indian subcontinent is covered in 13 tiles and NDVI data is available from February 2000 onwards.

NDVI is derived from 2-band information (Red and Near-infra Red) of a multi-spectral imagery of a satellite data and is a contrast–stretch ratio calculated from the Red band and Near-Infrared band (NIR) of sensors such as LANDSAT – TM; AVHRR; IRS-1B, 1C, 1D, P6: LISS-3/LISS-4; and MODIS besides several others. NDVI from AVHRR and MODIS data with Red reflectance in Band 1 and NIR reflectance in Band 2 is calculated as [band 2-band 1/(band 2 + band 1)]. The NDVI takes advantage of the typical low-reflectance values of vegetation in the Red wavelength range, which corresponds to chlorophyll absorption and high-reflectance values in the NIR range, which signifies leaf structure, thereby enhancing the contrast between vegetated, unvegetated and sparsely vegetated areas. Land Use and Land Cover (LULC) analysis helps in identifying NDVI variations in agriculture, forest and open scrubland. Correlating rainfall pattern with NDVI time-series data can indicate which areas are vulnerable to climate change owing to higher temperature and rainfall. Use of NDVI is particularly advantageous in the sub-tropical regions in Asia and Africa where dependence of agriculture is high among developing economies and study of vegetation response to rainfall and temperature in the event of scarce climate data can help in drawing strategies to manage and adapt to weather aberrations.

Standardized Precipitation Index

SPI, which represents the total difference of precipitation for a given period of time from its climatological Mean and then normalized by Standard Deviation (SD) of precipitation for the same period, provides an improved tool to assess variations in precipitation and the impacts associated with it (Saikia & Kumar, 2011). Hence, SPI instead of actual rainfall data was used for this study. India Meteorological Department (IMD) provides daily rainfall data of more than 100 years for many stations from its archives. Daily gridded rainfall data set for the period 1901–2007, developed by Rajeevan et al (2008) for 1384 stations, was used for the present study. The gridded rainfall data on a regular grid of 1^0 Latitude x 1^0 Longitude was used to calculate SPI value using the following formula:

$$SPI = \frac{a - A}{sd}$$

where
a is the current precipitation for a given period
A the long-term normal of precipitation for the same period
sd the Standard deviation of precipitation for the given period

The long-term precipitation record was fitted to a probability distribution, which was then transformed into a normal distribution, so that Mean SPI for a location and desired period is equal to zero. Positive SPI values indicated greater than Median precipitation, whereas negative values indicated less than Median precipitation. As SPI is normalized, both wetter and drier climates can be presented in a similar manner, and both wet and dry periods denoting flood and drought can be monitored using SPI, thus making it location- and time-independent. McKee *et al*. (1993) used SPI values to define drought intensities in the US. Accordingly, SPI of ≤ 1.00 for any given period is considered as the beginning of the reduced rainfall period, which could lead to drought, if prolonged. Thus, drought is said to occur at any time when SPI is continuously negative and reaches –1.0 or less. Drought event is said to end when SPI becomes positive. Thus, using SPI instead of actual rainfall data for the time period 1901–2007, rainfall data was analyzed to identify drought and flood events and their corresponding AVHRR-based NDVI data. Figure 2 indicates the methodology used for this study.

Review of Literature

Early studies reporting the use of AVHRR data pertained to analysing global vegetation phenology in temperate and sub-arctic region in the northern hemisphere during the period 1981–1991 (Myneni *et al.*, 1997), thus establishing its utility for temporal analysis. Since then, several studies on global biophysical land surface, land use/land cover identification (Jakubauskas *et al.*, 2000), harmonic periodicity of NDVI change in global vegetation mapping, global continuous fields of percentage of woody vegetation, herbaceous vegetation and bare ground from AVHRR 8 km NDVI data have been reported (Defries *et al.*, 2000), thus firmly establishing its use for vegetation mapping. AVHRR 1 km data for global land cover classification was used to calibrate the MODIS sensor (Hansen *et al.*, 2000), thus providing a seamless transition with improved resolution capability for future applications as mentioned earlier. Since then, both AVHRR and MODIS have been the main workhorses for studies on vegetation across the globe (Bacour *et al.*, 2006; Chen *et al.*, 2003; Friedl *et al.*, 2002; Huete *et al.*, 2002; Hensen *et al.*, 2002; Nemani *et al.*, 2003; Krishnaswamy *et al.*, 2004; Thenkabail *et al.*, 2004, 2007; Celis *et al.*, 2007; Heumann *et al.*, 2007; Jain *et al.*, 2009; Sehgal *et al.*, 2011). For topographically complex terrains

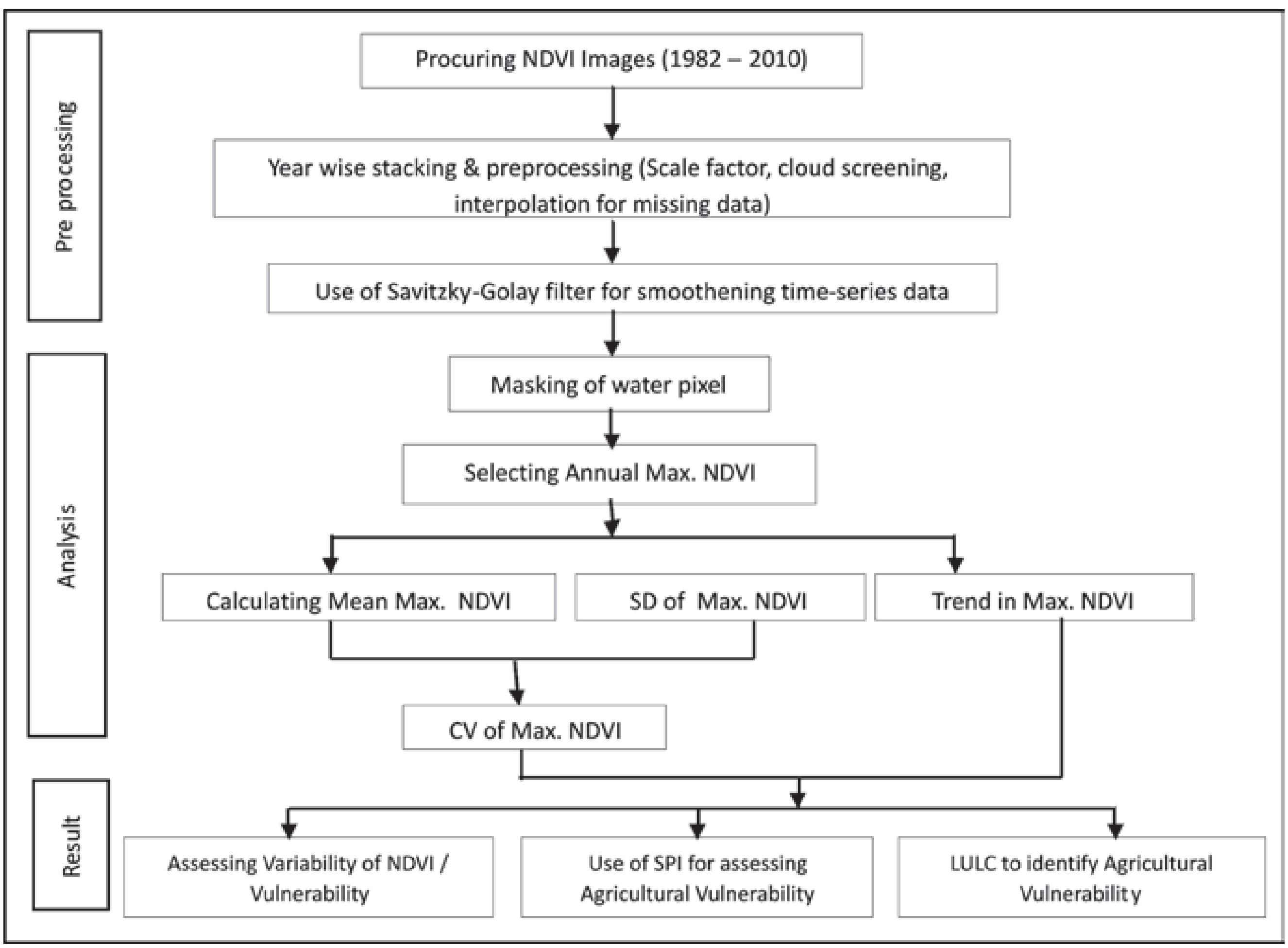

Figure 2 Methodology used for the study

such as the Himalayan ranges in Jammu & Kashmir and in Arunachal Pradesh in India, downscaling of real-time vegetation dynamics by fusing multi-temporal MODIS and Landsat NDVI has been recommended (Hwang *et al.*, 2011). However, for the present study we have omitted these snow-clad regions from analysis due to extreme variability in Maximum NDVI values. Global evaluation of AVHRR-NDVI datasets (Beck *et al.*, 2011) and temporal composting for LULC mapping in semi-arid ecosystems (Huettich *et al.*, 2011) for understanding vegetation dynamics have guided the present study in assessing the vulnerability of Indian agriculture to rainfall variations. Several studies have also been undertaken to model time series data such as NDVI and integrate it with climate change research (Qiangyi *et al*., 2012; Lhermitte *et al*., 2008; Lei & Bian 2010; Beaurs & Henebry 2010; Yang *et al*., 2011). For the present study, a functional interdisciplinary cross-scale framework was used to help improve our understanding of temporal change in the Vegetation Index in India based on AVHRR and MODIS time series datasets (Chen 2004; Justice *et al.*, 1985; Rouse *et al.*, 1973; Tarnavsky *et al.*, 2008; Wunderle 2003).

Results

Climate change is an insidious process and hence long-term studies are essential for understanding the trends and magnitude of the problem. In India where agriculture is largely rain-dependant, more so in the rain-fed arid, semi-arid and sub-humid regions where vegetation growth is sparse and slow, discerning change in vegetation growth is difficult. However, this change, as indicated by temporal variations in NDVI, could be invaluable to the understanding of dynamics of vegetation growth both seasonal and permanent, namely crop and forest cover, respectively. This information is critical for planning strategies and adaptation mechanisms to mitigate or reduce agricultural vulnerability to rainfall variations and extreme weather events that may lead to climate change.

Rainfall and Temperature Pattern During 1982–2006

Figures 3 and 4 indicate the variations in rainfall and temperature across the country in both time and space. Although 1982 was a wet year as 205.28 Mha in India received rainfall > 800mm, the SW monsoon period was

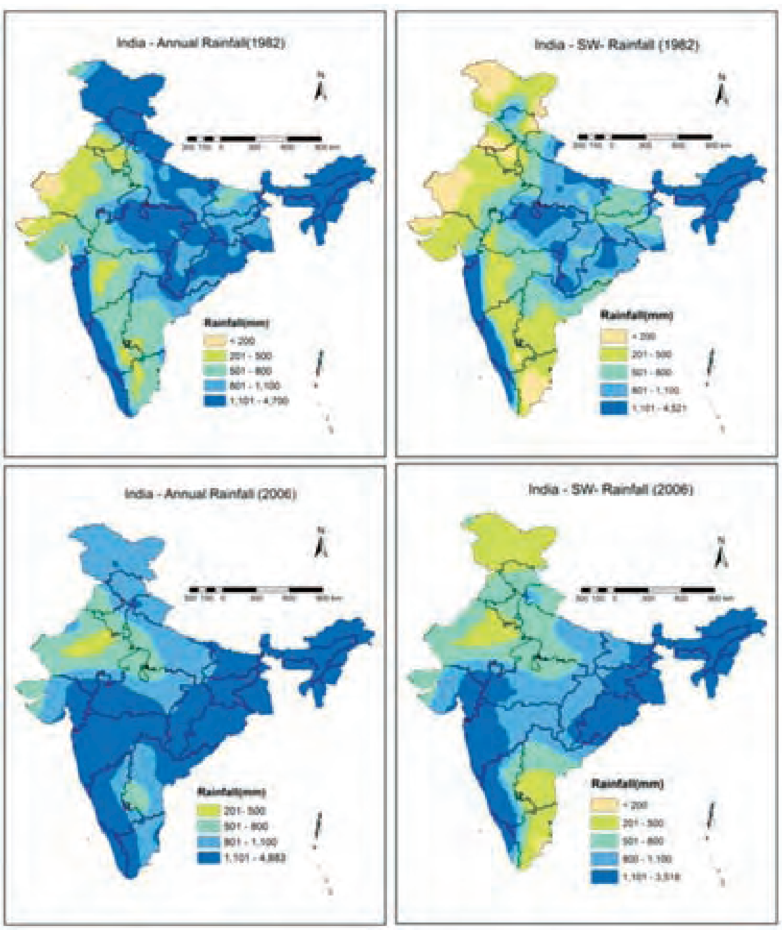

Figure 3 Variations in annual and SW monsoon rainfall in 1982 and 2006

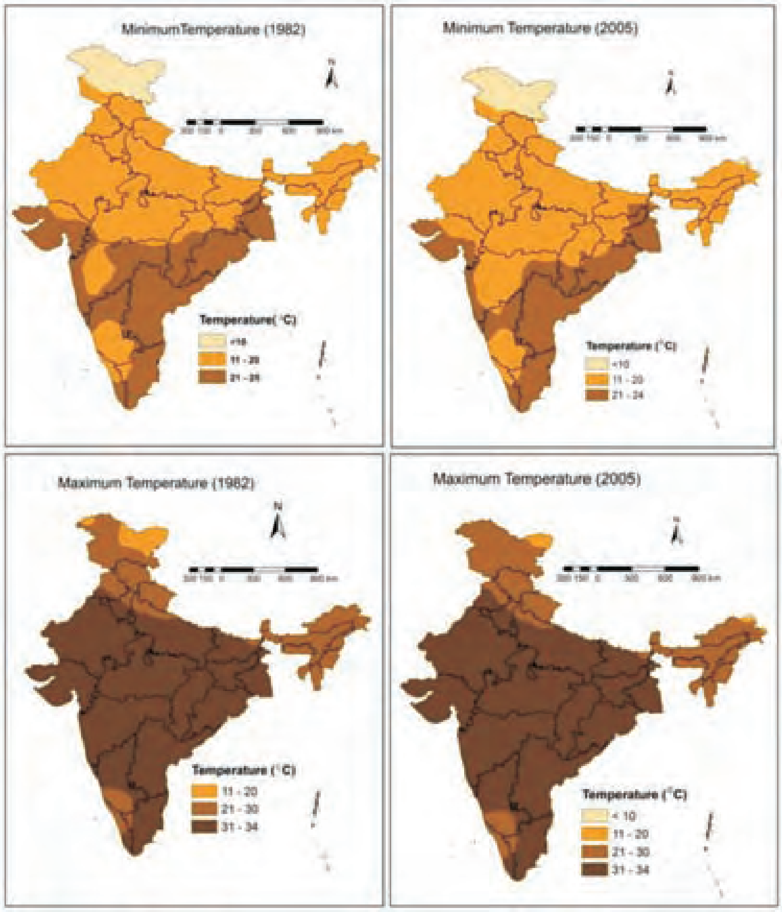

Figure 4 Variations in minimum and maximum temperature in 1982 and 2006

drier as 87.76Mha land received <500mm rainfall, 74.5 Mha between 500–800mm and over 124.35 Mha over 800mm. On the contrary, in 2006, both annual rainfall and SW monsoon season saw copious and well-distributed rainfall. Whereas the annual maximum rainfall was 4700mm in 1982, it was over 4883mm in 2006. During 2006, over 134.46 Mha received rainfall ranging from 200 to 800mm, whereas over 193.43 Mha received a seasonal rainfall of over 800–1100mm. Maximum rainfall during the SW monsoon period in 1982 was 4521mm along the western Konkan coast and the north-eastern region; however, over 32.1 Mha area in western Rajasthan, Kutch, southern Punjab and western Kashmir received <200mm rainfall. On the contrary, in 2006 only over 0.82 Mha received a seasonal rainfall of <200mm, whereas over 274.70 Mha received an annual rainfall of over 800mm.

Temperature-wise not much variation was observed in the two years considered for this study. Using gridded temp data ($1^0 \times 1^0$) available from 1982 to 2005, temperature variations were studied. It was seen that both in 1982 and in 2005, maximum temperature ranging from 31 to 34°C was experienced in over 250 Mha in the country (see Figure 4). Minimum temperature of <10°C was felt in over 19 Mha in both years. Such low temperature adversely affected *Rabi* and other winter crops, fruits and vegetables.

Rain-fed agriculture face aberrant weather conditions such as decrease in duration of the crop-growing period due to early onset or withdrawal of monsoon, increase in intense rainfall events with reduction in the number of rainy days as studies do not indicate any significant reduction in actual rainfall received, monsoon failure with attendant drought or floods with more intense rainfall events accompanied by a general shift in spatial pattern. For instance, analysis of rainfall pattern in the last 107 years (Rajeevan *et al.*, 2008) has shown an increase in rainfall in the drought-prone Anantapur district in Rayalseema region in Andhra Pradesh but a decline in the north-eastern region in India (Ravindranath *et al.*, 2011). This could spell disaster in the country as the two typical ecosystems cannot cope with the surplus or deficit rainfall. Even irrigated agriculture may not be immune to these variations as snow cover and glaciers shrink and perennial rivers receive lesser water-flow on the one hand, while on the other hand, groundwater recharge would decrease. Hence, rainfall pattern was analysed and

SPI was used to understand the trend in NDVI time-series data for the country.

Trends in SPI and Resultant NDVI

There are large variations in vegetation dynamics in the country owing to climatic variability. In arid regions in western Rajasthan and Gujarat and south-central India in Bellary and Anantapur districts, where sparse vegetation and large livestock population prevail, the dependence of livestock on this sparse vegetation cover makes it critical for vulnerability monitoring and evaluation as implementation of any adaptative mechanism would depend on it. In the semi-arid and sub-humid zones, which account for a large area under rain-fed agriculture, the poor natural resource base like poor shallow soil cover and falling groundwater table in addition to the large number of marginal and small farm holdings that depend on SW monsoon rainfall for carrying out agricultural operations, vulnerability increases. In humid regions where two or three cropping seasons may be possible, floods or drought could be devastating, whereas in per-humid regions as in northeast India, a decline in rainfall, as indicated in our study, could be devastating. Figure 5 shows the temporal trend in NDVI and actual rainfall during the study period.

As indicated in Figure 5, maximum NDVI values are essentially outlier values and are bound to be unamenable to smoothing. Hence, the R^2 in this case is seen to be 0.29, or explaining nearly 30% of variations. On the other hand, the time-series data of Mean NDVI shows a smooth trend and with an R^2 of 0.56 or 56%. To understand the trend in annual rainfall, a 2-year moving average was taken to understand its impact on the Vegetation Index.

Spatiotemporal Pattern of NDVI and SPI in India

AVHRR NDVI product, which is available for the whole of the Indian subcontinent, was a subset from the global coverage in the form of one tile for each year. Bimonthly NDVI images were stacked and pre-processed, followed by identification of pixel-wise maximum NDVI for arriving at Maximum Greenness for any pixel during the corresponding year from 1982 to 2006. This was followed by estimation of Mean and SD for maximum NDVI. To understand variability in Greenness as an Indicator of Vulnerability, CV of maximum NDVI was calculated, which formed the basis of the Vulnerability Analysis presented in this paper. Pattern of AVHRR (8 km) based on maximum NDVI value helped in identifying AESR that was vulnerable to rainfall variability and climate change. This exercise also helped in the estimation of spatial extent of vulnerable regions in the country.

Spatial pattern of rainfall (1982 and 2006) was mapped by interpolating $1^0 \times 1^0$ rainfall grid data by kriging to obtain 8-km resolution to correspond with the ground resolution of AVHRR NDVI data. SPI was calculated from 107-year daily rainfall records for each grid point. This data was used to interpolate SPI data at 8-km resolution. Analysis revealed that rainfall was the highest during the months of July–August and occurrence of maximum NDVI followed during the months of September–October annually. Analysis of

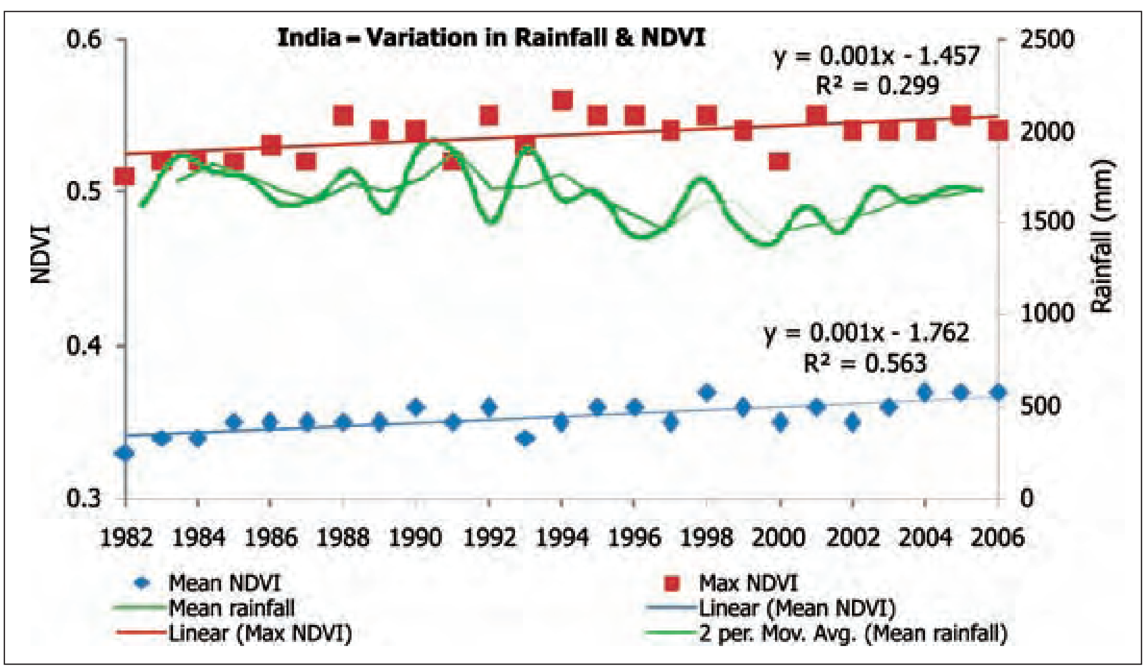

Figure 5 Variations in All-India rainfall and NDVI

annual and SW monsoon rainfall data was used for the study, with 1982 taken as the base year. Figure 6 indicates the pattern of Mean and maximum NDVI in India during 1982 and 2006 in addition to the corresponding SPI distribution in each year. Mean NDVI ranged from 0.0 to 0.79 while maximum NDVI ranged from 0.014 to 0.995. Although the country saw normal rainfall across various ecozones, SPI indicated a moderate drying condition in West Bengal, eastern Bihar and Jharkhand, in a small part in Vidharba and southern Madhya Pradesh and around National Capital Region, southeast Punjab, southern Himachal Pradesh and southwest Uttarkhand, which is an important sugarcane-producing belt in northern India.

In 2006 (see Figure 6), the upper limit of Mean NDVI fell to 0.75 when compared to the base-year. Range of maximum NDVI showed a decrease at the lower limit, i.e., 0.012 as against 0.014 in 1982 while the upper limit increased to 1.0 instead of 0.995 as in 1982. Analysis of rainfall data revealed good rainfall in large parts of the country; however, SPI revealed large parts of Maharashtra, Gujarat and western Rajasthan besides a small part in north Andhra Pradesh and adjoining Orissa reeling under floods. The infamous Mumbai floods also occurred during the same year, although a part of the country like northern Chattisgarh suffered from drought during this period.

Changing Trend of NDVI During Kharif and Rabi Seasons in an Annual Cycle of 1982–1983 and 2005–2006

Seasonal NDVI was studied using mean and maximum NDVI values for *Kharif* and *Rabi* seasons during a cropping system continuum during 1982–83 and 2005–2006. The *Kharif* cropping season in 1982–83 started in the 1st week of May instead of June as is normal and ended in the first week of November in 1982, whereas the *Rabi* season started in the 1st week of November and ended in the last week of March in 1983. In 2005 the *Kharif* season started in the 2nd week of June and ended in the last week of November. The *Rabi* season started in the 1st week of December and ended in the last week of March in 2006. Thus, we see a delay in the start of both *Kharif* and *Rabi* cropping seasons in 2005–2006 and an effective reduction in the length of both cropping seasons (see Figure 7).

There is a need to study the annual trend in maximum NDVI for each year during the period 1982–2006 to

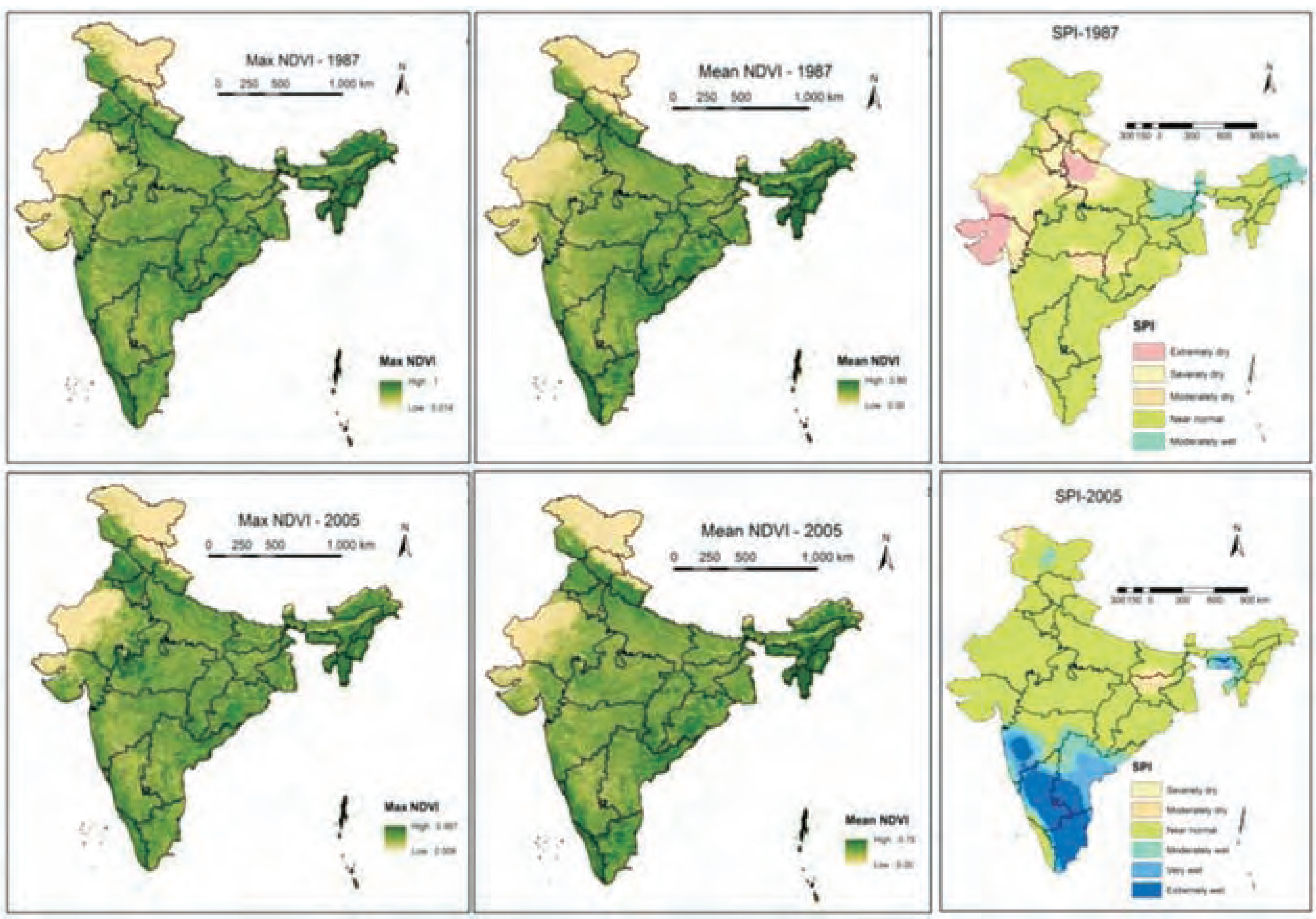

Figure 6 Mean, maximum NDVI and SPI in 1982 and 2006

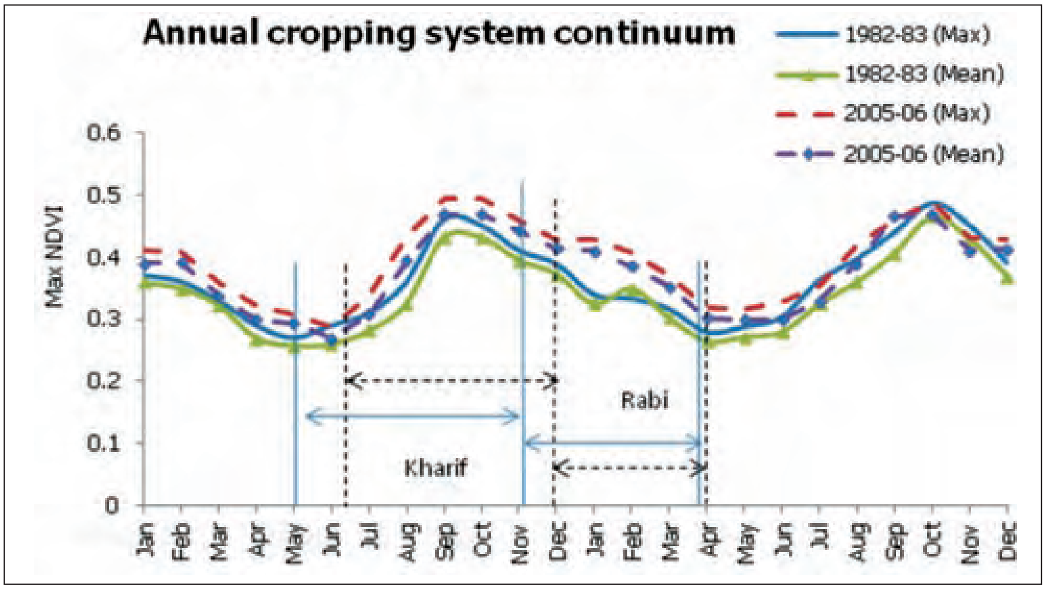

Figure 7 Shift in seasonal maximum NDVI in India

conclude with a degree of certainty if there is a discernable trend in the reduction of length of cropping season in the country. A corresponding fall in area under food grain production was however seen; in 2005–2006 the area under food crops production decreased to 122.05 Mha from 125.56 Mha in 1982–1983 (www.eands.dacnet.nic.in). However, food grain production registered an increase from 129.519 Mt to 208.60 Mt in the intervening period, indicating the role of improved hybrids, irrigation facilities and better crop management practices (CMIE Database) in increasing food crop production. NDVI from permanent vegetation like forest cover, seasonal vegetation and plantations has not been segregated and accounted for in the present study.

NDVI change and trend in Maximum and Mean NDVI and Actual Rainfall During Two Typical Years – 1982 and 2006

Quantitative analysis of the relationship between AVHRR (8 km) NDVI – Mean and Maximum with actual rainfall occurrence in the whole of India in two typical years – 1982 and 2006 revealed the following trends. While standard deviation among NDVI was less, STDEV in rainfall was nearly 60 mm. CV of Mean NDVI explained the 8.1% variation between the years. Between 1982 and 2006, there was only 5% variation in all-India rainfall and 10% in Mean NDVI and 5% in maximum NDVI; hence, no conclusive trends were seen on a national scale. This necessitated a detailed study of the spatio-temporal pattern as described in the subsequent section in this paper.

Statistics	Mean NDVI	Maximum NDVI	Actual Rainfall
SD	0.028	0.021	59.39
CV	0.0808	0.0404	0.036
CV (%)	8.1%	4%	3.6%

Spatiotemporal Pattern of NDVI and SPI in Typical Regions Across India

Due to the complexity of climate, weather and vegetation phenology across the country, it was deemed fit to analyse the correlation of NDVI, SPI and actual rainfall in typical regions across the country. Table 1 indicates the variations in NDVI and actual rainfall trends to explain trends in SPI.

Trend in NDVI and SPI in Typical Drought and Flood Years

Analysis of SPI indicated that 1987 was a typical Drought Year in India when Gujarat and western Uttar Pradesh experienced severe drought (SPI<–2, extremely dry). In Rajasthan, SPI ranged from –1.0 to –2.0 (moderately to severely dry). Moderate drought prevailed in central India (SPI –1 to –1.49). During the year, maximum NDVI in Gujarat ranged from 0.15 to 0.73 while Mean NDVI was 0.11–0.43. In Rajasthan, maximum NDVI ranged from 0.11 to 0.54 and Mean NDVI between 0.08 and 0.33. In western Uttar Pradesh, maximum NDVI ranged from 0.48 to 0.70 and Mean from 0.31 to 0.49. In case of central India where moderate drought occurred, maximum NDVI ranged from 0.12 to 0.72 and Mean NDVI from 0.09 to 0.50.

Table 1 Spatiotemporal pattern of NDVI and SPI in typical agro-ecological regions in India

District	1982					2006				
	SPI	Annual rainfall (mm)	SW monsoon (mm)	Maximum NDVI	Mean NDVI	SPI (mm)	Annual rainfall (mm)	SW monsoon	Maximum NDVI	Mean NDVI
Himachal Pradesh - Outer Himalayas - Shivaliks										
Kangra	0.36	1680.0	832.0	0.60	0.37	-0.81	918.2	517.8	0.57	0.39
Mandi	0.61	1399.1	615.7	0.73	0.48	-0.57	979.3	625.6	0.67	0.49
Una	0.05	1279.9	688.8	0.67	0.48	-0.56	901.6	580.8	0.67	0.51
Solan	0.01	1108.2	557.9	0.72	0.49	-0.30	1017.7	698.7	0.68	0.50
Reasons: Incidence of flood in Himachal Pradesh in 1982, leading to negative correlation between SW monsoon rainfall and Maximum NDVI (–94%). In 2006 there was a positive correlation of 85%.										
Hoshiarpur	–0.06	1157.3	603.0	0.66	0.44	–0.47	861.1	565.5	0.65	0.48
Reasons: The district has irrigation facility and hence despite negative SPI it shows a positive NDVI.										
Western Rajasthan										
Jaisalmer	–0.11	143.9	103.2	0.13	0.09	2.18	624.2	603.3	0.17	0.11
Jodhpur	0.09	330.6	184.3	0.20	0.14	1.04	462.8	495.9	0.23	0.16
Barmer	–0.16	239.5	159.3	0.15	0.11	1.50	612.3	589.7	0.20	0.14
Reasons: In 1982 high correlation among Maximum NDVI and SPI (82%) and with SW monsoon rainfall (94%) was seen. Flood in arid parts of western Rajasthan in 2006 resulted in negative correlation between Maximum NDVI and SPI (–99%) & SW monsoon (–92%).										
Gujarat Plains										
Surendranagar	–0.32	552.7	337.9	0.32	0.22	1.19	938.3	949.0	0.45	0.29
Rajkot	–0.23	567.3	374.4	0.37	0.23	1.01	835.0	848.8	0.54	0.33
Amreli	–0.29	580.8	335.5	0.45	0.26	0.84	964.0	1010.5	0.51	0.33
Junagadh	–0.30	685.4	435.7	0.54	0.33	0.78	912.2	935.8	0.60	0.40
Reasons: Irrigated agriculture predominates arid and semi-arid tracts in Gujarat. In 1982 there was a positive correlation between SW monsoon and Maximum NDVI (71%) while in 2006 there was a negative correlation between SPI & Maximum NDVI (–81%) due to floods.										
Tamil Nadu										
Periyar (Erode)	–1.03	614.6	287.7	0.64	0.47	0.72	1384.7	726.0	0.67	0.52
Dindigal (Anna)	–1.03	508.0	124.5	0.58	0.43	0.48	1255.8	473.4	0.62	0.50
Tiruchchirappalli	–1.00	528.4	181.8	0.58	0.45	0.40	997.0	263.3	0.62	0.50
Thiruvanamalai	–1.22	678.1	315.4	0.60	0.48	0.03	1019.1	313.0	0.60	0.50
Reasons: The region receives rainfall from NE returning monsoon. In 1982 a negative correlation was seen between SPI and annual rainfall (–82%) due to drought. In 2006 there was a positive correlation among SPI, annual rainfall & Maximum NDVI (85%).										
Central India										
Garhchiroli	–0.58	1170.4	1012.7	0.69	0.47	–0.10	1233.8	987.6	0.65	0.49
Adilabad	–0.47	1028.7	818.9	0.60	0.39	0.28	1136.7	899.7	0.61	0.43
Dantewada	–0.60	1250.8	1145.4	0.70	0.50	0.37	1364.6	1039.5	0.68	0.53
Bastar	–0.68	1134.5	1052.5	0.66	0.44	0.21	1395.1	1127.5	0.63	0.47
Reasons: Predominantly deciduous forest region in central India. In 1982 there was a positive correlation between Maximum NDVI & SW monsoon rainfall (90%). In 2006 there was a low correlation between SPI, SW monsoon & Maximum NDVI (11%) as normal conditions prevailed.										

Eastern India – Chottanagpur Plateau										
Puruliya	–1.17	973.3	775.7	0.50	0.34	0.35	1502.6	1268.1	0.56	0.37
Bankura	–1.36	1027.4	762.5	0.54	0.36	0.13	1495.4	1240.1	0.58	0.39
Singhbhum	–0.99	1083.4	888.6	0.62	0.43	0.37	1548.2	1295.3	0.63	0.44
Mednapur	–1.28	1277.8	944.2	0.60	0.40	0.17	1564.7	1301.6	0.66	0.43
Mayurbhanj	–1.08	1110.3	860.3	0.65	0.45	0.30	1599.6	1329.9	0.65	0.48
Reasons: The region covers agricultural area in West Bengal and forested area in Jharkhand and Orissa. In 1982 there was a positive correlation between SW monsoon rainfall & Maximum NDVI (74%). In 2006 with a 40% increase in rainfall, a positive correlation (81%) was seen.										
Northeastern region – Middle Brahmaputra Valley										
Sibsagar	–0.19	2491.3	1747.1	0.59	0.39	– 0.54	2462.8	1724.5	0.59	0.41
Papumpare	–0.36	2047.3	1331.6	0.81	0.53	–0.30	2486.7	1678.4	0.73	0.58
Lakhimpur	–0.24	2348.1	1566.1	0.68	0.46	–0.27	2579.7	1748.2	0.66	0.50
Dibrugarh	–0.18	2934.5	2052.6	0.56	0.39	–0.46	2711.4	1853.0	0.57	0.39
Reasons: The broad riverbed and water logging in 1982 imparted negative NDVI and a negative correlation between SPI & Maximum NDVI (–99%). In 2006 there was a decrease in waterlogging and hence a positive correlation between the two (80%).										
Semi-arid tract in Deccan region										
Anantapur	–0.42	517.7	271.7	0.41	0.27	0.36	719.7	429.7	0.49	0.33
Bellary	0.00	591.2	338.2	0.44	0.31	0.97	946.5	687.6	0.53	0.35
Raichur	–0.10	596.8	405.5	0.43	0.29	1.00	874.6	597.4	0.53	0.35
Koppal	0.08	557.3	304.3	0.39	0.26	1.15	1002.5	715.8	0.44	0.30
Reasons: In the semi-arid tract, rain-fed agriculture with livestock rearing is predominant. In 1982 there was a low positive correlation between SW monsoon & Maximum NDVI (71%) while in 2006 it was mildly negative (–15%) due to floods in Koppal, in Karnataka.										

SPI analysis indicated 2005 as a Flood Year when flood occurred extensively in Andhra Pradesh, Karnataka, Tamil Nadu and the southwest parts of Maharashtra when SPI ranged from very wet to extremely wet (SPI>1.5). In 2005, maximum NDVI ranged from 0.47 to 0.72 and Mean NDVI ranged from 0.30 to 0.55 in Andhra Pradesh and Karnataka.

Discussion

To understand the dynamics of weather aberrations, a temporal analysis was carried out for each year during the study period. CV of maximum NDVI from AVHRR (8 km) data was calculated for a period of 25 years (1982–2006) and one CV of maximum NDVI value was arrived at, which was used to plot Vulnerability Map at a pixel-level for each state and AESR in the country (see Figure 8). As shown Fig. 8, there is a clear north–south axis to the spatial distribution of agricultural vulnerability to rainfall variability in the country. The vulnerable zones indicated therein correspond to arid and semi-arid regions, which include a transition belt between semi-arid and dry sub-humid zones. The map reveals that over 210 Mha in the country may be negligibly affected by climate change due to rainfall variability, whereas 76.56 Mha and 2.85 Mha would be moderately and severely affected, respectively; these zones have been termed as vulnerable to climate change. These regions are essentially located in the arid and semi-arid tracts in Rajasthan and Gujarat. Thus, while livestock in western Rajasthan may be critically vulnerable, prosperous farmers from the cotton- and groundnut-growing belt in Gujarat may also face severe economic hardships and losses due to climate change.

As stated earlier, vulnerability was analysed in tandem with land use/land cover based on LULC Atlas of NRSC (2011). Table 2 indicates that over 1.81 and 12.1 Mha of *Kharif* cropland may be severely and moderately vulnerable, respectively, to climate change. Additionally, over 0.5 and 6.86 Mha of *Rabi* cropland may be severely and moderately vulnerable, respectively. Rest of the agricultural land, including double- and triple-cropped area, current fallow, plantation and orchards in 5.24 Mha would be adversely affected, whereas 29.93 Mha may be only marginally vulnerable to climate change due to rainfall variability.

Analysis of vulnerability at agro-ecological sub-regions level (AESR) indicates that the Thar desert and the Kacchh Peninsula besides Malwa plateau, Vindhyan scrubland

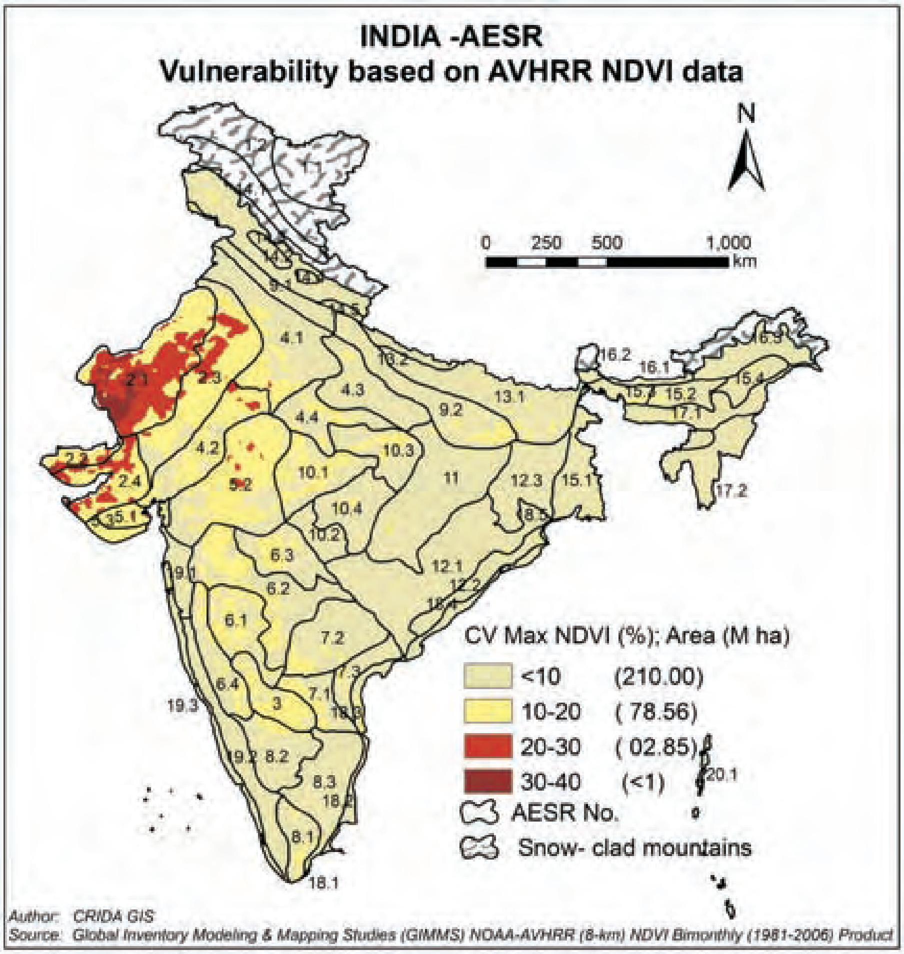

Figure 8 Coefficient of variation of Maximum NDVI across various AESR in India

Table 2 Extent of vulnerability in various LULC classes in India

Land use / Land cover in India (Source of NDVI)	Vulnerability (CV of Maximum NDVI)			
	<10	10 -20	20-30	30-40
	Extent of Vulnerability (Area, M ha)			
Agriculture (incl. double- and triple-cropped area, current fallow, plantation, orchard)	80.23	29.93	4.78	0.46
Forest (evergreen and deciduous forest)	59.84	4.77	0.07	0.006
Kharif only	34.99	12.1	1.63	0.19
Rabi only	14.96	6.86	0.49	0.01
Wasteland	10.06	6.72	3.08	0.69
Open scrub	10.86	4.78	2.27	0.66

Map source: LULC, NRSC (2007 - 08)

and Narmada river valley may be severely vulnerable to climate change followed by central India and northern Gujarat (see Table 3). As mentioned earlier, MODIS 16-day 250 m NDVI data was used to refine the vulnerability analysis further (see Figure 9) to district level, which would help in translating adaptation strategies at the local administration level. Geostatistical analysis indicated that instead of 210 Mha as estimated using AVHRR 8-km NDVI data, over 239.14 Mha may be marginally affected by climate change-induced vulnerability. Over 55 Mha may be moderately vulnerable, whereas over 8 Mha may be severely affected.

Table 3 Vulnerability to climate change in various ASERs in India

AESR No.	Geographical region in India	Climate type	Geog. area (M ha)	Soil type	Vulnerability (CV of Maximum NDVI)			
					<10	10-20	20-30	30-40
					Extent (Area in M ha)			
2.1 & 2.2	Thar desert & Kacchh Peninsula	Hot hyper-arid	14.3	Shallow to deep sandy desertic; deep loam; saline & alkali	0.82	3.61	5.52	4.02
2.3	Plains of Rajasthan, N Gujarat & SW Punjab	Hot Typic arid	11.5	Deep loamy desertic	3.7	4.3	2.99	0.42
2.4 & 3.0	S Kacchh, N Kathiawar & Karnataka Plateau	Hot arid	7.0	Deep loamy; saline & alkali; mixed red & black	2.72	6.77	1.07	0.30
4.1	N Punjab Plain; Ganga-Yamuna Doab; Rajasthan Upland	Hot semi-arid	11.8	Deep loamy alluvium-derived	9.45	2.17	0.16	0.01
4.2, 5.1, 7.1 & 6.1	N Gujarat Plain (incl. Aravalli & E Rajasthan Uplands); Central Kathiawar; S Telangana & N Karnataka Plateau & E Ghat; SW Maharashtra	Hot dry semi-arid	21.8	Deep loamy grey brown & alluvium-derived; Shallow to medium loam; clayey black; mixed red & black; shallow - medium loam	11.78	9.2	0.66	0.09
5.2 & 5.3	Plateaus of Central India, W Malwa, W & E Maharashtra, N Karnataka & NW Telangana; E Gujarat plain; Vindhyan & Satpura ranges; Narmada valley	Hot moist semi-arid	42.1	Medium to deep clayey black; Deep loamy coastal alluvium; Shallow to medium loam; clayey black; Deep loamy to clay; mixed red & black	29.93	11.59	0.18	0.31
10.1	Malwa plateau; Vindhyan hills & Narmada valley	Hot dry sub-humid	8.1	Medium and deep clayey black; shallow loamy black	0.48	2.09	3.29	2.22

Table 4 List of vulnerable districts in India based on variability of MODIS data

State	District
CV of Maximum NDVI (10–20%)	
Andhra Pradesh	Anantapur, Kurnool, Mahbubnagar, Prakasam
Bihar	Gaya, Jahanabad, Nawada
Gujarat	Ahmadabad, Jamnagar, Rajkot, Surendranagar
Karnataka	Belgaum, Bijapur, Chitradurga, Dharwad, Gadag, Gulbarga, Haveri, Koppal, Raichur
Madhya Pradesh	Barwani, Bhind, Dhar, Guna, Ratlam, Sheopur, West Nimar
Maharashtra	Ahmednagar, Aurangabad, Pune, Sangli, Satara, Solapur
Rajasthan	Ajmer, Alwar, Bhilwara, Ganganagar, Jaipur, Jhunjunu, Karauli, Sawai Madhopur, Tonk
Uttar Pradesh	Jhansi
CV of Maximum NDVI (20-30%)	
Gujarat	Kacchh
Rajasthan	Barmer, Bikaner, Churu, Hanumangarh, Jodhpur, Nagaur
CV of Maximum NDVI (30 – 40 %)	
Rajasthan	Jaisalmer

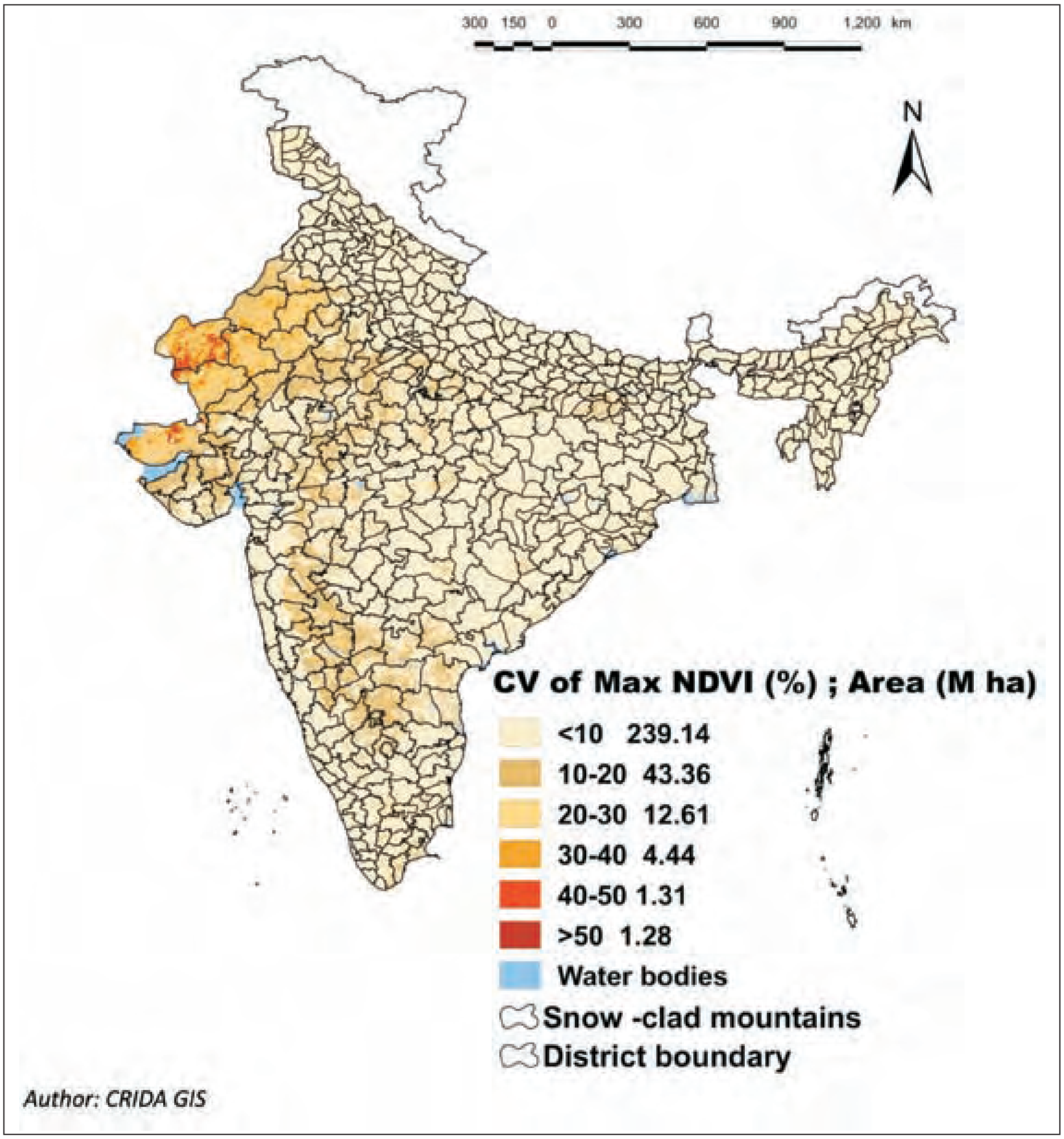

Figure 9 Vulnerability of agriculture in India based on MODIS (250m) NDVI data product

In most parts of the country, vulnerability based on CV of maximum NDVI ranged from 10 to 20% only. However, western Rajasthan was seen to be the most vulnerable, with an estimated CV of 30–40%. As mentioned earlier, the snow-clad Himalayan regions were excluded from this study. Table 4 describes the list of districts that were identified as vulnerable to climate change owing to rainfall variability at various degrees of intensity.

Conclusion

This study revealed that AVHRR and MODIS NDVI time-series data are useful for investigating the slow process of climate change due to rainfall variability. Satellite sensor-based products provide an authentic spatial reference to the analysis of vulnerability to climate change. As these data are readily available, their inclusion in planning for adaptation and mitigation strategies is essential. Due to restriction in ground resolution, AVHRR 8 km data was used to arrive at a synoptic view of vulnerability across the country in various AESRs. MODIS 250 m NDVI products helped in observing vulnerability at a district level, which would help in drawing actual implementable strategies at the local level. The study was strengthened by use of SPI instead of actual rainfall data. Although nearly 241 Mha of India may be safe from climate change, 81.3 Mha may be vulnerable in Rajasthan, Gujarat, Marathwada and Vidharbha regions in addition to the semi-arid tracts of Karnataka and Andhra Pradesh, where rain-fed agriculture is widely practiced.

It was seen that in both 1982 and 2005,maximum temperature ranging from 31 to 34^{0}C was experienced in over 250 Mha in the country, whereas minimum temperature of <10^{0}C was felt in more than 19 Mha in both years. Such low temperatures adversely affected *Rabi* and other winter crops, fruits and vegetables.

Rain-fed agriculture faces aberrant weather conditions such as decrease in length of crop-growing period due to early onset or withdrawal of monsoon, increase in intense rainfall events with a decline in the number of rainy days. As this study indicates, no significant reduction in actual rainfall received, monsoon failure with attendant drought or floods with more intense rainfall events accompanied by a general shift in spatial pattern is evident. Delay in start of both *Kharif* and *Rabi* cropping seasons in 2005–2006 and an effective reduction in length of both cropping seasons resulted in a decrease in area under food production from 125.56 Mha in 1982–1983 to 122.05 Mha. Between 1982 and 2006, there was only 5% variation in all-India rainfall and 10% in Mean NDVI and 5% in maximum NDVI; hence, no conclusive trends were seen on a national scale. However, NDVI and SPI could be used as good robust indicators for analysis of agricultural vulnerability.

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