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a Study of Telangana Region in Peninsular India

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# Use of NDVI to Assess Variability in Length-of-Crop-Growing-Period Inducing Agricultural Vulnerability: a Study of Telangana Region in Peninsular India

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## Abstract

The satellite data-based Normalized Difference Vegetation Index (NDVI) was used to assess the state of agriculture and crop vigour on a temporal basis to study agricultural vulnerability to climate change on a regional scale in a semi-arid red and black mixed soil region in Telangana, in the southern part of the Indian peninsula often referred to as the Deccan Plateau extend across 11.48 million hectares (mha) with 6.98 mha under rainfed agriculture. It provides a source of livelihood for 3.3 million farmers with small land holdings and 4.3 million farm labour and their dependants. The annual rainfall ranges from 600–1100 mm, of which 71% is received during the southwest monsoon period. Rainfed agriculture is the major land-use activity and increased climatic variability in recent decades has resulted in frequent losses, forcing governments to find suitable solutions. In order to understand factors that contribute to increasing agricultural variability in Telangana, and to understand trends in climatic variability and extreme weather events and their impact on agricultural production, time-series AVHRR NDVI data products were analysed and corroborated with the Standard Precipitation Index (SPI). The length of crop-growing period (LGP) was estimated from NDVI and studied as a *Sensitivity Indicator* for agricultural vulnerability, as it indicates crop health and vigour, which determine agricultural yield.

The results indicate which crops can be cultivated, which are vulnerable and the possible spatial extent of agricultural vulnerability based on an analysis on a regional scale, viz., the agro-ecological sub-region (AESR) delineated on the basis of agro-climatic parameters. This study belongs to the spatial vulnerability assessment category, and a lack of best practices in this field has been addressed using NDVI, SPI and LGP to test and verify their utility for assessing agricultural vulnerability. A methodology was developed to determine LGP from NDVI. The study's results indicate that the northern and southern parts of Telangana registered a significant increasing trend in LGP, while major centrally located districts cultivating high-value crops like paddy, maize, sugarcane and cotton were vulnerable to reduction in LGP. Implementation of natural resource management interventions in harvesting of rainwater and supplementing irrigation to minimize crop losses would help reduce hardship and improve farmers' adaptive capacity.

**Key words:** agro-ecological sub-region (AESR), length of crop-growing period (LGP), Normalized Difference Vegetation Index (NDVI), rainfed agriculture, Standard Precipitation Index (SPI), vulnerability

## 1. Introduction

Rainfed dryland agriculture is practiced in arid, semi-arid and hot, dry sub-humid tropical regions of India that account for 76.74 million hectares (mha) of a total geographic area of 90.4 mha in Peninsular India. Telanganathe, the newest, 29th state in India (administrative unit – the basis for a federal government system

formed by bifurcation of erstwhile Andhra Pradesh state), extends across 11.48 mha and accounts for 15% of the total area. It is a major agricultural region with a population of 35.3 million persons, of which 22.5 million are rural inhabitants who depend directly on agriculture (Fig. 1).

The region receives an average annual rainfall of 900 mm (600–1,100 mm), which occurs in 50–60 rainy

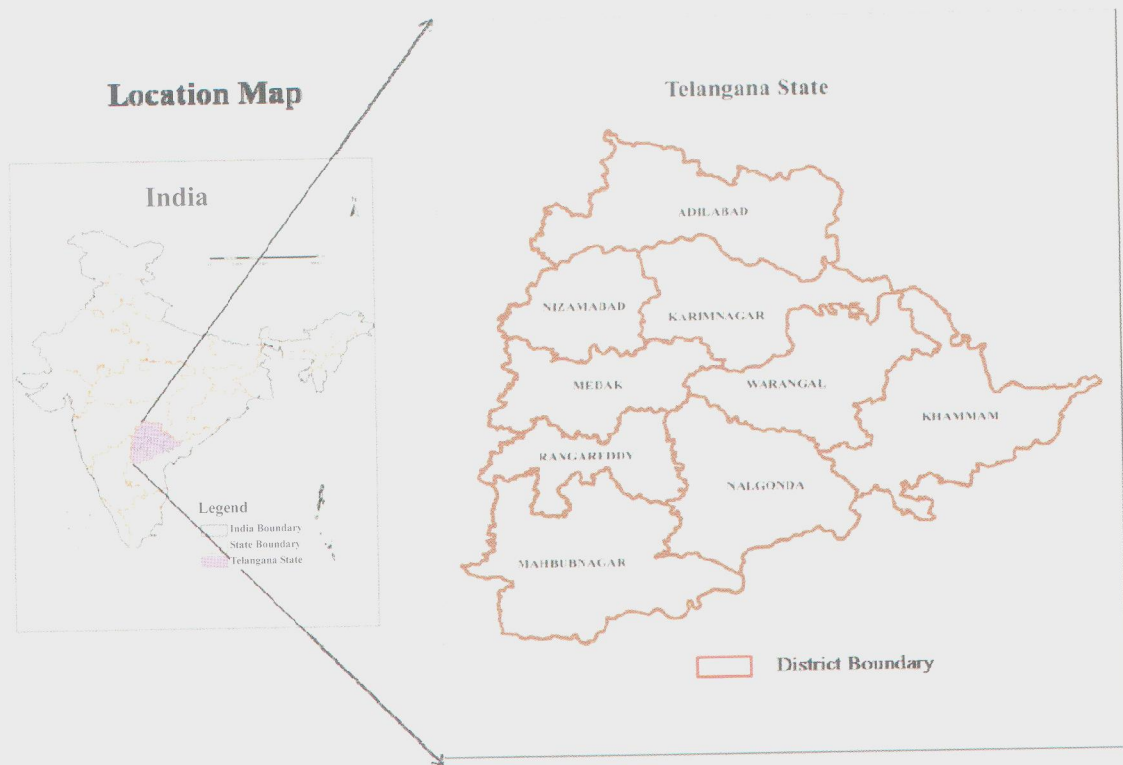


Fig. 1 Location of the study area.

days which are essentially associated with thunderstorms of short duration, causing runoff and soil erosion. Drought and flood events are common and adversely impact agricultural production. In recent years there has been an increase in climate variability and extreme weather events, like heat waves, thunderstorms associated with hail, unseasonal rain, etc., that repeatedly affect agricultural operations in the region, making study and analysis of climatic change essential. In order to understand trends in climatic variability, it was deemed fit to study variations in the state of vegetative cover, especially under agricultural land use, using satellite data, which expresses the state of several bio-physical factors influencing of vegetation in an integrated manner. Permanent vegetation, such as forest cover, was masked, as subtle changes would be difficult to assess given the nature of deciduous forest cover in study. Agricultural land use in the form of anthropogenic interventions on land was analysed using Normalized Difference Vegetation Index (NDVI) data products obtained from the AVHRR global dataset, as it indicates vegetation vigour and dynamics and variations therein in a comprehensive manner. Tools and techniques of remote sensing and GIS facilitate such spatial analysis when carried out in India and elsewhere (Ramachandran *et al.*, 2009; NRSC, 2011; SessaSai *et al.*, 2011; de Sherbinin, 2014).

The current study is part of a research program initiated in 2011 to assess agricultural vulnerability in rainfed regions of India. It was funded by the Indian Council of Agriculture Research (Ministry of Agriculture, Government of India) under the National Initiative for Climate Resilient Agriculture. Agricultural R & D in recent times in India has been guided by climate change research, which has dominated political, economic, social and

international discussions and dealings world-over since the severe drought events of 1979 and 1987 that impacted millions of humans and livestock in India and across the world, and IPCC reports ascribe aberrant weather situations across the world to anthropogenic causes such as increasing GHG emissions (IPCC, 2007a, b, c, 2008, 2012; US-EPA, 2014). Large-scale land-use and land-cover change (abbreviated as LULC below) has impacted the state and vigour of vegetation and crops adversely, leading to lower agricultural potential. Several concepts, frameworks (Turner *et al.*, 2003a, b) and indicators (US-EPA, 2014) have been put forward for climate change studies, using various methods and assumptions for varied purposes (Schroter *et al.*, 2004; Preston *et al.*, 2011; USAID, 2013; de Sherbinin, 2014). By and large vulnerability of human society or a sector thereof to climate change has been studied using socio-economic approaches (Adger & Kelly, 1999) or bio-physical approaches (Olsen *et al.*, 2000) or integrated approaches combining both (IPCC, 2007).

Vulnerability has been defined as the degree to which a system is susceptible to or unable to cope with adverse effects of climate change, including climate variability and extremes. Thus, vulnerability is considered to be a function of the character, magnitude and rate of climate variation to which a system is exposed, its inherent sensitivity, and its adaptive capacity, that enables recovery and /or the ability to withstand impact (McCarthy *et al.*, 2001; Fussel & Klein, 2006). There has been wide agreement that analysis of adaptive capacity is supported by socio-economic approaches and the study of sensitivity, by biophysical approaches, as both are internal dimensions of ecosystems while the aspect of exposure deals with external dimensions or occurrence of bio-



physical phenomena like droughts, floods or cyclones. An integrated approach, however, is what is desirable to address the issue of climate change, although there are severe limitations in the present state-of-knowledge and understanding owing to inherent issues of scale, linkages, telescoping connections and scenarios of future projections, and a lack of authentic datasets leading to a lack of standard methods for combining biophysical aspects with socio-economic approaches to help in policy-making (Deressa *et al.*, 2008). These lacunae have impacted the development of spatial vulnerability assessments or mapping of vulnerability the world over, although it is a useful tool for assessing the sensitivity of populations and ecosystems to climatic stresses and the interplay of spatially-related adaptive capacities (USAID, 2013; de Sherbinin, 2014).

The present study acknowledges these issues and strives to bring insights into the sensitivity of rainfed agriculture in India to climatic variability through a study of the NDVI vegetation index, to get an understanding of climate change phenomena and their adverse impact on agriculture, dependant populations, livestock and the economy. The Standard Precipitation Index (SPI) was used instead of actual precipitation data and LULC was analysed to understand variations in LGP.

Integrating bio-physical data for analysis of vulnerability as a result of climate change requires a spatial framework for vulnerability assessment (abbreviated as 'Spatial VA' here). Although numerous Spatial VA studies have been reported, there is no consensus on best practices to be followed. US-EPA (2014) has used a set of indicators suitable to the USA, while ATEAM-Germany (Schröter *et al.*, 2004) have used indicators suitable for Europe. USAID in Africa (de Sherbinin, 2014) has used a different set of indicators including NDVI and SPI as exposure indicators and length of crop-growing period (LGP) as a sensitivity indicator, broadly following the IPCC framework. US-EPA (2014) has grouped indicators under six headings and used LGP as an indicator to assess the impact on health and society, and leaf and bloom dates, akin to vegetation vigour, as an ecosystem indicator.

In view of these various approaches, authors of this paper decided to assess the sensitivity of rainfed agriculture using NDVI, and correlate it with variations in SPI instead of actual rainfall, to gain an understanding of resultant variations in LGP that manifest in the form of increases/decreases in food grain, fodder and fibre production in India, broadly following the IPCC framework (Parry *et al.*, 2007). As a result a methodology evolved which loosely fits into the Extended Vulnerability Framework of Turner *et al.* (2003a, b), Brinkmann (2006) and IPCC's Special Report on Climate Extremes (SREX) risk management for analysing the impact of drought/flood events and general variability in rainfall on rainfed dryland agriculture in Telangana.

NDVI datasets with varied ground resolutions have overlapping scales and thus contribute to nested analysis, but for lack of expertise in this field, the present study has

not established clear tele-connections between variations in NDVI from agricultural land and land-use change due to anthropogenic factors, although it falls in the domain area of the Coupled Human-Environment System Framework. Our study was restricted to examining variations in NDVI and SPI as exposure indicators and change in LGP as a sensitivity indicator to grasp the extent of agricultural vulnerability in rainfed regions in India without assessing possible variations under different climatic scenarios. As our study mainly focuses on analysing variability in stressors, viz., drought and floods, through SPI on the NDVI vegetation index by examining past trends and assessing their impact on variations in LGP impacting agricultural production, it may be insufficient for elucidating their impact under different socio-economic scenarios (Preston *et al.*, 2011; IPCC, 2012; USAID, 2013; de Sherbinin, 2014; US-EPA, 2014).

## 2. Materials and Methods

The objectives of this study were to identify trends in length of crop-growing period (LGP) in agricultural land use in the Telangana region derived from time-series NDVI datasets and to identify areas that were agriculturally vulnerable based on variations in NDVI due to climate variability and frequent extreme weather events indicative of climate change. Large-scale changes in LULC and resulting variations in NDVI can be used as indicators of land-use intensification, desertification and climate change or variability (Celis *et al.*, 2007). Interventions like watershed development programs under natural resource management have been shown to be useful strategies for improving the adaptive capacity of farmers in the event of climate change (Ramachandran *et al.*, 2009; Wani *et al.*, 2011).

A temporal study of NDVI variations was carried out using NDVI products from NOAA-AVHRR (15-day, 8 km) which is part of GIMMS and is available from 1982 till 2006 after corrections and can be downloaded from the Global Land Cover Facility (GLCF) website <[www.landcover.org](http://www.landcover.org)> (<http://www.glcfc.umd.edu/data/gimms/>) as the 15-day Maximum-Value Composite. Time-series NDVI datasets were used to assess the sensitivity of cropping systems in various agro-eco-sub-regions (AESR) that are typical climatic zones delineated using soil quality, soil water-holding capacity, moisture index and LGP, estimated using the FAO model (FAO, 1983; Velayutham *et al.*, 1999). SPI estimated from actual rainfall data was used to corroborate the sensitivity of agriculture during the study period (Tucker *et al.*, 1985; Mckee *et al.*, 1993; Thenkabail *et al.*, 2004; Dadhwal, 2011; Saikia & Kumar, 2011).

NDVI from AVHRR with red reflectance in Band 1 and NIR reflectance in Band 2 was calculated as  $(\text{Band 2} - \text{Band 1}) / (\text{Band 2} + \text{Band 1})$  as it takes advantage of 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, un-vegetated and sparsely vegetated areas that are typical of the Telangana region. LULC analysis helped in identifying NDVI contrasts among agriculture, forest and open-scrubland. Bi-monthly NDVI images were stacked and pre-processed, followed by identification of the pixel-wise maximum NDVI for estimating the maximum greenness of any pixel during the corresponding year (1982–2006). The 8 km ground resolution of AVHRR permitted identification of agricultural vulnerability at a regional scale as it was available for a relatively longer period of 26 years (1982–2006) and in line with most climatic analysis requiring a 30-year time-series dataset; hence MODIS-TERRA NDVI data products with 250 m ground resolution available from 2001 were not selected. The coarse resolution of the AVHRR data, however, increased the likelihood of mixed pixels being classified erroneously, thus adversely affecting accuracy in estimating areas under agricultural vulnerability. A methodology was developed for estimating LGP using NDVI based on White *et al.* (1997) and reported in Ramachandran *et al.* (2014).

The India Meteorological Department (IMD) provides daily rainfall data spanning more than 100 years for many stations, and the present study used daily gridded rainfall data (1901–2007) developed by Rajeevan *et al.* (2008) for 661 rain-gauge stations in the study area. Gridded rainfall data at 1° latitude x 1° longitude were used to calculate SPI and long-term precipitation records were fitted to a probability distribution and transformed into a normal distribution, so that the mean SPI for any location and desired period, were equal to zero. Positive SPI values indicated greater than median precipitation, while negative values indicated less than median precipitation. As SPI was normalized, both wetter and drier climates could be presented in a similar manner and wet and dry periods denoting flood and drought could be assessed (McKee *et al.*, 1993). An SPI of  $\leq 1.00$  for any given period was considered the start of a reduced rainfall period that could lead to drought if prolonged; drought

was indicated when the SPI was continuously negative and reached  $-1.0$  or less, and it ended when the SPI turned positive. The SPI was used to identify drought and flood events and the corresponding NDVI reflectance coefficient to study variations in LGP.

Spatial rainfall patterns were obtained by a kriging interpolation of rainfall data to obtain an 8 km resolution corresponding with the ground resolution of the AVHRR-NDVI dataset. Analysis indicated that rainfall was highest during July–August while max. NDVI occurred subsequently in the months of September–October, and 1982 was considered the base year for the study.

The dates of start-of-season (SOS) and end-of-season (EOS) of LGP were identified using an NDVI reflectance coefficient of 0.5 (White *et al.*, 1997; Vrieling *et al.*, 2008), which was higher than that usually obtained from vegetation cover in semi-arid and dry sub-humid regions of India. Hence typical NDVI reflectance coefficient values were generated for each AESR (agro-ecological sub-region) of Telangana. The NDVI threshold value was identified for each AESR using the average NDVI value of three normal years (when annual/ seasonal rainfall equalled the long-term average) for each crop growing season, viz., the *Kharif* (summer monsoon) and *Rabi* (post-monsoon) of 1986, 1991 and 1999. To find the threshold value, the actual NDVI value of the 15-day composite for each AESR was plotted. The SOS for the *Kharif* season was estimated by extracting and stacking the 15-day NDVI composite from June–October for each year and the SOS threshold was assumed as the value after which NDVI showed an increasing trend. The EOS for the *Kharif* was identified as the fortnight when the NDVI value fell, continuing a decreasing trend. The point when the NDVI coefficient fell continuously was taken as the threshold value of the EOS. For analysing LGP variations during the *Rabi* season, NDVI composites of November to March were taken and the SOS and EOS were identified similarly (Ramachandran *et al.*, 2014). The results of this study can help in formulating suitable packages of practice for farming in the region (Fig. 2).

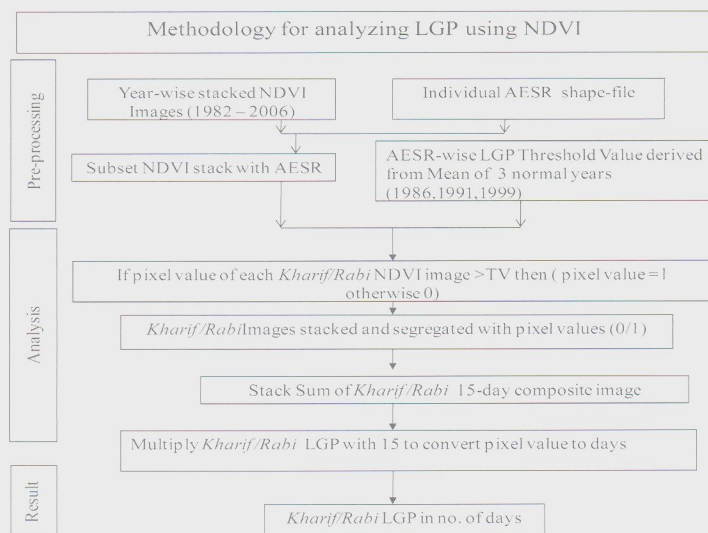


Fig. 2 Methodology for analysing LGP using NDVI (after Ramachandran *et al.*, 2014).

### 3. Results and Discussion

#### 3.1 Assessment of agricultural vulnerability using NDVI from the AVHRR dataset

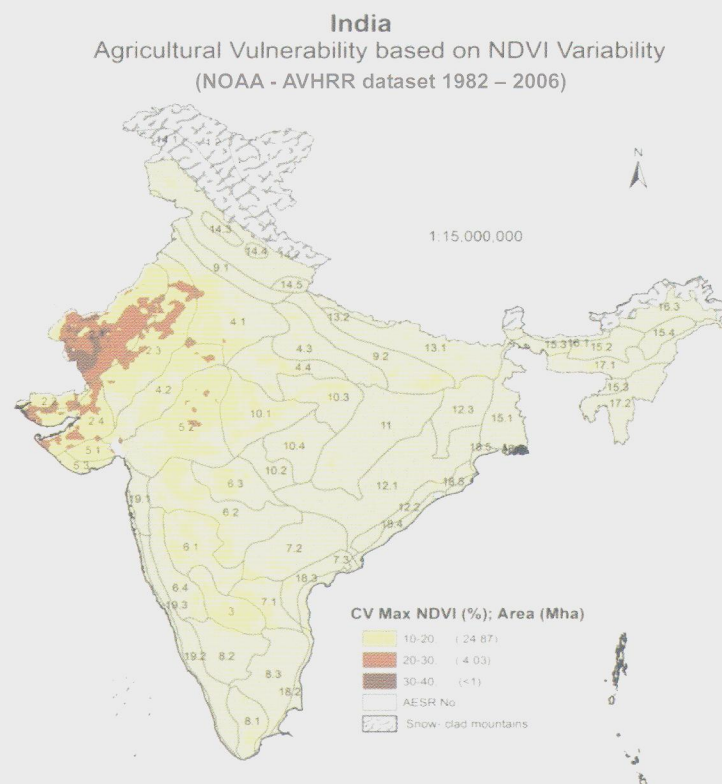
In semi-arid tropics, water is the major constraint to crop production (Celis *et al.*, 2007; CRIDA, 2014). In India the southwest monsoon is the predominant source of water for agriculture during the *Kharif* season. The mean and standard deviation of max. NDVI were estimated for agricultural land use to gain an understanding of variability in greenness that indicates crop vigour and health and correlates highly with crop yield in the season, as mentioned earlier. The pixel-wise max. NDVI indicates maximum greenness during the corresponding year (1982 to 2006) and variability in greenness was taken as indicator of vulnerability. The coefficient of variation of max. NDVI was calculated and used to indicate agricultural vulnerability (Ramachandran *et al.*, 2013) (Fig. 3). The general trend in rainfall and NDVI in India denoting variations in vegetation dynamics in the country owing to climatic variability is indicated in Fig. 4. It formed the basis for identifying the spatial extent of agricultural vulnerability in India (Ramachandran *et al.*, 2013).

#### 3.2 Pattern of LGP trends in Telangana

The Telangana region comprises three major agro-ecological sub-regions (AESR), which have been given unique nomenclature (Velayatham *et al.*, 1999) based on their agro-climatic parameters, as stated earlier.

The three AESR in Telangana have the following designations and characteristics: AESR 6.2, denoting central and western Maharashtra Plateau, northern Karnataka Plateau and northwestern Telangana Plateau with a hot moist semi-arid climate and shallow to medium loamy and clayey black soils having water-holding capacities of 100–200 mm with a normal LGP of 120–150 days estimated using the FAO model (1983); AESR 6.3, denoting a region comprising eastern Maharashtra Plateau with a hot semi-arid climate, medium to deep clayey black soils having water-holding capacities of 100–200 mm and a normal LGP of 120–150 days; and AESR 7.2, encompassing a major part of the Telangana Plateau with a hot, moist semi-arid climate and deep loamy and clayey mixed red and black soils with water-holding capacities ranging from 100 to >200 mm and a normal LGP of 120–150 days. Parts of Telangana falling under AESR 6.2 are the districts of Medak, Karimnagar and Nizamabad, while half of the Adilabad district falls under AESR 6.3 while the rest of Telangana falls under AESR 7.2, comprising the districts of Mahabubnagar, Nalgonda, Warangal, Khammam, Rangareddy and Hyderabad. As mentioned earlier, NDVI (reflectance coefficient) values of normal years were taken to identify the threshold value for SOS and EOS for the *Kharif* season in each AESR, which were estimated at 0.25 for AESR 6.2, 0.26 for AESR 6.3 and 0.33 for AESR 7.2 (Ramachandran *et al.*, 2014) (Fig. 2).

The NDVI dataset of the *Kharif* season (10 in a year)



Author: NICRA-CRIDA  
Source of data: Global Inventory Modeling & Mapping Studies (GIMMS) NOAA-AVHRR (8-km) NDVI Bimonthly (1982-2006)  
Product

Fig. 3 Extent of agricultural vulnerability in India (after Ramachandran *et al.*, 2013).



pertaining to June–September was stacked and the pixel-wise sum of the NDVI was derived. This value was multiplied by 15 (number of days of the NDVI composite) to derive LGP in number of days.

This method was applied to *Kharif* season images for 1982–2006 to study deviations in LGP, as a result of variations in SOS and EOS in the three AESRs in Telangana, and variations in LGP were compared with the value of normal years. LGP values were classified

according to types of crops cultivated in a given period and variability in the extent of area under each class during the study period. LGP values in various AESRs in Telangana ranged from <60 days in the south of Mahabubnagar with an average SPI of 0.02 and districts of Nalgonda (SPI of 0.22) to over 150 days in northern districts of Khammam (SPI of 0.47) and Nizamabad (SPI of 0.15) (Fig. 5a, b). Figure 6 indicates that the area under the LGP class of 120–150 days was largest in 2001 (SPI

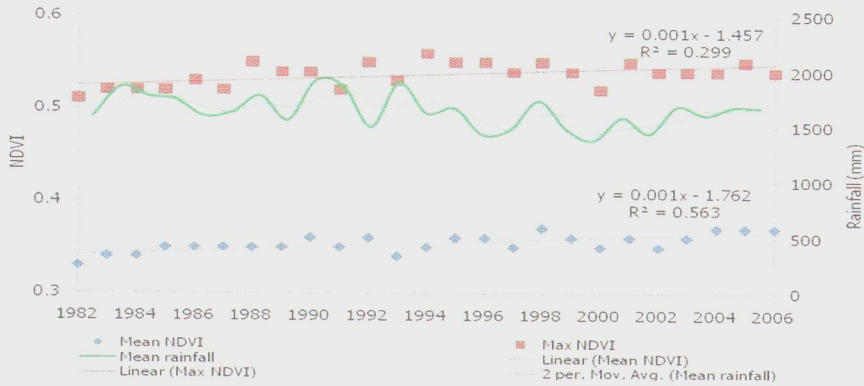


Fig. 4 Variations in all-India rainfall and NDVI (after Ramachandran *et al.*, 2013).

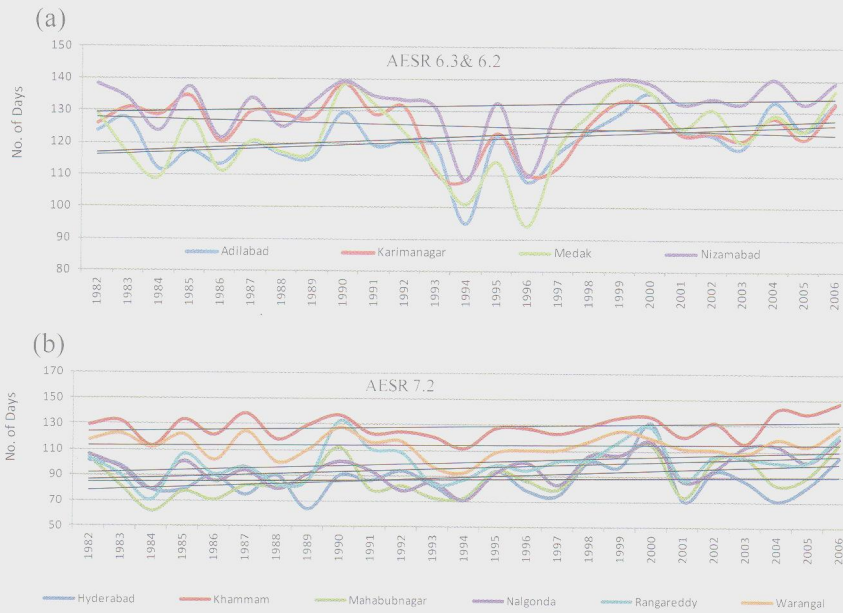


Fig 5 (a) Variations in LGP in the northern Telangana region (ACSR 6.3 & 6.2).  
(b) Variations in LGP in the southwestern Telangana region (ACSR 7.2).

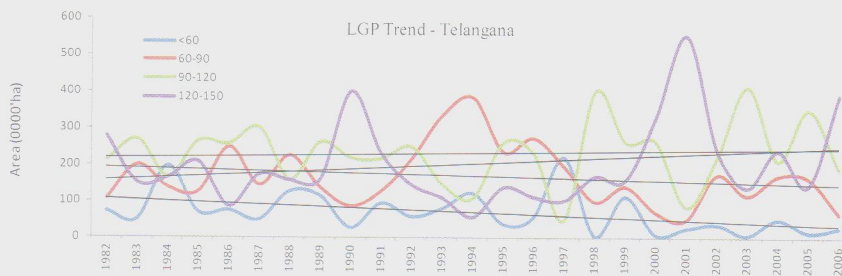


Fig. 6 Trends in LGP classes in Telangana (1982–2006).

of  $-0.22$ ) and 2006 (SPI of  $0.748$ ) indicating near normal rainfall for crops like paddy, maize, pigeon pea, soybean, cotton and sugarcane. The SPI ranged from  $-1.46$  (moderately dry) in 1985 to  $0.75$  indicating near normality of 2006. In 2001 the agricultural area under this class of LGP was  $5.5$  mha, indicating good agricultural production during that year. The area under the LGP class of 90–120 days was over  $4.0$  mha in 1998 and 2003 when an SPI of  $0.44$  indicated near normal rainfall.

The area under the LGP class of 60–90 days increased in 1994 to  $4.4$  mha when the SPI was  $-0.97$ , indicating near normal for the Mahabubnagar, Nalgonda, Rangareddy and Warangal districts. In 1984 and 1997 the LGP class of  $<60$  days extended across  $1.9$  mha and the SPI was  $-0.21$  denoting near normality in the dry semi-arid tract of Nalgonda, Rangareddy and Mahabubnagar. Figure 7 shows temporal variations in LGP in various districts of the Telangana region. As Mahabubnagar and Nalgonda were identified as marginally vulnerable with a coefficient of variation of max.  $NDVI < 10-20$  and the LGP showed an increasing linear trend, it was essential to analyse this variability using a Mann-Kendall Test performed at two levels – AESR and district. It was seen that under AESR 6.2 and 6.3, covering northern Telangana, the LGP derived from the NDVI demonstrated a significantly increasing trend (significance of  $p = 0.0002^{**}$  &  $p = 0.0038^{**}$  at the 1% level) while under AESR 7.2, denoting southern Telangana, the LGP indicated a lower significance ( $p = 0.04^{*}$  at the 5% level) (Table 1). Our study indicated that out of the ten districts of Telangana,  $4.82$  mha in Adilabad, Mahabubnagar and Nalgonda showed an increasing trend in LGP while other districts showed no significant trend (Table 2). In the case of the Karimnagar and Warangal districts, covering  $2.47$  mha of prime agricultural area, where cash crops like groundnut, cotton and maize are grown, decreasing LGP could adversely affect the regional economy.

#### 4. Conclusions

Time-series NDVI datasets from NOAA-AVHRR (15-day, 8 km) which helped in identifying agriculturally vulnerable regions in India, were used to assess variations in length of crop-growing period (LGP) that induced agricultural vulnerability in rainfed areas of the Telangana region. The SPI was used to corroborate trends in the NDVI. An increase in spatial extent under the LGP class of 120–150 days, which is favourable for major cereals, pulses and cash crops, viz., paddy, maize, pigeon pea, soybean, cotton and sugarcane, was suitable for agriculture. However an increase in extent under the LGP class of 90–120 days that facilitates cultivation of maize, pearl millet and mustard could adversely affect crop production. Crops under the LGP class of 60–90 days are major oilseeds, viz., groundnut, sunflower and castor, and millets like sorghum and pearl millet. A decrease in rainfall and shortening of LGP, however, would affect these crops. An LGP of  $<60$  days denotes failure of the monsoon and losses to agriculture, as only pearl millet and cluster beans can be cultivated. Regionally, southern Telangana is drier with a shorter LGP and hence more vulnerable to climate change. Districts of northern Telangana with favourable SPIs have longer LGPs and are hence suitable for cultivation of cereals like paddy and maize and cash crops like cotton and sugarcane. A reduction in LGP, however, would cause hardship to farmers and adversely affect the economy. A closer look at variations in LGP using the Mann-Kendall Test indicated that LGP was increasing in Adilabad, Nalgonda and Mahabubnagar while it was decreasing in the Karimnagar and Warangal districts, which are prime agricultural districts cultivating high-value cash crops. Our study indicated that variability in LGP could adversely impact rainfed agriculture and in order to minimize the impact of climate change, NRM interventions like watershed development could be useful for improving adaptive capacity among farmers.

**Table 1** Mann-Kendall analysis of LGP variations at the AESR level.

AESR	S	Z	P	Equation	Significance
6.2	158	3.667	0.0002	$Y = -1507.7 + 0.7895X$	**
6.3	171	2.892	0.0038	$Y = -1044.8 + 0.5518X$	**
7.1	130	3.013	0.0026	$Y = -854.43 + 0.4486X$	**
7.2	87	2.009	0.0445	$Y = -646.68 + 0.3498X$	*

\*\* :  $p < 0.01$ , \* :  $p < 0.05$

**Table 2** Significance of variability in LGP at the district level, Telangana.

AESR	District	S	Z	P	Equation	Significance
6.3	Adilabad	95	2.196	0.0281	$Y = -794.10 + 0.4588X$	*
7.2	Hyderabad	97	1.718	0.0857	$Y = -1157.8 + 0.6250X$	NS
6.2	Karimnagar	-34	-0.771	0.4406	$Y = 551.05 - 0.2122X$	NS
7.2	Khammam	61	1.402	0.161	$Y = -885.50 + 0.5089X$	NS
7.2	Mahabubnagar	103	2.383	0.0172	$Y = -2001.9 + 1.046X$	*
6.2	Medak	69	1.589	0.1122	$Y = -790.60 + 0.4582X$	NS
7.2	Nalgonda	93	2.149	0.0316	$Y = -1634.6 + 0.8675X$	*
6.2	Nizambad	38	0.865	0.387	$Y = -91.361 + 0.1127X$	NS
7.2	Rangareddy	77	1.775	0.0758	$Y = -1481.7 + 0.7941X$	NS
7.2	Warangal	-11	-0.188	0.8511	$Y = 166.56 - 0.2735X$	NS

\* :  $p < 0.05$



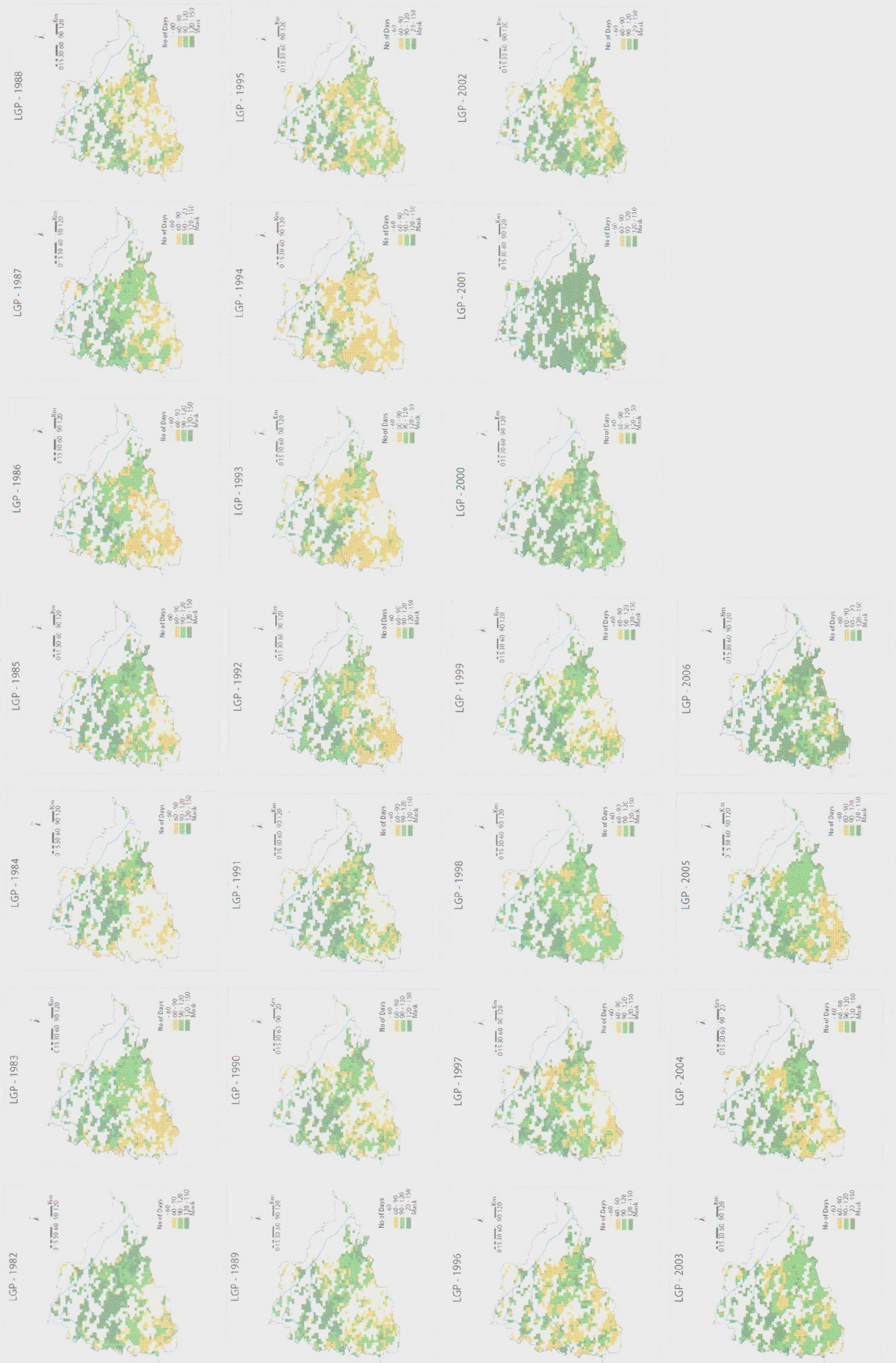


Fig. 7 Temporal variations in LGP at the AESR level in Telangana (1982–2006).

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