



Quantification of agricultural drought over Indian region: a multivariate phenology-based approach

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Abstract

The objective, accurate and rapid quantification of agricultural drought is the key component of effective drought planning and management mechanism. The present study proposed a new index, i.e. multivariate phenology-based agricultural drought index (MADI), for quantification of the agricultural drought using long-term (1982–2015) crop phenological parameters. The 15-day global inventory modelling and mapping studies time-series normalized difference vegetation index (NDVI) data (~8 km) were interpolated at daily scale and smoothed using Savitzky and Golay filtering technique. Different crop phenological parameters, i.e. start of season, end of season, length of the growing period (l_{gp}), integrated NDVI (iNDVI), etc., were estimated using a combination of threshold and derivative approaches for individual pixels during kharif season. Based on the time of occurrence, the agricultural droughts may lead to delay in crop sowing, reduction in cropped area and/or decreased production. Hence, the l_{gp} and iNDVI were selected among all phenological parameters for their capability to represent alterations in crop duration and crop production, respectively. The long-term l_{gp} and iNDVI of individual pixel were detrended and transformed into standardized l_{gp} ($S_{l_{gp}}$) and standardized iNDVI (S_{iNDVI}) to eliminate the existing trends developed due to technological improvements during study period and existing heterogeneity of Indian agricultural system, respectively. The MADI was calculated by fitting $S_{l_{gp}}$ and S_{iNDVI} into joint probability distribution, where the best joint distribution family along with associated parameters was selected based on the goodness-of-fit for individual pixel. The values of MADI vary between -4 and +4, where the negative and positive values represent drought and non-drought conditions, respectively. The efficacy of the proposed index was tested over the Indian region by comparing with the multivariate standardized drought index, which considers the impacts of both meteorological and soil moisture drought using copula approach.

Keywords Agricultural drought · Multivariate phenology derived agricultural drought index · Length of crop growing period · Integrated normalized difference vegetation index · Multivariate standardized drought index

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1 Introduction

Drought is a widespread hydro-climatic disaster involving complex interactions among climate, natural resources and socio-economical parameters (Wilhite 2000; Wilhite and Pulwarty 2017). Due to its complex interplays among weather, soil, water and crop systems, it significantly impacts on the crop production, food–water scarcity, economy, labour migration, etc. (Cumani and Rojas 2016). In India, around 65% of the total cropped area was reduced due to drought during 1987 affecting around 285 million populations, whereas the devastating drought incidence in 2009 affected around 400 million people (Anonymous 2016). In 2002, India faced its shortest ever monsoon affecting around 350 million people with around 3.1% reduction in agricultural contribution to GDP (<https://www.downtoearth.org.in/blog/drought-forever-44976>). The frequent drought incidences have long-lasting and adverse impact over the environment, agriculture, economy and societal health of the nation. Although the intensity, extent and of the drought incidences may vary in different parts of the globe, the drought incidences are expected to rise in different parts of the globe as an impact of climate change (Seneviratne 2012; Dai 2013; Li and Zhou 2015).

The overall drought phenomenon is generally categorized into four broad group, i.e. meteorological, agricultural, hydrological and socio-economic droughts, for better understanding, monitoring and assessment of the incidence (Seneviratne 2012; Teuling et al. 2013; AghaKouchak 2014). Being the aftermath of meteorological drought and precursor of socio-economic drought, agricultural drought plays a key role in country's overall sustainability and development. Meteorological droughts are the prime basis of the agricultural droughts, but that may not essentially lead to agricultural drought always (Wilhite and Glantz 1985). The agricultural drought, a multifaceted phenomenon, evolves due to the complex interactions among rainfall, evapotranspiration (ET), soil moisture, crop, etc. Many researchers have addressed the agricultural drought in different ways, like negative anomaly in soil moisture during specific crop phenological stages, significant reduction in ET and associated yield loss, gap between actual crop water demand and existing moisture in soil profile and so on (Wilhite and Glantz 1985; Vermes 1998). However, till now there is no universally accepted definition of agricultural drought, leading to uncertainties among stake holders for declaring drought (Tate and Gustard 2000). According to Panu and Sharma (2002), “the definitions of agricultural droughts hover around the soil moisture deficiency in relation to meteorological droughts and climatic factors and their impacts on agricultural production”.

Many researchers have proposed several indices for identifying and assessing the impact of drought involving different kinds of parameters (Vogt and Somma 2000; Quiring and Papakryiakou 2003; Boken et al. 2005). Some of the commonly used meteorological drought indices include rainfall anomaly index (RAI; Van Rooy 1965), standardized precipitation index (SPI; McKee et al. 1993), Palmer drought severity index (PDSI; Palmer 1965), standardized precipitation–evapotranspiration index (SPEI; Vicente-Serrano et al. 2011) and multivariate moisture anomaly index (MMAI; Das et al. 2017). On a similar line, several soil moisture-based drought indices have been developed, namely soil moisture drought index (SMDI; Hollinger et al. 1993), soil moisture deficit index (SMDI; Narasimhan and Srinivasan 2005), standardized soil moisture index (SSMI; Hao and AghaKouchak 2013), soil water deficit index (SWDI; Martínez-Fernández et al. 2015), drought severity index (DSI; Cammalleri et al. 2016), soil moisture anomaly percentage index (SMAPI; Mao et al. 2017). Similarly, many indices have also been proposed to address the impact of drought on agriculture, like integrated evapotranspiration deficit index (IEDI;

Zhao et al. 2017), integrated surface drought index (ISDI; Wu et al. 2013), irrigation processes based on the Palmer drought severity index (IrrPDSI; Yang et al. 2017), etc. Of late, due to the advancement of earth observations satellite and its reliability, many indices have been developed to study the impacts of drought on crop area, health and production, like normalized difference vegetation index (NDVI; Rouse 1973); crop water stress index (CWSI; Idso et al. 1981), vegetation condition index (VCI; Kogan 1995), vegetation health index (VHI; Kogan 1997), perpendicular drought index (PDI; Ghulam et al. 2008), etc.

According to Das et al. (2019), the impacts of drought on agriculture depend on the time of occurrence of droughts. The early-season drought would lead to delayed crop sowing, i.e. either decrease in cropped area or reduced crop duration, whereas the mid- and late-season droughts might directly lead to reduction in crop production. The significant impacts of climate and soil moisture on length of growing period (Igp) and crop production were also observed by Pinjarla et al. (2017). Hence, the alterations in crop phenology matrix may provide important information for quantifying the impacts of drought. Moreover, due to its multi-scalar nature, proper quantification of drought parameters remains a challenge using single variable (Shiau et al. 2007; Vicente-Serrano et al. 2013). Hence, the present study aims at quantifying the impact of agricultural drought using multivariate approach by combining crop phenological parameters using joint probability distribution approach.

2 Study area

The study has been conducted over Indian mainland, extending within 08° 04' N to 37° 06' N latitude and 68° 07' E to 97° 25' E longitude (Fig. 1). Being an agrarian country, around 54.6% of the Indian population is directly or indirectly involved in agriculture allied sectors for their livelihood. Agriculture plays a key role in country's economic development and sustainability by contributing around 16.0% of gross value added (GVA) during 2018–2019. Around 68% of the Indian agricultural area is still drought prone covering almost 278 districts of 11 states (Nandakumar 2009; Nagaraja 2012). During 2018–2019, some states covering Andhra Pradesh, Karnataka, Maharashtra, Jharkhand, Gujarat, Rajasthan and Odisha have declared drought situations. In India, there exists a lot of heterogeneity based on land use and land cover, soil types, water resources, cropping pattern, etc. However, based on its effective rainfall, growing period and soil groups it is divided into 20 agro-ecological zones, whereas based on Koppen's scheme India is classified into nine major climatic groups depending on its mean annual and monthly temperature and precipitation.

3 Data used and methodology

3.1 GIMMS NDVI data processing

The GIMMS NDVI3g represents the “Global Inventory Modelling and Mapping Studies” time-series NDVI data product, available for 1981–2015. It is a bi-monthly (15-day interval) composited NDVI images with spatial resolution of 1/12° (~8 km). The datasets have been corrected for orbital drift, water vapour, sensor attenuation, solar zenith angle and atmospheric effect due to volcanic aerosols (Tucker et al. 2005; Pinzon and Tucker 2014).

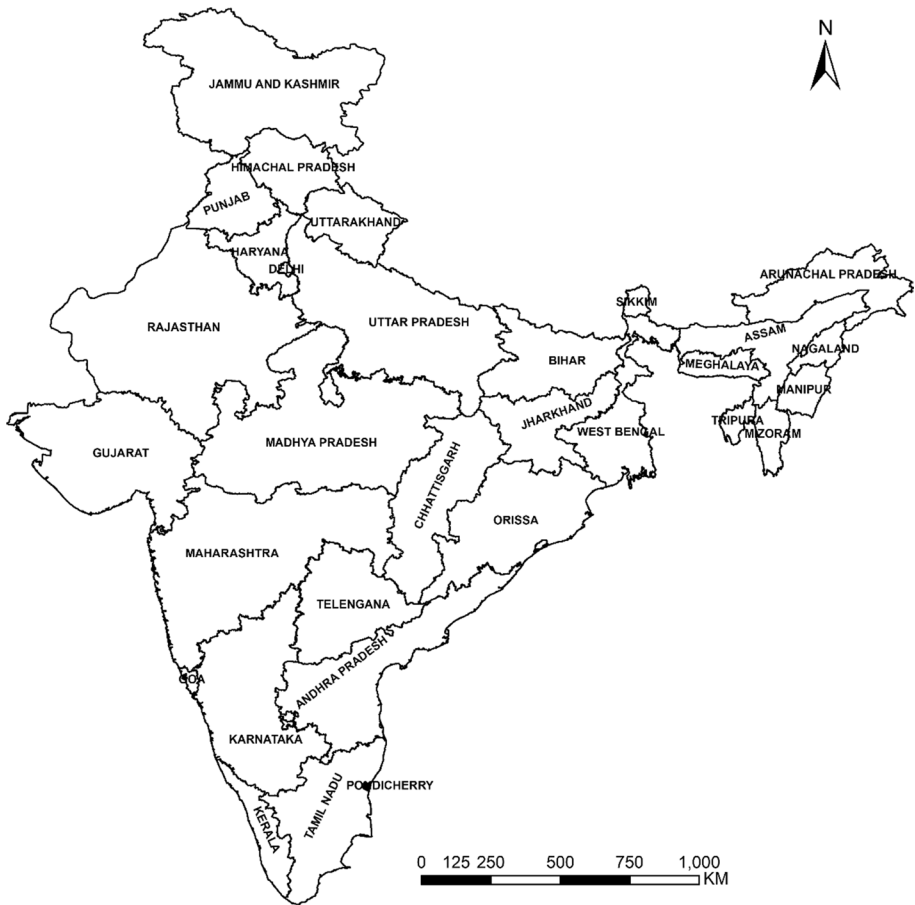


Fig. 1 Study area with state boundaries

Due to unavailability of NDVI dataset during entire monsoon season, i.e. June to November, the NDVI dataset of 1981 was not considered in the present study. For long-term vegetation analysis, the GIMMS NDVI dataset was found to be superior to other coexisting data products (Dutta et al. 2013). The GIMMS NDVI data can be freely obtained from <http://www.glcf.umiacs.umd.edu/data/gimms/>.

The NDVI is generally derived from the near infrared (NIR) and red spectral bands of AVHRR (Advanced Very High Resolution Radiometer) onboard NOAA (National Oceanic and Atmospheric Administration), using the following equation:

$$\text{NDVI} = \frac{(R_{\text{NIR}} - R_{\text{red}})}{(R_{\text{NIR}} + R_{\text{red}})} \quad (1)$$

where R_{NIR} and R_{red} are the reflectance values at NIR and red spectral bands, respectively.

The 15-day interval NDVI dataset was converted into daily data using linear interpolation, and it was further smoothed using second order and 5-window Savitzky and Golay filtering technique. Different crop phenological parameters, viz. start of season (SOS), end

of season (EOS), length of season (lgp) and integrated NDVI (iNDVI), were estimated from the time-series smoothed NDVI data using thresholds and derivative approaches (Jeganathan et al. 2014). The script for extraction of phenological parameters was developed using R-software. The SOS was determined by identifying the day on which the rate of change of NDVI values, i.e. first derivative of NDVI, was maximum and NDVI was greater than 0.2. The NDVI threshold of 0.2 was used to confine the study within vegetation pixels only. In a similar way, the EOS was also calculated; however, the change in NDVI was in negative direction. The SOS and EOS represent the growing season onset and end, respectively. Whereas, the lgp is the duration between the SOS and EOS, i.e. the difference between EOS and SOS. The iNDVI represents the area under NDVI curve during lgp, i.e. the cumulative NDVI values between SOS and EOS.

3.2 Trends analysis of the crop phenological parameters

The long-term trends of the different crop phenological parameters, viz. SOS, EOS, lgp and iNDVI, were carried out over entire India using Sen's method (Sen 1968). This method is advantageous over parametric statistics since the missing values in time-series data are included and the conformation of the data to any particular distribution is not required (Yu et al. 1993). Sen's slope is able to estimate the magnitude of the trends along with the direction of the trends, i.e. the rate at which the targeted parameters are decreasing or increasing. In the present study, the significant increasing and decreasing trends were estimated over individual grid at 95% level of significance. In SOS and EOS, the positive trends signify the delay in start and end of season, respectively, and vice versa. Similarly, the increasing trend in lgp and iNDVI represents the prolonged crop duration and increased crop production, respectively, and vice versa. The details of the Sen's slope can be found in Das et al. (2010).

3.3 Developing Multivariate phenology-based Agricultural Drought Index (MADI)

The impacts of drought on agricultural system vary based on the time of drought occurrences. The early-season drought would lead to delayed crop sowing, i.e. either decrease in cropped area or reduced crop duration, whereas the impacts of mid- and late-season droughts might lead to reduction in crop production. Hence, in crop phenology matrix, the length of growing period (lgp) as well as integrated NDVI (iNDVI) is capable of estimating the impacts of droughts in terms of reduced crop duration and decrease in crop production, respectively. Hence, among all crop phenological parameters, lgp and iNDVI were selected for developing the proposed index.

The detrending approach was applied on both of the phenological parameters to eliminate the existing trends developed due to technological improvements during last three decades, i.e. 1982–2015 (Chakraborty et al. 2019). Due to the existing heterogeneity in Indian agriculture, it would not be justified to directly compare the lgp or iNDVI anomalies of one pixel to another towards estimation the impact of droughts on agricultural system. Hence, the long-term lgp and iNDVI of individual pixel were transformed into standardized l_{lgp} (S_{lgp}) and standardized iNDVI (S_{iNDVI}), respectively, using empirical probability distribution approach, instead of any specific distribution function, i.e. parametric (Farahmand and AghaKouchak 2015). In the present study, the marginal distribution of both lgp and iNDVI was derived using empirical Gringorten plotting position (Gringorten 1963):

$$p(x_i) = \frac{i - 0.44}{n + 0.12} \quad (2)$$

where ‘ n ’ and ‘ i ’ represent the sample size and rank of nonzero data in ascending order. $p(x_i)$ is the corresponding empirical probability. The S_{Igp} and S_{iINDVI} were computed by fitting the output of Eq. (2) in the following equation:

$$S_{\text{Igp}} \text{ or } S_{\text{iINDVI}} = \phi^{-1}(p) \quad (3)$$

The ϕ^{-1} represents the normal distribution function, and p denotes the probability values derived from Eq. (1).

The Sklar’s theorem describes that if there exists p correlated random variables M_1, M_2, \dots, M_p with their marginal distributions $F_{m_1}(m_1), F_{m_2}(m_2), \dots, F_{m_p}(m_p)$, respectively, the multivariate distribution function would be (Sklar 1959):

$$F_{m_1, m_2, \dots, m_p}(m_1, m_2, \dots, m_p) = C(F_{M_1}(m_1), F_{M_2}(m_2), \dots, F_{M_p}(m_p)) \quad (4)$$

Of late, the capability of copula in describing the nonlinear interactions among multivariate parameters has been effectively utilized by the scientific communities (AghaKouchak et al. 2010; Das et al. 2017). The popularity of copula techniques in studying the drought risk, frequency and modelling is being increased due to the multi-scalar nature of drought phenomena (Bardossy 2006; Serinaldi et al. 2009; Das et al. 2017).

In the present study, the multivariate phenology-based agricultural drought index (MADI) has been developed by fitting the S_{Igp} and S_{iINDVI} into joint probability distribution. For individual pixel, the best joint distribution model along with its associated parameters was estimated based on Akaike information criteria (AIC) and goodness-of-fit tests (Das et al. 2017). The R-based VineCopula package was utilized for the same (Schepsmeier et al. 2017). Further, the selected models and the parameters were deployed on S_{Igp} and S_{iINDVI} , followed by its transformation into normal distribution. For details of the methodology, one may refer Das et al. 2017.

The values of MADI are ranging between -4 and $+4$, i.e. in the same scale of well-established drought indices like standardized precipitation index (SPI), standardized precipitation–evapotranspiration index (SPEI), etc. The negative values denote the drought conditions, whereas the positive values indicate normal or above normal conditions.

3.4 Validation of the proposed index

According to Das et al. (2018), the validation of any drought index remains a challenge due to lack of any universally accepted drought definition as well as methodology to quantify the impact of drought on agricultural sectors. Hence, generally the proposed indices are being compared with other well-established indices to prove its efficacy in monitoring, assessing or quantifying the drought conditions. Hao and AghaKouchak (2013) developed a new index, i.e. multivariate standardized drought index (MSDI), for overall characterization of drought conditions using both precipitation and soil moisture information. As agricultural droughts are the consequences of either significant deficit of precipitation or soil moisture or both. In the present study, we have compared the newly developed index, i.e. MADI, with SPI, SSMI as well as MSDI to prove its effectiveness in quantifying impact of agricultural drought.

3.5 Calculation of Multivariate Standardized Drought Index (MSDI)

The long-term (1982–2015) total surface precipitation and total profile soil moisture content from the Modern-Era Retrospective analysis for Research and Applications-2 (MERRA-2) were downloaded through Goddard Earth Sciences Data and Information Services Centre (<http://disc.sci.gsfc.nasa.gov/mdisc/>). The datasets are available in a $1/2^\circ$ (latitude) by $2/3^\circ$ (longitude) grid at monthly interval over the period of 1979–2015. The datasets are downloaded in netcdf (.nc) format, and further spatial sub-setting was carried out to restrict our study within Indian mainland.

The long-term precipitation (PRECTOT) and soil moisture (PRMC) data were transformed into 6-month standardized precipitation index (SPI) and standardized soil moisture index (SSMI), respectively. The gamma probability distributions were adopted for calculating SPI, whereas it was empirical distribution for SSMI (McKee et al. 1993; Farahmand and AghaKouchak 2015). Subsequently, the SPI and SSMI were coupled to generate the MSDI. The details of the copula and methodology of creating joint probability distributions are already provided in Sect. 3.2.

The MADi was generated at higher spatial resolution, i.e. ~ 8 km, in comparison with the MERRA-2-based SPI or SSMI or MSDI, i.e. ~ 50 km. Hence, the district level weighted MADi values were calculated, followed by its classification into several drought severity classes to bring all the datasets into almost similar scales for comparison. The details of the methodology are given in Fig. 2.

4 Results and discussion

4.1 Alterations in crop phenological parameters under drought conditions

The crop phenology stages are being altered based on the types of drought. Das et al. (2015) categorized the drought events into early-, mid- and late-season drought based on their time of occurrences. The alterations in the crop phenological parameters over a pixel during kharif season of a given year are shown in Fig. 3. The two curves (solid and dotted) represented the normal and drought years, respectively. In normal year, the start of the sowing (SOS) was at 199 Julian day, i.e. at around third week of July, and the end of season (EOS) was at 297, i.e. last week of October, with an effective length of growing period (lgp) of 98 days. On the other hand, due to early-season drought the SOS was found to be delayed by 23 days. It was interesting to observe that the EOS was advanced by 5 days during the drought year which led to reduced length of growing period (lgp) for almost 1 month. Moreover, the progression of crop growth, based on the NDVI profiles, was also found to be lower in drought years in comparison with normal year, which ultimately led to significant reduction in integrated NDVI (iNDVI), a proxy indicator of crop production (Fig. 3). Hence, it can be inferred that based on the time of occurrence and severity of droughts, different crop phenological parameters, like SOS, EOS, lgp and iNDVI, etc., get altered and the same may be utilized to quantify the impact of droughts on agricultural systems.

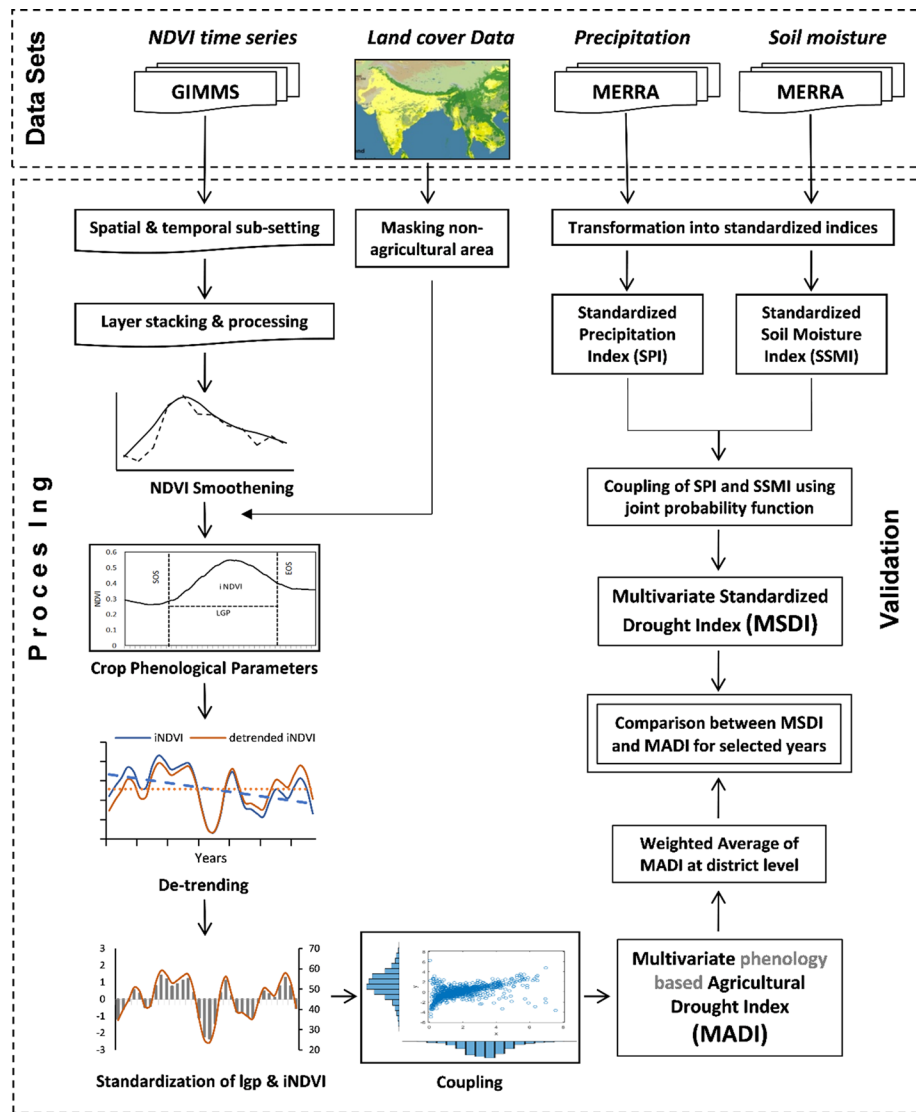
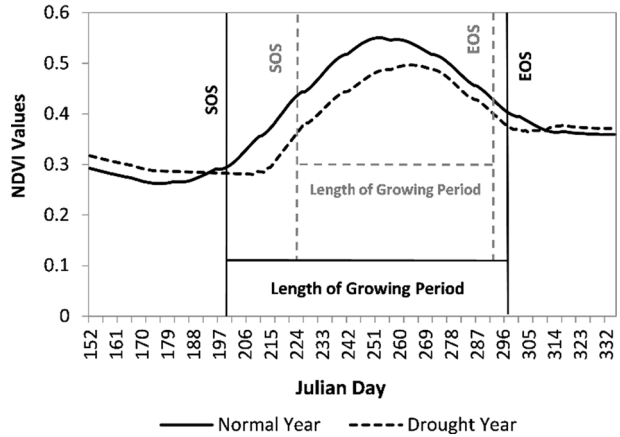


Fig. 2 Schematic diagram of detailed methodology

4.2 Trends of different crop phenological parameters

The trend analysis of different crop phenological parameters revealed that in major parts of Indian mainland, the SOS was delaying except some parts of Andhra Pradesh, Tamil Nadu and Kerala. The magnitudes of delay were found to be varying spatially. The higher values, i.e. > 0.5 day year⁻¹, were mainly found over parts of Rajasthan, Telangana, Madhya Maharashtra and isolated parts of Punjab, Haryana, Uttar Pradesh and Chhattisgarh. Whereas, in rest parts of the country, the values were either lower (< 0.25 day year⁻¹) or moderate (0.25–0.50 day year⁻¹). Similarly, the trend analysis showed that EOS was delayed in

Fig. 3 Curves representing different crop phenological stages under normal and drought years



major parts of the India; however, the magnitudes were lesser than SOS. The moderate (0.25–0.50 day year⁻¹) magnitudes were mainly confined over parts of Rajasthan, Telangana, Madhya Maharashtra, north Karnataka and isolated parts of Chhattisgarh, Haryana and Punjab, West Bengal, etc. In major parts of the study area, the trends’ values were positive with low (<0.25 day year⁻¹) magnitude, except southern parts of Andhra Pradesh and parts of Tamil Nadu and Kerala with negative EOS trends, representing advancement in crop maturity. The resultant of the SOS and EOS trends reflected in the trends of lgp, and it was interesting to find that in major parts of the country the values were negative, i.e. the overall crop season is decreasing. However, in some parts of Tamil Nadu, Andhra Pradesh, Rajasthan and isolated parts of north-eastern India positive trends were also detected. The higher negative values (<-2.0) were found mainly over major parts of Madhya Pradesh, Chhattisgarh, Orissa, Jharkhand, Bihar and isolated parts of Karnataka, Maharashtra, Uttar Pradesh and West Bengal. It was interesting to find that though the length of crop season (lgp) is decreasing, the overall crop production, in terms of integrated NDVI (iNDVI), was increasing over major parts of the study area. Most of the districts were coming under moderate iNDVI (0.05–0.20) increase, whereas positive iNDVI with higher (>0.20) values was found over parts of Rajasthan and isolated parts of Maharashtra and north-eastern India. The decreasing and increasing trends in lgp and iNDVI, respectively, may be due to the introduction of hybrid crop varieties under India’s green revolution programme during 70–80’s (Fig. 4).

4.3 Detrending and standardization of crop phenological parameters

The present study intends to address the impact of drought on agricultural system by eliminating the existing trends within crop phenological parameters developed due to technological improvements during study period. Hence, a linear detrending approach was executed on both lgp and iNDVI over individual pixels of the Indian mainland. Figure 5a, b represents the time-series and detrended lgp and iNDVI, respectively, for a single grid over study area. It was observed that in both the integrated NDVI and length of growing period, there exist significant negative trends during last 35 years. However, after detrending the inter-annual deviations in the phenological parameters are devoid of long-term technological impacts. Subsequently, the detrended time-series crop phenological parameters were

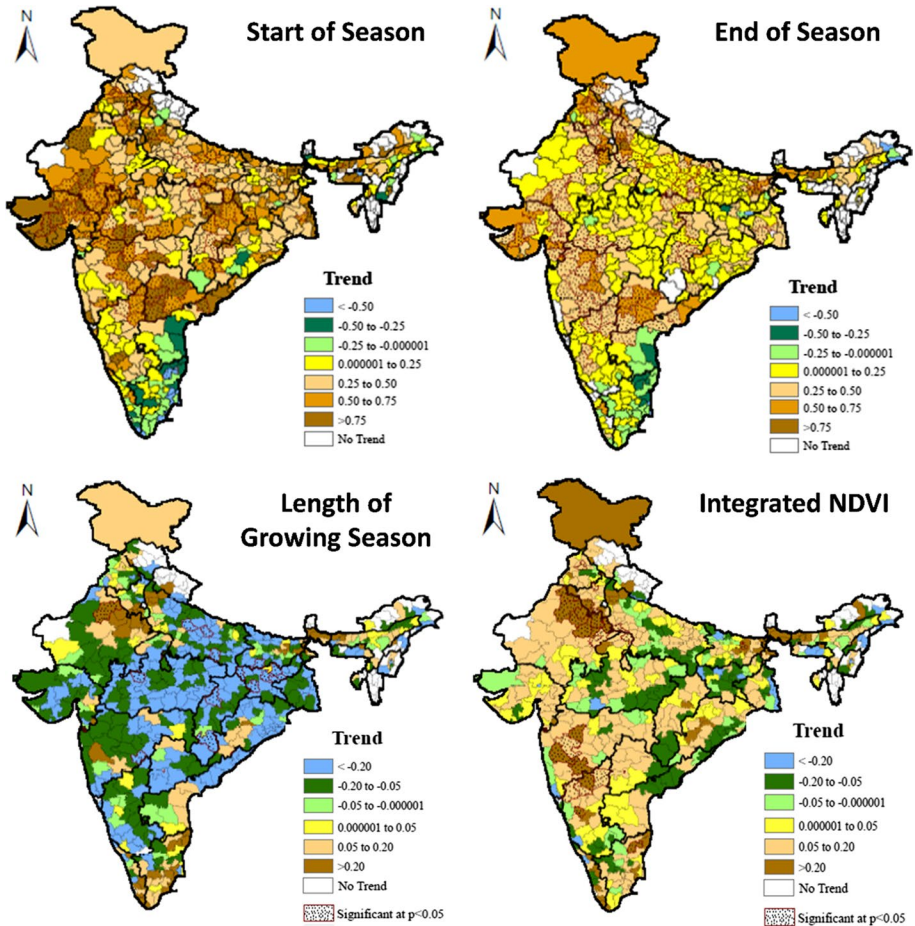


Fig. 4 Maps showing trends of different crop phenological stages

normalized to eliminate the spatial heterogeneity. Figure 5c, d revealed that the inter-annual variations in phenological parameters were successfully captured in the negative and positive anomalies of standardized lgp (S_{lgp}) and standardized iNDVI (S_{iNDVI}) for a single grid over Indian mainland.

4.4 Quantifying agricultural drought using Multivariate phenology-based Agricultural Drought Index (MADI)

The agricultural drought for different years was quantified using the proposed approach, i.e. multivariate phenology-based agricultural drought index (MADI). The spatial extent and intensity of the drought were successfully captured by the new index. In 1982, the drought was mainly confined in the northern parts of the country along with parts of Uttar Pradesh, Maharashtra and Karnataka, and the same was represented in MADI (Fig. 6). Similarly, almost entire Indian mainland was under the effect of drought during the year

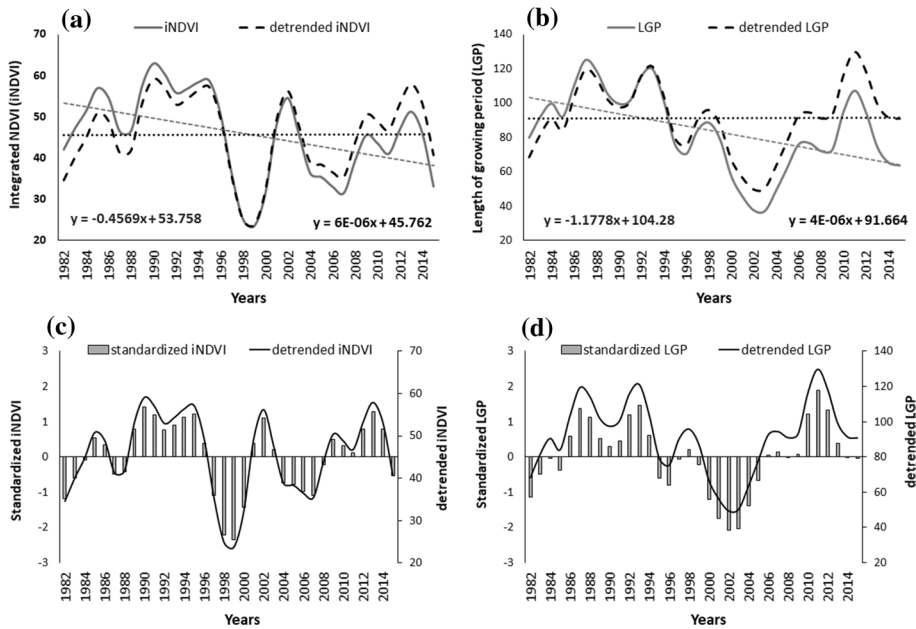


Fig. 5 Curves representing detrending and normalization of time-series integrated NDVI and length of growing period for a given grid

of 1986, 1987 and 2002, but the variations in the inter-annual drought intensity were effectively quantified using the MADL. In 1986, most of the area was under mild drought conditions except Rajasthan, whereas in 1987 and 2002, it was mainly the moderate and severe drought in major parts of the country. On the contrary, 2011 was a normal year except southern India covering Andhra Pradesh, Karnataka and Tamil Nadu. The proposed index, i.e. MADL, was capable of effectively characterizing both the normal as well as drought affected regions. Similar observation was also recorded during 2012, which was eventually an early-season drought year in parts of southern India. The MADL could able to successfully capture the same with associated intensities. Hence, it was found that the proposed index was capable of effectively detecting, monitoring the spatial extent and quantify the intensity of drought over the study area.

4.5 Validation of the proposed index

The agricultural drought is manifestations of meteorological and soil moisture droughts. The meteorological and soil moisture droughts may or may not lead to a significant agricultural drought, which again depends on multiple drivers like, severity of rainfall and soil moisture anomalies, soil properties, crop type, varietal information, etc. Hence, it is obvious that the agricultural drought may not exactly resemble with meteorological and soil moisture droughts. In the present study, the outputs of the newly developed index, i.e. MADL, under different drought years were compared with the meteorological, soil moisture and combined drought products to find their agreement in terms of spatial extent and intensity.

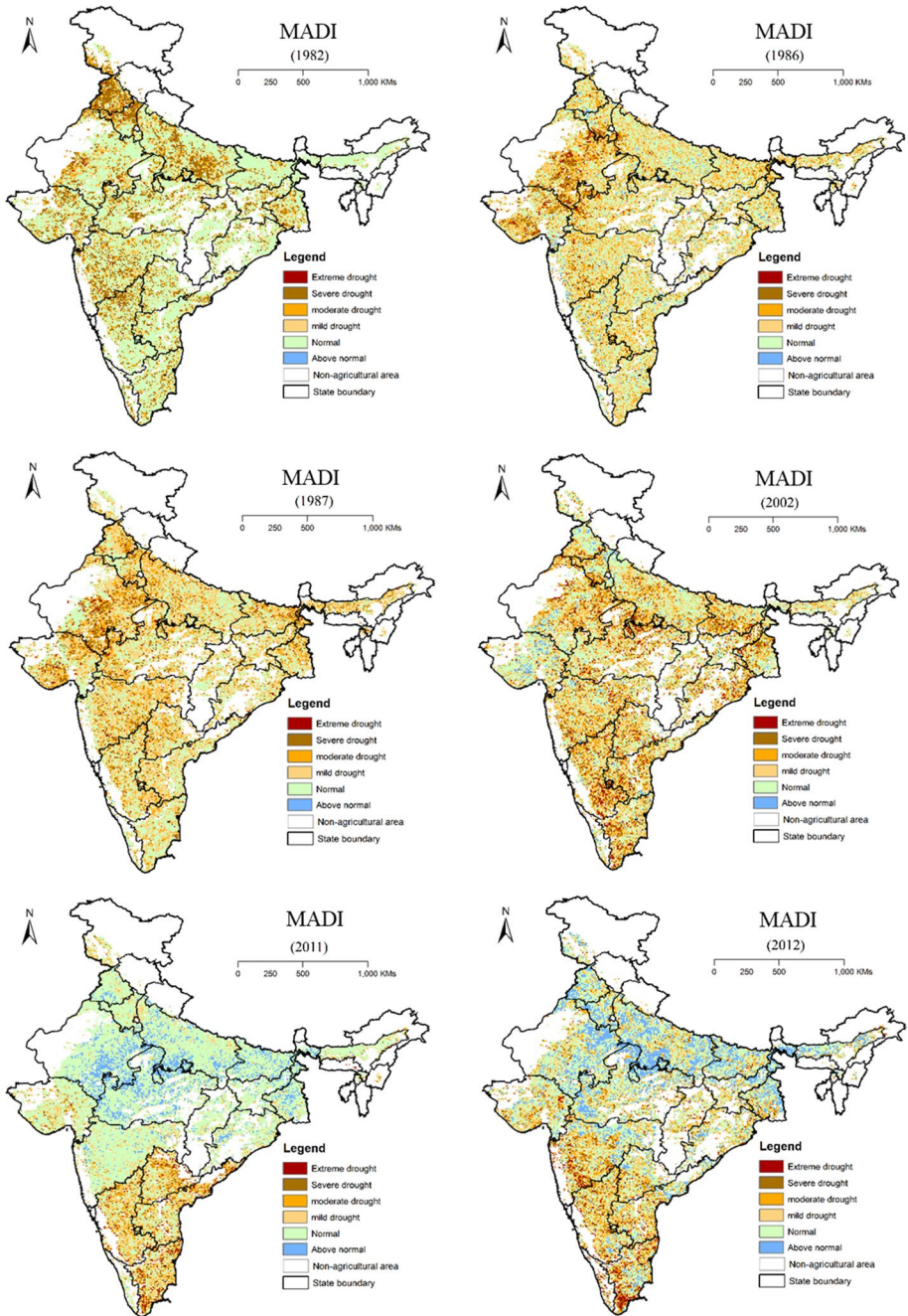


Fig. 6 Maps showing multivariate phenology-based agricultural drought index (MADI) for different years

During 1982, meteorological droughts were observed based on SPI over almost entire Punjab, Tamil Nadu and Bihar, northern parts of Haryana, western parts of Gujarat, central parts of Maharashtra and isolated parts of Madhya Pradesh, Rajasthan, Odisha, etc. (Fig. 7). On the contrary, above normal conditions were found over central Uttar Pradesh and parts of Chhattisgarh, Odisha and Kerala. Based on SSMI, almost similar observations were found in case of soil moisture drought also with some additional mild drought areas over parts of Maharashtra, Rajasthan, Andhra Pradesh and Odisha. The multivariate standardized drought index (MSDI), a multivariate drought index by combining both the meteorological and soil moisture droughts, could show the drought affected areas along with their intensities over different parts of Indian mainland. It was quite encouraging to find that the district weighted MADI was in corroboration with the SPI-, SSMI- and MSDI-based drought conditions in major parts of the study area. However, few disagreements were also noted over parts of Uttar Pradesh, Bihar and Tamil Nadu.

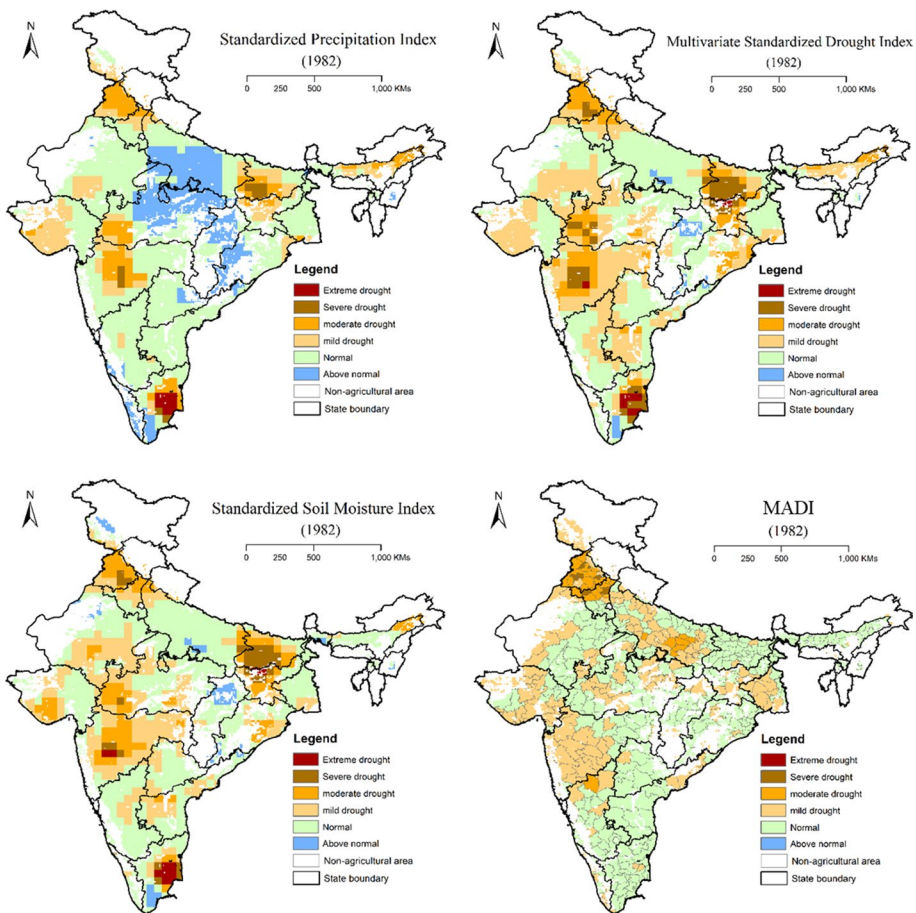


Fig. 7 Standardized precipitation index (SPI), standardized soil moisture index (SSMI), multivariate standardized drought index (MSDI) and multivariate phenology-based agricultural drought index (MDI) maps for 1982

Similarly, the comparison of MADI-derived agricultural drought during 1987 was carried out with meteorological, soil moisture and combined drought conditions derived from SPI, SSMI and MSDI, respectively. It was found that almost entire India was under moderate to extreme drought conditions based on both meteorological and soil moisture drought indices, except some parts of Karnataka, Bihar and Maharashtra (Fig. 8). The devastating impact of drought on agricultural sector was also successfully captured by multivariate phenology-based agricultural drought index (MADI), as mild to moderate agricultural droughts were observed over almost entire India.

The extensive drought events covering almost entire study area except parts of Maharashtra, Madhya Pradesh, Jharkhand and West Bengal with intensities varying from mild to severe were observed using SPI, SSMI and MSDI during 2002 (Fig. 9). The proposed agricultural drought index could able to capture the impact of drought in the agricultural system effectively. Based on MADI, the agricultural drought intensities were lower than

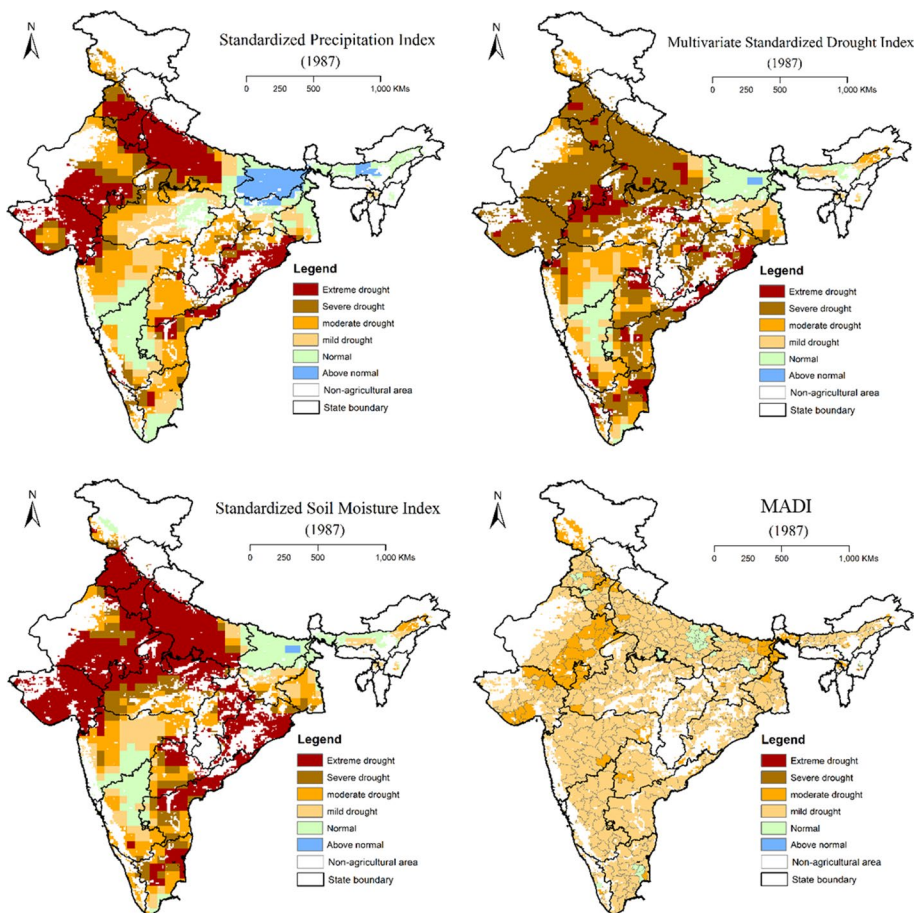


Fig. 8 Standardized precipitation index (SPI), standardized soil moisture index (SSMI), multivariate standardized drought index (MSDI) and multivariate phenology-based agricultural drought index (MDI) maps for 1987

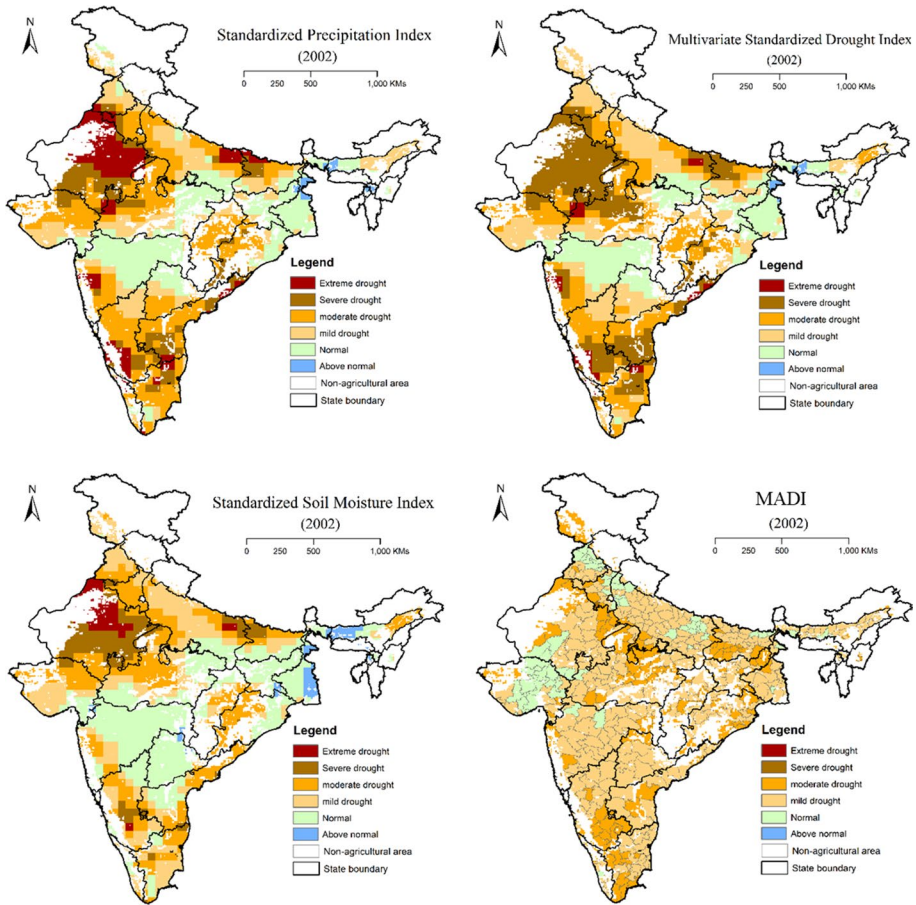


Fig. 9 Standardized precipitation index (SPI), standardized soil moisture index (SSMI), multivariate standardized drought index (MSDI) and multivariate phenology-based agricultural drought index (MDI) maps for 2002

SPI and SSMI, i.e. mainly mild to moderate, which may be attributed to the resilience of soil as well as agricultural systems.

The impact of drought was mainly restricted within southern India covering parts of Maharashtra, Karnataka, Andhra Pradesh, Kerala and Tamil Nadu during 2012, whereas it was normal or above normal in rest of the parts of the country (Fig. 10). According to the annual report published by Ministry of Agriculture (GOI), the production of all the food grains, coarse cereals as well as fibre crops was significantly lower than the previous year, i.e. 2011–2012 (<http://agricoop.nic.in/sites/default/files/Annual%20Report%202013-14.pdf>), leading to around 0.5% reduction in Indian’s gross domestic product (Udmale et al. 2014). During 2012, 13 out of 36 meteorological sub-divisions were under deficient rainfall, whereas around 41% of the districts received deficient or scanty rainfall (Pai and Bhan 2012). According to IMD, the major part of the country was under severe to moderate arid condition during the early part of the kharif season (Ray et al. 2015). As per the NAD-AMS report, the moderate drought condition was prevalent over the state of Maharashtra,

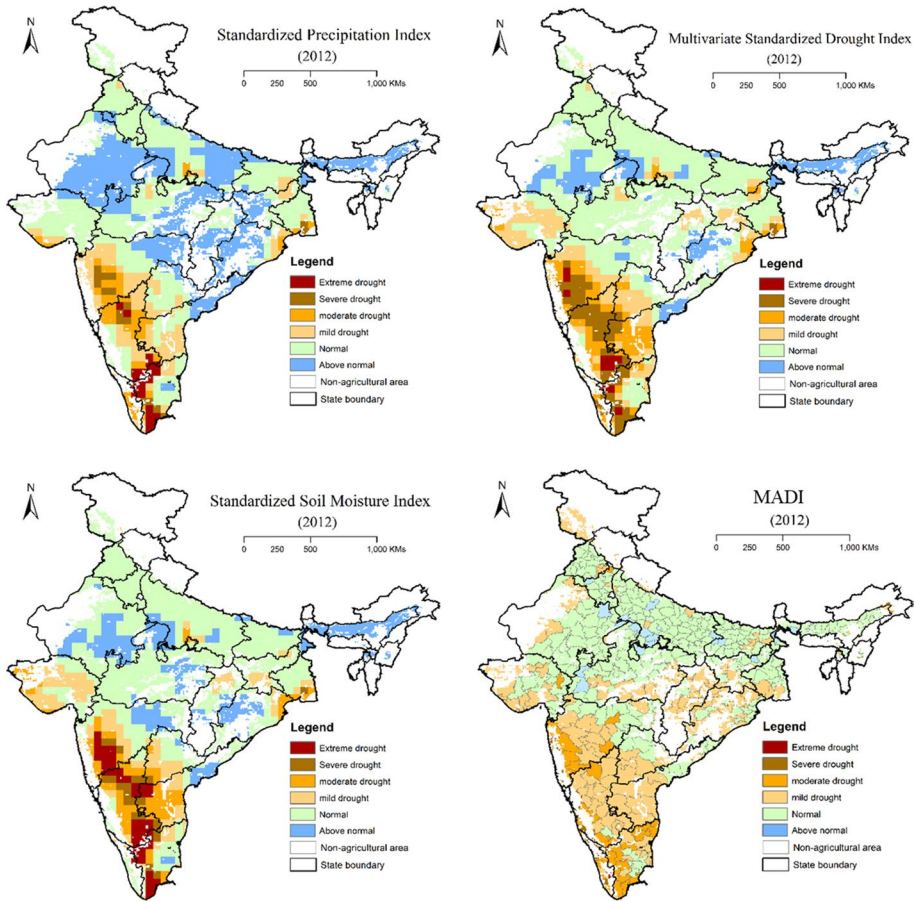


Fig. 10 Standardized precipitation index (SPI), standardized soil moisture index (SSMI), multivariate standardized drought index (MSDI) and multivariate phenology-based agricultural drought index (MDI) maps for 2012

Karnataka, Andhra Pradesh, Gujarat and Rajasthan during 2012 (<https://www.ncfc.gov.in/nadams>). It was interesting to find that the agricultural drought intensity map generated using the proposed index has good agreement with the above findings and were in corroboration with maps derived from SPI, SSMI and MSDI.

Hence, it can be inferred that multivariate phenology-based agricultural drought index (MADI) has the potential to successfully detect the drought affected area for proper quantification of both intensity and extent of the agricultural drought situations.

5 Conclusion

The present study aims at developing an index, i.e. multivariate phenology-based agricultural drought index (MADI), for quantification of agricultural drought based on the probable alterations in the crop phenological parameters. In comparison with other existing

indices, the proposed index is phenologically tuned and capable of quantifying the impacts of different kinds of drought on agricultural system in terms of reduced length of crop period and/or crop production. The NDVI threshold and derivative-based approaches could estimate different crop phenological parameters over the entire study region during 35 years. The trend analysis could reveal that in major parts of the study area, both the start of sowing (SOS) and end of sowing (EOS) showed positive trends representing delay in crop sowing and harvesting. However, negative trends of length of growing (lgp) were observed over most of the parts of Indian region with positive trends of integrated NDVI (iNDVI), representing shortening of crop period and increase in crop production, respectively. The existing trends in the crop phenological parameters, which developed due to technological improvements during last 35 years, were effectively eliminated after detrending the time-series phenological parameters. Moreover, the effects of spatial heterogeneity could be overcome by normalizing the crop phenological parameters. The new index, i.e. MADI, is in same scale of other multi-scalar drought indices, like standardised precipitation index (SPI), standardised soil moisture index (SSMI) and multivariate standardized drought index (MSDI) and can be directly compared. The efficacy of the MADI was tested in terms of its ability to detect and quantify the spatial extent and intensity of agricultural droughts for different drought years over the study region. The outputs of the MADI for several drought years were compared with other well-established drought indices, like SPI, SSMI and MSDI, and the results showed a good agreement in terms of spatial extent and drought intensities. Hence, the new index is capable of quantifying the impacts of meteorological droughts on agricultural system based on its resilience and can be successfully utilized for agricultural drought monitoring and assessment.

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