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## Mapping drought-induced changes in rice area in India

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### ABSTRACT

Rice is a staple food crop of India and is grown on 44 Mha (2011–12), 58.6% of which are irrigated. An inevitable phenomenon which looms over all aspects of human life and affects rice production in India is drought. Assessing drought damage using geospatial datasets available in the public domain, such as the Normalized Difference Vegetation Index (NDVI) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS), can provide specific and local ecoregion information for developing drought-resistant rice varieties. Based on multi-temporal NDVI data and field observations in 2009, we developed a methodology to identify and map drought-affected areas in India. A long-term (10-year) average of NDVI during the rainy (*khariif*) season (June–October) was compared with NDVI from a known drought year (2002–03) to identify changes in rice area. Rainfall data from the Tropical Rainfall Monitoring Mission (TRMM) was used to support the drought analysis. Spectral matching techniques were used to categorise the drought-affected rice areas into three classes – severe, moderate, and mild based on the intensity of damage assessed through field sampling. Based on these ground survey samples, spectral signatures were generated. It was found that the rice area was about 16% less in the drought year (2002–03) than in a normal year (2000–01). A comparison of the MODIS-derived rice area affected by drought in 2002 for each state and district against the difference in the *khariif* season harvested rice area between 2000 and 2002 (from official statistics) revealed a substantial difference in harvested area in 2002 that was largely attributable to drought. An 84.7% correlation was found between the MODIS-derived drought-affected area in 2002 and the reduction in harvested area from 2000–01 to 2002–03. Good spatial correlation was found between the drought-affected rice areas and reduction of rice harvested areas in different rice ecologies, indicating the usefulness of such geospatial datasets in assessing abiotic stress such as drought and its consequences.

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## 1. Introduction

Rice is grown on over 44 Mha in India, in almost every state. Meteorological drought can affect any rice-growing region of India, with farm households in rainfed areas at particular risk. Drought is the main cause of inter-annual changes in cultivated rice area in India that leads to a reduction in expected rice harvest, but there is little spatial information on which areas are affected, by how much and how often. Vegetation index time-series derived from hyper-temporal, moderate resolution, optical remote sensing imagery can be used to detect water stress in plant canopies across large areas. Here we present a method to detect and characterise drought-affected rice-growing areas under the assumption that there is a strong negative linear correlation between inter-annual changes in rice area and the extent of meteorological drought.

Agriculture accounts for 17.8% (2011–2015) of the Gross Domestic Product (GDP) of the Indian economy (WorldBank 2016). Two-thirds of the arable land (96 Mha) is under rainfed farming and 44% of the total production comes from rainfed regions (Chandrasekar et al. 2010). The yield of rainfed crops is significantly influenced by weather, especially rainfall distribution (Kumar et al. 2011). Droughts occur frequently in India, resulting in water shortages and economic crises for rural people, eventually leading to food insecurity. Population growth and increased wealth in India between 1980 and 2000, led to increased demand for water and other natural resources which exacerbated the impact of droughts (Thenkabail, Gamage, and Smakhtin 2004). More recently, the 2009–10 drought affected more than 100 million people, with severe impacts felt in the states of Uttar Pradesh, Bihar, and Andhra Pradesh, as well as in Pakistan's Sind and Baluchistan provinces (DRMS 2010).

Based on the Köppen classification, India has several climates: monsoon with a short dry season in the south; tropical savannah in the central region; semi-arid in the west; monsoon with dry winters in the north, and; cold-humid in the north-east. The monsoon and tropical savannah climates are most dominant in the rice growing areas of the country and as such there are four seasons defined by the Indian Meteorological Division (IMD), which are: winter in January and February; pre-monsoon from March to May; south-west monsoon from June to September, and; post monsoon from October to December. Over 75% of the annual rainfall is received during the south-west monsoon. The average annual rainfall is 119 cm, but with high spatial and temporal variations over the country. The Western Ghats, the Sub-Himalayan areas in the north-east and the Meghalaya Hills receive over 250 cm annually, whereas the northern parts of Kashmir and Western Rajasthan receive less than 40 cm (IMD 2015).

We define drought as a long period of extremely dry weather when there is insufficient rain to successfully grow crops or replenish water supplies (Thenkabail, Gamage, and Smakhtin 2004). Drought assessment is useful for identifying problem areas in which to disseminate new technologies and fund interventions to improve rural livelihoods. As places with different rice environments respond to drought differently, the spatial and temporal extent of drought needs to be assessed and characterised.

Satellite imagery can be used to monitor agricultural areas in order to identify changes in land use dynamics, assess drought stress, and estimate physical properties related to productivity, such as the leaf area index (Potter et al. 1993; Running et al. 1999; Chandrasekar et al. 2010; Gumma et al. 2011b, 2015b, 2015a; Behrenfeld et al. 2001). The Normalized Difference Vegetation Index (NDVI), based on the visible

and near-infrared light that is reflected by vegetation, is a good indicator of vegetation condition and particularly drought stress. Healthy vegetation absorbs most of the red radiation (for photosynthesis and creation of chlorophyll) and reflects most of the near-infrared radiation, whereas water stressed vegetation reflects slightly more red radiation but absorbs much more near-infrared radiation (Kumar et al. 2002; Murthy et al. 2009; Zhang and Guo 2008; Daughtry et al. 1992). As a result, NDVI has been commonly used to monitor major crops (Jensen 1996; De Bie et al. 2011), often using temporal NDVI information to assess vegetation condition (Murthy et al. 2009).

Many studies on agricultural drought have been carried out at scales ranging from the micro level to global level (Eriyagama, Smakhtin, and Gamage 2009; Peel, Pegram, and McMahon 2004; Murthy et al. 2009). Several studies have used the National Oceanic & Atmospheric Administration (NOAA), Advanced Very High Resolution Radiometer (AVHRR) and MODIS data to monitor drought and estimate biomass (Goward, Tucker, and Dye 1985; Teng 1990; Benedetti and Rossini 1993; Murthy et al. 2009; Pinjarla et al. 2017; Bhuiyan, Singh, and Kogan 2006; Anderson et al. 2010; Justice et al. 1985; Justice and Hiernaux 1986). Goward, Tucker, and Dye (1985) analysed annual and inter-annual variability of vegetation using multi-temporal AVHRR data, and demonstrated the application of AVHRR based vegetation monitoring at a global scale. Justice and Hiernaux (1986) monitored grassland conditions from local to regional scales in the Sahelian zone of Niger and reiterated the importance of analysing vegetation condition using maximum value composite (MVC) data. MVC takes the highest or best value pixel as a representation of a consecutive time series of pixels, to identify major changes in biomass during the growing season while removing shorter duration variations and reducing the effect of cloud contamination and other causes of data gaps. Teng (1990) monitored the effects of the 1988 drought on crops in the US Corn Belt by using multi-temporal NDVI data from NOAA-AVHRR to provide an objective assessment of the drought's extent and severity. Bhuiyan, Singh, and Kogan (2006) monitored drought dynamics in the Aravalli region of India using NOAA AVHRR data and derived different vegetation drought indices, such as vegetation condition index (VCI), temperature condition index (TCI) and vegetation health index (VHI) along with NDVI. Pinjarla et al. (2017) assessed long-term agriculture drought using time series MODIS NDVI, meteorological and irrigation datasets. Anderson et al. (2010) assessed the impact of drought during 2005 in the Amazon forest using MODIS enhanced vegetation index (EVI) and normalized difference water index (NDWI). Different vegetation indices expressed varied degree of response to drought for grass land vegetation. Extended vegetation index (EVI) and NDVI lagged behind Land surface water index (LSWI) in the sensitivity analysis of vegetation condition (Bajgain et al. 2015; Chandrasekar et al. 2010). Changes in irrigated area resulting from water shortage in command areas and large river basins have been mapped using MODIS eight-day time series data (Biggs, Gangadhara Rao, and Bharati 2010; Gumma et al. 2011c; Gaur et al. 2008). Based on the above studies, agricultural drought due to insufficient soil moisture during the crop growing season leads to vegetation water stress that can be observed by spatial and temporal deviations between NDVI in a drought and non-drought year between a drought year and average conditions (Chandrasekar et al. 2010).

Several studies have used Spectral Matching Techniques (SMTs) with multi-temporal, moderate resolution optical remote sensing imagery for mapping and monitoring vegetation. For example, Gumma et al. (2014 and 2016) used SMTs to map seasonal

rice areas and rice ecosystems in South Asia using MODIS time series data and Gumma et al. (2016) mapped rice-fallows in South Asia using SMTs. Thenkabail et al. (2007) used SMTs to map irrigated areas for different time periods using AVHRR data for the year 1982 and 2000. The success of these studies in monitoring changes in rice area and changes in water management in Asia suggest that SMTs would be an appropriate technique for drought detection in rice-growing areas of India.

The objective of this study was to categorise drought in rice-growing areas of India by means of MODIS time series data. When using the NDVI for this purpose, many assumptions have to be made, but their validity can be assessed by collecting and analysing additional information from the field. We used spectral matching techniques to assign drought to one of three categories on the basis of field information. India was chosen as the study area because it is one of the largest rice-growing countries, and droughts occur periodically in several parts of the country. We focused on the 2002–03 drought, one of the worst recorded after the droughts of 1918 and 1972 (Bhat 2006; Niranjana Kumar et al. 2013; Zampieri et al. 2018).

## 2. Study region

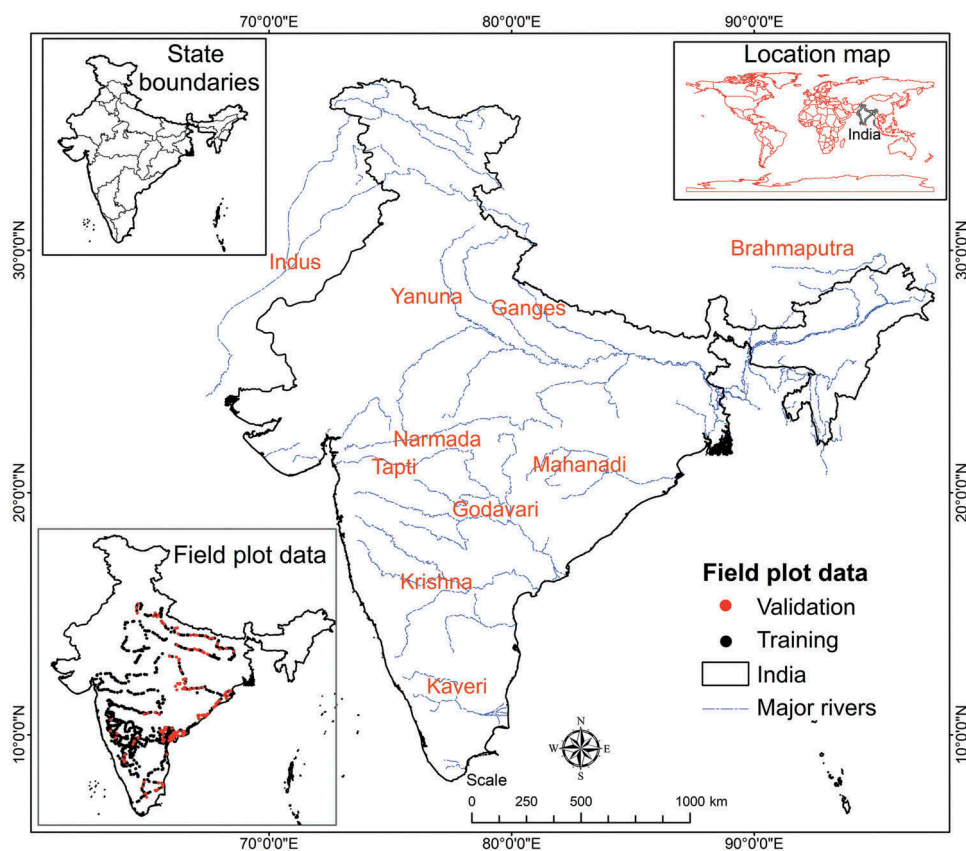
India lies in South Asia, extending between 6°34′1.1″N and 36°54′35″N and 68°11′10.5″E and 97°47′23.6″E. Spanning about 345 Mha, the country includes 208 Mha of agricultural land and 17 major river basins. It is the second largest populated country in the world. Around 72.2% of the total population live in rural areas (Census 2012) and most of them depend on agriculture for their livelihood. Agricultural and rural development are seen as key interventions to eradicate poverty and create conditions for sustainable and equitable economic growth.

The study area includes nine major river basins: Indus, Ganges, Brahmaputra, Narmada, Tapi, Godavari, Krishna, Kaveri, and Mahanadi (Figure 1), which according to the Central Board of Irrigation and Power (CBIP) cover a total irrigated area of 133 Mha (CBIP 2007). According to national statistics, 44 Mha of rice were cultivated in 2000–01, which was considered to be a normal year, compared with 39 Mha during 2002–03, which was classified as a drought year (Niranjana Kumar et al. 2013). India has the largest rice area in the world, it can be grown in three seasons in India; kharif (June–October), rabi (November–February) and summer (February–May) (Manjunath and Panigrahy 2009; Gumma et al. 2016).

## 3. Data

### 3.1. Satellite imagery

The MODIS Terra Surface Reflectance 8-day composite product (MOD09A1) uses the best observations during an 8-day period (Vermote, El Saleous, and Justice 2002). The spatial resolution of the data is approximately 500 m. Although the data have already undergone atmospheric correction (Vermote and Vermeulen 1999) and cloud screening, each MODIS 8-day composite was further processed and cloud contamination was removed as explained in Gumma et al. (2014). We downloaded eight-day composites (from [www.modis.land.gsfc.nasa.gov](http://www.modis.land.gsfc.nasa.gov)) that overlapped with the rainy season (or *kharif* season) between June and December for each year from 2000 to 2009. In India, the *kharif* season runs from June to October, however



**Figure 1.** Major rivers and river basins in India.

Note: River networks and basin catchments extracted from SRTM 90 m DEM, <http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp>. Also shown are the 584 locations from which field plot data were collected for this study.

**Table 1.** Characteristics of the satellite sensor data used in the study.

MOD09A1 Product <sup>a</sup>				
Bands <sup>b</sup>	Band width (nm <sup>3</sup> )	Band centre (nm <sup>3</sup> )	Name	Application <sup>4</sup>
3	459–479	470	Blue	Soil/vegetation differences
4	545–565	555	Green	Green vegetation
1	620–670	648	Red	Absolute land cover transformation, Vegetation chlorophyll
2	841–876	858	NIR1	Cloud cover, vegetation, land cover transformation
5	1230–1250	1240	NIR2	Leaf/canopy differences
6	1628–1652	1640	SWIR1	Snow/cloud differences
7	2105–2155	2130	SWIR2	Cloud properties, land properties

Of the 36 MODIS bands, the 7 bands reported here are specially processed for land studies.

<sup>b</sup> MODIS bands are re-arranged to follow the electromagnetic spectrum (e.g. blue band 3 followed by green band 4).

<sup>3</sup> Nanometers (nm). <sup>4</sup> <http://modis-land.gsfc.nasa.gov>.

some areas may receive delayed rainfall, which leads to delayed sowing and hence our choice of December as the end point of the time series. Our drought assessment used four of the MODIS bands: 1, 2, 3, and 6 (Table 1).

### 3.2. Field plot data

Field plot data were collected from 584 farmer surveys linked to field plots during two different ground survey missions to map land use and land cover. Major cropland areas were chosen based on the knowledge of the district agricultural extension officers in order to ensure that adequate samples of rice as well as of other crops are collected. The farmers provided information on irrigation source, drought condition, crop calendar, cropping intensity (the number of times a crop is grown in a plot of land), and canopy cover (%) for these field plots. The interview included a question on three levels of drought intensity: mild, moderate, and severe. Severe drought meant the total area had either not been planted by the farmers or had been totally damaged after planting. Moderate drought meant that either the farmers had planted only part of the area or that 50–60% of the planted area had been damaged due to water shortage. Mild drought meant that either part of the area had been sown by the farmer or that 0–10% of the area had been damaged due to water shortage.

The first set of field plots (341) was collected during 11–26 October 2003 to map irrigated areas. Out of 341 plots, 143 that had detailed information were used for class identification and labelling. The remaining 198 points were used for accuracy assessment (Figure 1). The second set (243 field plots) was collected during August and September 2011. Interviews with farmers and district agricultural officers were conducted at each field plot location to determine drought intensity, crop types, and conditions during the 2009 *kharif* season. Out of 243 field plots, 205 points that had detailed information were used for class identification. Of these, 192 points were used for ideal spectra generation.

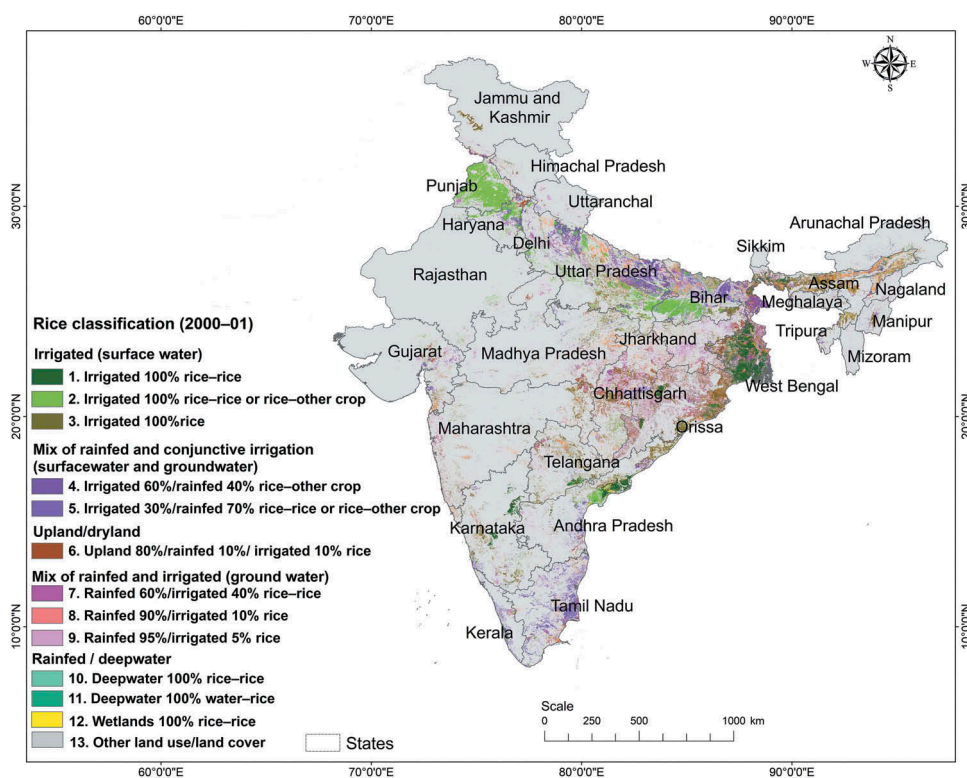
### 3.3. TRMM rainfall data

Monthly rainfall data for the 13-year period between 1998 and 2010 were downloaded from the Tropical Rainfall Measuring Mission (TRMM) (TRMM 2016) website at a spatial resolution of  $0.25^\circ \times 0.25^\circ$  (approximately 27 km  $\times$  27 km) (Kummerow et al. 1998). Average monthly rainfall estimates for each month in the *kharif* season were extracted for the selected 13 years, including for the 2002 drought year. In the absence of any official data on drought-affected areas, differences in monthly TRMM data between a drought year and average conditions were used as an accumulation of evidence of the spatial and temporal patterns of drought occurrence.

### 3.4. Rice-growing areas, national rice statistics, and previous drought studies

The maximum possible extent of rice in 2002–03 was derived from a previously published MODIS-derived rice extent map for 2000–01. The map includes 12 rice classes with a classification accuracy of 80% and a 97% agreement with rice areas from district statistics. The 2000–01 map is the most detailed publicly available map of rice extent in India (Figure 2). Our hypothesis was that there would be a slight change in the potential area that could be planted to rice between 2000–01 and 2002–03 and that most of the changes would be attributable to a deficit in available water, due to drought conditions (Bhat 2006). Data on rice area per state for 2000–01 and 2002–03 was obtained from the Directorate of Economics and Statistics,





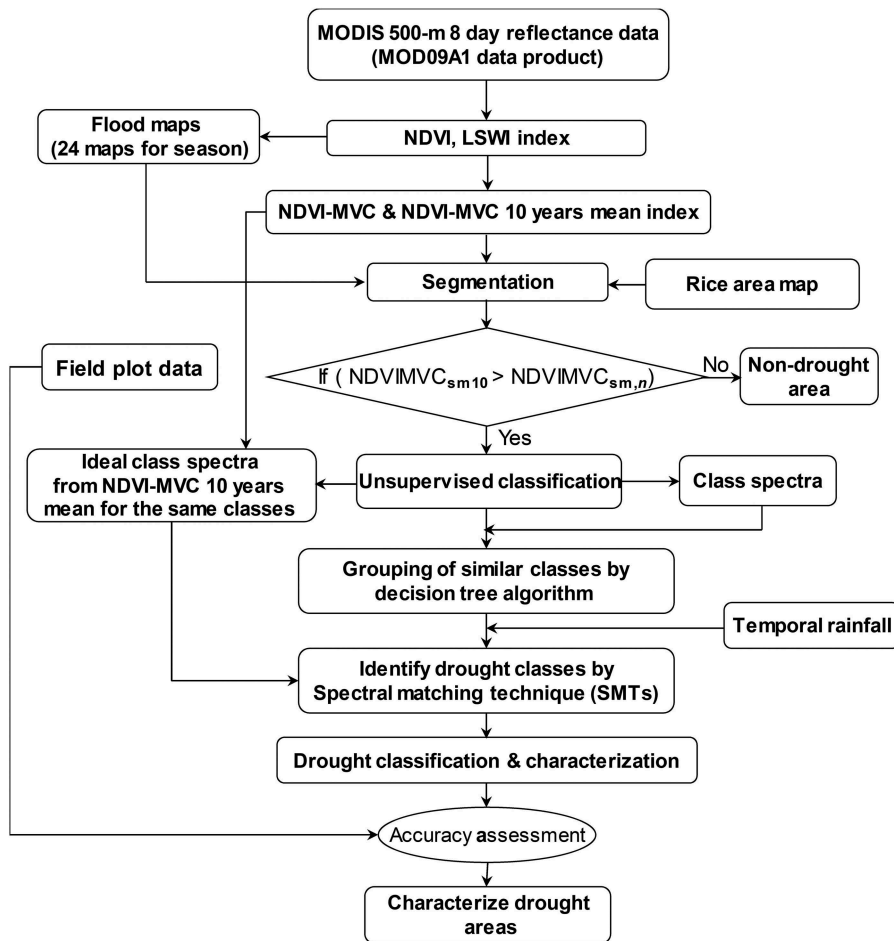
**Figure 2.** Rice extent map for a normal year: the final 12 rice classes for a good year 2000–2001, from (Gumma et al. 2011a).

Government of India (<http://dacnet.nic.in/rice/>) (INDIASTAT 2015) to compare with the MODIS-derived rice-growing area in the respective years. Finally, we compared the drought areas from our analysis with those of previous studies (Biggs, Gangadhara Rao, and Bharati 2010).

#### 4. Methods

Figure 3 provides an overview of the methods used. The first dataset prepared for a time series analysis was the Mega File Data Cube (MFDC), which is a stack of MODIS 8-day reflectance composites for the entire study period 2000–09. A cloud-removal algorithm was applied using a threshold to band 3 where all band values for that pixel were set to null if band 3 was greater or equal to 18% (Gumma et al. 2011a). Using the same stack, another MFDC of NDVI layers was derived from the red and near-infrared (NIR) bands. Monthly MVC of NDVI was then derived to provide smooth representations of changes in vegetation condition during the *kharif* season, while reducing noise due to shorter duration fluctuations and by filling gaps due to cloud contamination (Gumma et al. 2014). The rice extent map for the 2000–01 *kharif* season, was used as a mask to estimate the inter-annual change in drought-affected rice area (Gumma et al. 2011a). A drought indicator was derived by comparing the seasonal MODIS NDVI from the well-documented drought during the 2002–03 *kharif*





**Figure 3.** An overview of the methodology used for mapping drought areas using MODIS data.

season against the average seasonal MODIS NDVI over 10 years (2000–09) for the same season. An unsupervised classification of rice areas in which in 2002–03 the NDVI was lower than the average NDVI resulted in a large number of drought classes that were then grouped and labelled as having no, mild, moderate or severe drought, based on the similarity of their temporal signatures. TRMM monthly rainfall data for the same period and information from previous studies were used as independent sources of corroborative evidence for the validity of our resulting drought map.

#### **4.1. Vegetation indices, maximum value composite (MVC)**

The maximum rice crop extent was derived from the 2000–01 rice map. The NDVI and LSWI (Xiao et al. 2006) were derived for each eight-day composite in the 2000–09 time series of images, using Equations (1) and (2).

$$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}}} \quad (1)$$

$$\text{LSWI} = \frac{\rho_{\text{NIR}} - \rho_{\text{SWIR1}}}{\rho_{\text{NIR}} + \rho_{\text{SWIR1}}} \quad (2)$$

The rationale for using NDVI to detect drought is that we would expect to see a lower NDVI signature (i.e. the temporal profile of NDVI during the growing season) for a given pixel in a drought year than in a normal year. However, flooding or crop submergence, which is another common problem in India, can also result in a lower than expected NDVI signal. Moreover, during the early parts of the season, the NDVI response is low, largely because reflectance is from the soil background rather than from the sparse crop cover. We used the LSWI, which is sensitive to soil water content and to leaf water content, to address this. The LSWI is related to liquid water in vegetation canopies, which interact with solar radiation (Gao 1996). We compared this water-sensitive index with NDVI and classified a pixel as being submerged if the LSWI exceeded the NDVI value for two or more consecutive 8-day periods (Xiao et al. 2006). This ensured that potentially submerged areas, that may be confused with drought in a purely NDVI based analysis, were excluded from the drought classification.

#### 4.2. Identification and mapping of drought areas

Monthly MVCs of NDVI were generated for each of the seven months of the *kharif* season for each year in the time series using Equation (3):

$$(\text{NDVIMVC})_i = \max[(\text{NDVI})_{i1}, (\text{NDVI})_{i2}, (\text{NDVI})_{i3}, (\text{NDVI})_{i4}] \quad (3)$$

where  $(\text{MVC})_i$  is the MVC of the  $i$ th month (for example, if ' $i$ ' is January–December),  $i1, i2, i3, i4$  are the data on every 8-day in a given month. April and October use only three 8-day composites instead of four. A mean of the  $(\text{NDVIMVC})_i$  for each month was created from the 10 years of NDVI data  $(\text{NDVIMVC})_{m,n}$  so that the monthly NDVI during the *kharif* season of the drought year, 2002–03, could be compared to average monthly conditions. The same process was performed to create a seasonal MVC across the *kharif* season. Rice areas with drought were identified using a simple threshold on these seasonal MVCs using 'Equation (4)':

$$(\text{NDVIMVC})_{\text{sm}10} > (\text{NDVIMVC})_{\text{sm},n} \quad (4)$$

where  $(\text{NDVIMVC})_{\text{sm}10}$  is the seasonal mean NDVI MVC over 10 years and  $(\text{NDVIMVC})_{\text{sm},n}$  is the seasonal NDVI MVC of the  $n$ th year, where  $n$  is year 2002.

This threshold was derived from experience in using NDVI time series for rice crop mapping in South Asia (Gumma et al. 2011b, 2015b, 2011a, 2016) and from a comparison of the drought conditions in the field and corresponding NDVI signatures for those locations. They represent the difference between NDVI in the observed *kharif* season and the average NDVI in the *kharif* season. As such, they are specific to the rice crop in South Asia and may not apply to other crops or geographies. However, some studies on wheat and multiple vegetation types have shown good correlation between

NDVI and biomass as well as photosynthetically active radiation (Wang et al. 2005; Hansen and Schjoerring 2003). This threshold on the seasonal MVC NDVI data was used purely to separate drought from non-drought areas. The method to further distinguish the severity of drought using the monthly MVC NDVI data is explained below.

### **4.3. Unsupervised classification for class spectra generation and drought classification**

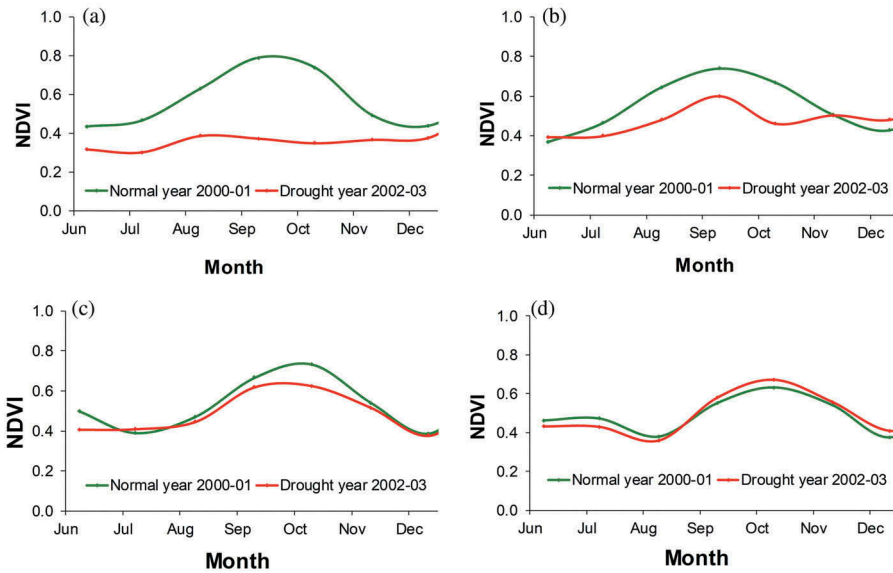
Unsupervised classification using the Iterative Self-Organized class (ISOCCLASS) cluster algorithm (using Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA) in Earth Resource Development Assessment System (ERDAS) Imagine 2010) followed by progressive generalisation (Cihlar et al. 1998; Nguyen et al. 2012) was applied to the NDVI MVC of the *kharif* season 2002–03. The classification was set at a maximum of 100 iterations and a convergence threshold of 0.99. Initially, 15 classes were extracted from the unsupervised classification. Class temporal profiles were generated using ISOCCLASS *k*-means classification of the MFDC. The signature files of the 15 classes were plotted and similar classes were grouped. Classes were further grouped on the basis of decision tree algorithms and spectral matching techniques (SMTs) to match and label the classes with the ideal spectral signatures for drought as explained below (Gumma et al. 2011a, 2011c; Thenkabail et al. 2009).

### **4.4. Drought classification and characterisation**

Drought areas were classified into four categories (severe, moderate, mild, and no drought), based on the intensity of drought that occurred in the field plots as per farmer's response, as explained in Section 2.3. This information was collected from 205 fields out of the 584 field plots.

NDVI signatures were extracted from the NDVI stack for the year 2009 for field plots surveyed in 2011. From the 205 field plots considered, we selected 192 on the basis of field plot information and spectral similarity to the four categories. NDVI signatures from the four categories based on farmers' responses were used to identify ideal spectral signatures for severe, moderate, mild, and no drought and no drought rice areas (Figure 4).

Drought characterisation normally involves the use of an index to describe drought severity or its absence (Table 2). This study used drought categorisation based on the difference between threshold values of maximum NDVI during the *kharif* season for the selected 10 years and that of the *kharif* season of the drought year. The threshold values obtained during 2009 were used for each year from 2001 to 2009 and categorised for drought. The thresholds of NDVI signature help determine the onset of a cropping season, its duration, severity, and end. Severe drought area signatures show continuously low NDVI (<0.201) compared with the 10-year mean monthly NDVI–MVC values, which may represent a fallow period due to lack of water. Moderate drought area signatures show lower NDVI values (0.151–0.200) than the 10-year mean NDVI–MVC value; this indicates crop damage due to drought. Figure 5 shows the different drought categories between drought years and a normal year.



**Figure 4.** Ideal spectra illustration (with a number of samples in brackets) for severe drought, moderate drought, and mild drought.

**Table 2.** Drought characterisation based on NDVI thresholds.

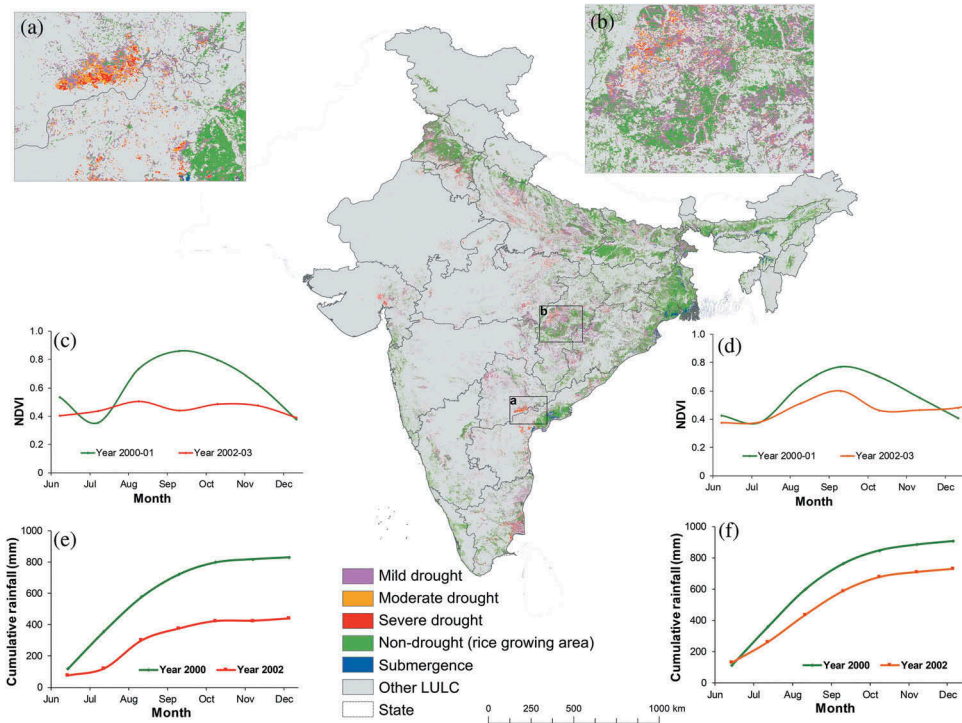
Drought class	Drought characterisation <sup>a</sup>	No. of field plots in sample
Mild	0.100–0.150	20
Moderate	0.151–0.200	23
Severe	>0.201	11
No drought	<0.100	138

<sup>a</sup>change in peak NDVI from normal to drought

**4.5. Drought classification accuracy assessment and comparison against secondary data**

An accuracy assessment of the drought classification was performed using an error matrix and kappa coefficient ( $\kappa$ ) (Congalton 1991). The assessment was based on 198 independent field plot points as explained in Section 2.3 that were not used in the drought classification and labelling process.

We compared the spatial distribution of drought-affected rice area to the difference in TRMM rainfall between 2002–03 and the 1998–2010 average. We also compared the mapped drought extent in 2002–03 to the reported change in harvested rice area between 2000–01 and 2002–03 on the basis that if drought was the major cause of rice area reduction across India in 2002–03 then we would observe a strong relationship between the drought mapped area and the change in reported harvested rice area. Finally, we compared our drought area estimates to those reported in previous studies, though they covered limited geographic extents.



**Figure 5.** Spatial extent of drought categories derived from MOD09A1 and signature: (a) Nagarjunasagar command area; (b) Mahanadi command area; (c) NDVI-MVC time series data for severe drought in Nagarjunasagar command area; (d) NDVI-MVC time series data for moderate drought in Mahanadi command area; (e) TRMM rainfall for severe drought in Nagarjunasagar command area; and (f) TRMM rainfall for moderate drought in Mahanadi command area.

#### 4.6. Sub-pixel area (SPA) calculations

We used MODIS 500 m spatial resolution data to mapping drought areas. Each pixel covers approximately 25 ha, which is larger than many agricultural fields in India. As a result, the full pixel area (FPA) is not a correct representation of the drought-affected rice area observed in the field and so a sub-pixel area (King et al. 2003) estimate of the drought-affected rice area was computed as follows. The field plot data observations included a visual estimate of the proportion of different land use (rice cropped area including other land use and land cover areas) within a 500 m × 500 m area. The SPA fraction was applied to each drought class to estimate the actual drought area for that drought class using Equation (5). We used 192 detailed field plot data observations for SPA estimation (the same points that were used for ideal spectra generation).

$$(SPA)_n = (FPA)_n \times (RAF)_n \quad (5)$$

where SPA = sub-pixel area; FPA = full-pixel area; RAF = rice area fraction

## 5. Results and discussion

### 5.1. Drought in rice-growing areas

Figure 5 shows the resulting drought map and the three categories of drought (mild, moderate, and severe) as well as non-drought and submerged areas. Surface water irrigated rice areas in major command areas such as the Nagarjunasagar command area (Figure 5(a)), Mahanadi basins (Figure 5(b)) are also illustrated. The areas under each drought category, including its sub-pixel and full pixel area, are provided in Table 3. About 14% of rice-growing areas were affected during 2002–03 compared to 2000–01 rice area (Table 3).

### 5.2. NDVI change analysis

Figure 5(c,d) show NDVI variations over India for 2000–01 and 2002–03. Some of the major irrigated command areas (Nagarjunasagar, Tungabhadra, Krishna/Godavari delta, and part of the Indo–Gangetic plain) observed peak NDVI (0.9) during September in the *kharif* season during 2000–01. However, the NDVI value never exceeded 0.85 in any month during the 2002–03 *kharif* season. In a good year, the mean NDVI was 0.59 during the *kharif* season, but in the drought year (2002) it was as low as 0.28 in severe drought areas. In moderate drought areas, NDVI was found to be 0.41 in a drought year compared to 0.50 in a good year.

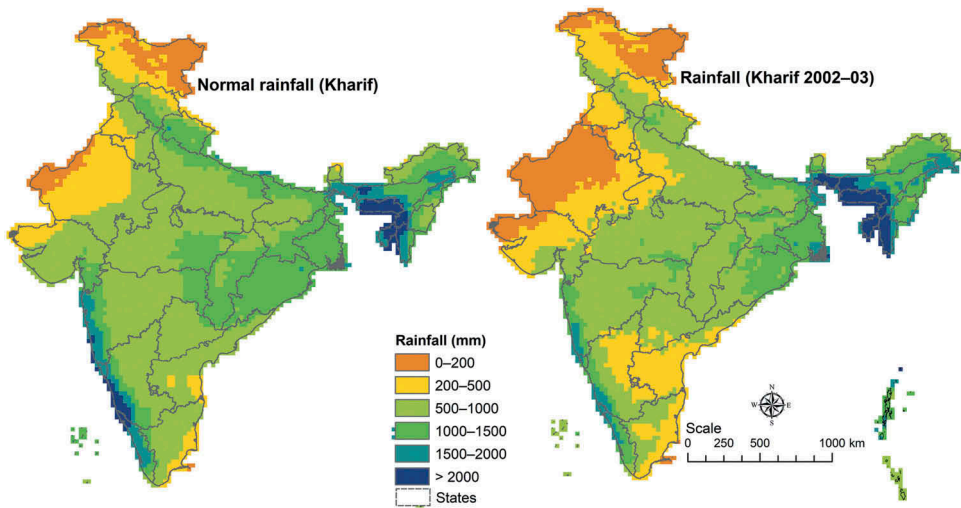
A state-level analysis of NDVI during a normal year revealed that it ranged between 0.60 and 0.70 under rainfed conditions and between 0.7 and 0.8 under irrigated conditions. The state of Andhra Pradesh, where most of the rice is grown on irrigated land and deltas, had a high NDVI value of 0.80, whereas the NDVI values for Odisha and Karnataka states were lower: 0.75 and 0.8, respectively, during a normal year. During a drought year, these important rice-growing states showed a drop in NDVI values, indicating water deficit. Andhra Pradesh and Odisha showed a 0.40 NDVI value during a severe drought and 0.50 during a moderate drought. In states, such as Bihar, Jharkhand, and Karnataka, where large areas are rainfed, the NDVI values ranged between 0.30 and 0.40.

### 5.3. Comparison against TRMM 3B42 rainfall

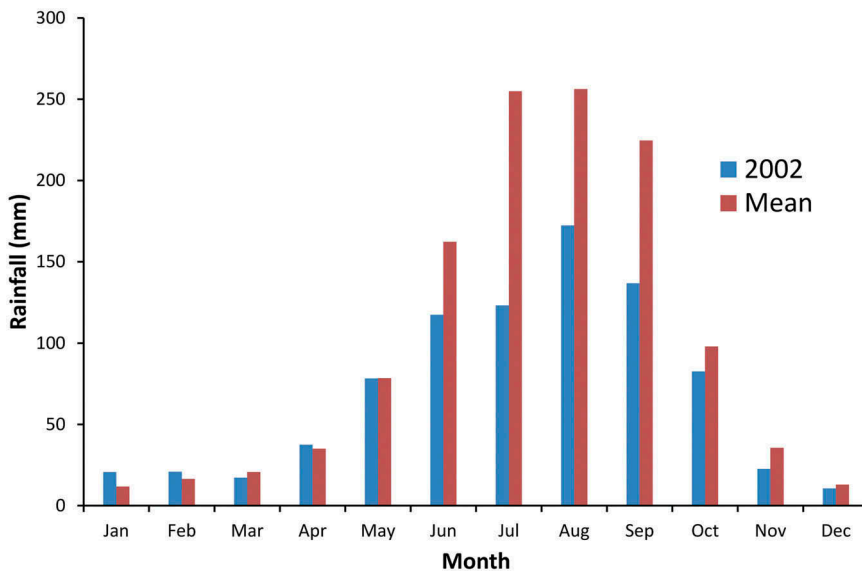
In Figure 5(e,f), cumulative monthly rainfall extracted from TRMM grids for areas that experienced severe and moderate drought during the *kharif* season of 2002 is plotted together with the monthly rainfall for 2000. A total rainfall of 840 mm was recorded during the drought year (2002) whereas 1207 mm was the normal rainfall in those areas. Figure 6 illustrates the TRMM rainfall for the *kharif* season during the 13-year period (1998–2010) and for 2002 showing a large difference between the two. From the 13-year data series, the average monthly rainfall during the *kharif* season (June–December) was derived and then

**Table 3.** Drought areas across India for 2002–03 as derived from MODIS data, using full and sub-pixel areas, classified as mild, moderate, or severe.

Drought class	Sample size	Full pixel area (ha)	Drought fraction (%)	Sub pixel area (ha)	Percentage (%)
Mild	20	14506875	25.6	3713760	10%
Moderate	23	2301376	52.3	1203620	3%
Severe	11	362919	100	362919	1%



**Figure 6.** Comparison of mean seasonal rainfall (mean of 13 years: 1998–2010) with a drought year (2002), using TRMM 0.25° rainfall data.



**Figure 7.** Monthly rainfall during 2002 (blue bars) compared with the mean monthly rainfall for 13 years (1998–2010). Low rainfall during the *kharif* season (June–December) clearly indicates a deficit during 2002.

compared with the corresponding monthly means during 2002 in order to reveal rainfall anomalies that could be associated with drought conditions (Figure 7). During the severe drought, no rainfall was recorded during the peak of the *kharif* season (July). Though not much variation was observed in moderate drought areas, during the peak season (in July) 196 mm was recorded in the drought year, compared with 281 mm for the 13-year July mean. Yet in July 2002, some areas were affected by flood. A comparison of the rainfall in



2002 and the normal rainfall during the peak season in July revealed that 123 mm was recorded in 2002 compared with 255 mm in the 13-year mean of July (Figure 7).

#### 5.4. Spatial dynamics of drought area in relation to rainfall pattern

The rainfall distribution and NDVI information from remotely sensed sources provide a synoptic overview of the difference between drought and non-drought years. Here we place the information into context with a description and discussion on rice-based cropping systems in India and their water resources.

The above analysis of rainfall indicates a deficit during the drought year which can be categorised into 3 classes: <50%, 51–75%, and >75% rainfall (Figure 8). A cross-tabulation between drought classes and rainfall deficit classes reveals useful correlations in the rice crop ecologies of India. The rice crop in Bihar and southern and eastern parts of Uttar Pradesh experienced mild drought even with <50% rainfall, because the crop is mostly irrigated. Similarly, in states such as Punjab and Haryana and along the coastal plains and deltas which are highly irrigated, mild drought was experienced when rainfall was less than 51–75% of the mean. In most of Tamil Nadu, where the rice crop is mostly grown under rainfed conditions and is supplemented with surface and groundwater, mild to severe drought was observed when rainfall was 51–75% less than the mean. But in Kerala, except for a couple of districts which are moderately and severely affected by drought, mild drought occurred in most of the rice-growing areas when rainfall was <50% of the mean,

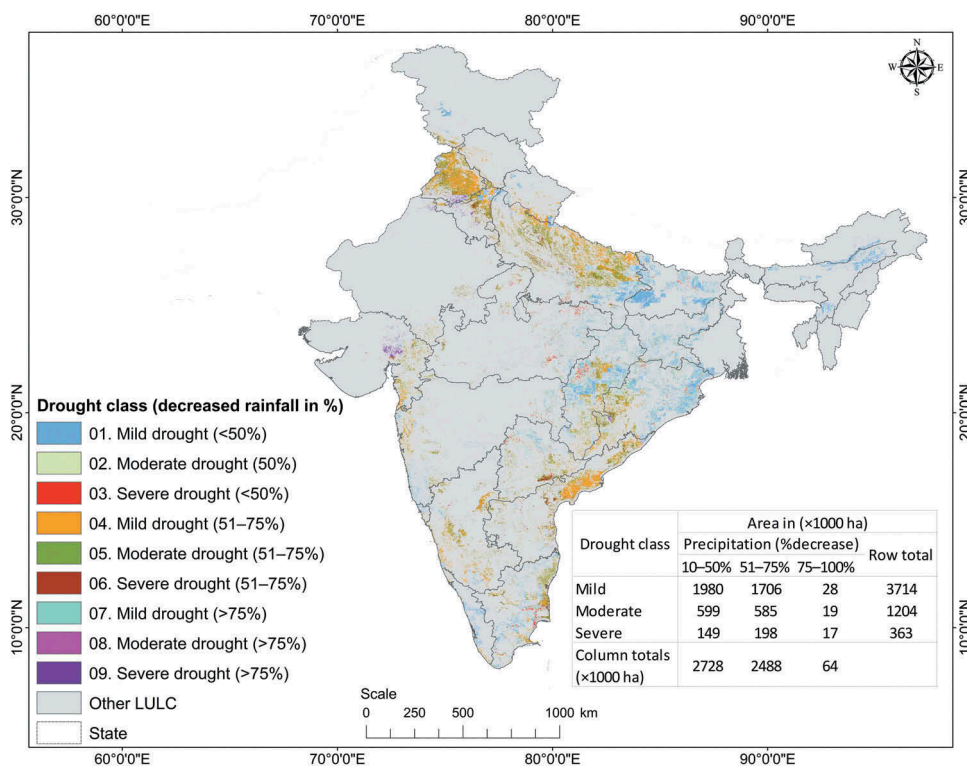


Figure 8. Spatial comparison of drought area in relation to rainfall pattern.

because it is a high rainfall state. In Karnataka, where rice is mostly irrigated, 51–75% less rainfall than the mean resulted in mild to moderate drought in areas supported by irrigation projects but severe drought elsewhere. The state of Maharashtra exhibited a uniform pattern of drought correlated with the amount of rainfall and its impact on the rice crop. The western districts grow a mix of rainfed/irrigated rice, interspersed with patches of 100% irrigated rice mixed with wetland rice. Due to the availability of groundwater, these areas incurred mild to moderate drought even when rainfall was 51–75% less than the mean. The areas with 100% irrigated rice mixed with wetland rice experienced mild drought because of the low deficit (<50% rainfall). Thanks to surface water irrigation, even with a rainfall deficit of <50% the eastern districts of Maharashtra, in which all rice is irrigated, were not affected by mild to moderate drought. In Madhya Pradesh, different rice ecologies are present in the eastern districts. Most of the rice irrigated solely by surface water is surrounded by wetland rice. Elsewhere in the eastern districts, the rice is rainfed and is mixed with irrigated rice receiving conjunctive irrigation from surface water or groundwater. All these rice-growing areas experienced mild and moderate drought, since the rainfall deficit was less (<50%). Most of Chhattisgarh is located in the Mahanadi basin and Godavari basin in the south (Figure 2). The central non-forested land is arable where rice is exclusively and extensively grown with 100% irrigation, interspersed with extensive patches of rainfed and irrigated (with groundwater) rice. In the Godavari basin, rice is irrigated with surface water and the second crop of rice is planted in the next season (November). Thanks to the good groundwater resources in this state, when there was a < 51–75% deficit in rainfall most of the rainfed rice-growing areas were affected by mild and moderate drought (Figure 8).

### **5.5. Accuracy assessment and comparison with national statistics and other studies**

The accuracy varied from 67% to 93% across the four classes (severe, moderate, mild, and no drought), with an overall accuracy of 83% (Table 4).

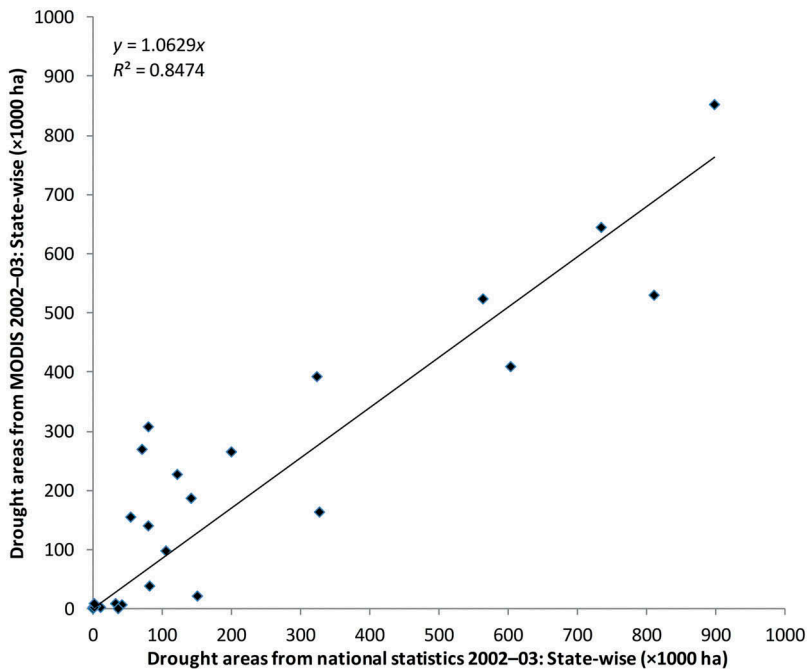
National rice area statistics data (Bhuvan-NRSC 2011) were compared with the rice areas derived from MODIS data for 2002. According to national statistics, the reduction in rice area was found to be about 5.48 Mha. MODIS-derived drought was estimated to be 5.28 Mha. The positive correlation has been obtained between MODIS revised rice areas and national statistics ( $r = 0.92$ ). The significant reduction in 2002 is attributed to reported drought conditions (INDIASTAT 2015) correlated with MODIS-derived drought areas ( $R^2 = 84.7\%$ ) (Figure 9). For details see Table 5. States with relatively small rice areas or small changes in rice area (e.g. Himachal Pradesh) should be interpreted with care due to the moderate spatial resolution of the MODIS data and the accuracy of the method as summarised in Table 4.

The changes in rice-growing areas during 2000–01 and 2002–03 were compared with the figures reported in other publications and with census data for four major rice-growing districts in southern India (Table 6). The table shows that during 2000–01 the area under rice was 1.43 Mha but shrank to 0.92 Mha in 2002–03. By comparison, the MODIS-derived rice area was 1.41 Mha during 2000–01 and 0.88 Mha during 2002–03, whereas Biggs et al. (Biggs, Gangadhara Rao, and Bharati 2010) reported the rice area was 1.24 Mha during 2001–02 and 0.90 Mha during 2002–03.



**Table 4.** Accuracy assessment of the MODIS drought classes based on field plot data.

MODIS drought classes	Field plot data (2002)						Reference totals	Number of correctness	Producers accuracy (%)	Users accuracy (%)	kappa (k)
	Drought class	Severe +Moderate	Mild	None	Class totals						
Severe +Moderate		14	5	1	15	20	14	93	70	0.68	
Mild		0	29	11	43	40	29	67	73	0.65	
None		1	9	128	140	138	128	91	93	0.75	
Column Total		15	43	140	198	198	171				
Overall Classification Accuracy = 83%											
Overall kappa coefficient (k) = 0.7007											



**Figure 9.** Comparison of MODIS vs. National agriculture statistics estimates. The drought areas derived using MODIS 500 m compared with state-wise agricultural statistics.

### 5.6. Identification of stress-prone areas

Given the relatively sound accuracy of the drought map for 2002–03, we applied the same classification to every *khari*f season in the 10-year MODIS time-series to identify drought prone rice-growing areas. We assigned a drought frequency class to each pixel (Figure 10 and Table 7). This product cannot be validated based on available data, and there are no official drought statistics to compare it against. However, it may serve as a first indication of which areas should be investigated further for drought occurrence and eventual prioritisation for interventions to mitigate drought. From this purely exploratory extension of our method, we estimated that 9,901,000 ha were affected by drought 1–2 times (mainly in crop years 2002–03 and 2009–10), while 3,684,800 ha were affected 3–5 times. A relatively small area (1,611,000 ha) was affected five or more times.

### 5.7. Discussion on assumptions, methods, and data

We used SMTs, field plot data, MODIS time series imagery, and TRMM rainfall estimates to map drought stress in rice-growing areas of India. The method maps the estimated rice area affected by drought for the main growing season and, based on a good validation for a known drought year, it was applied to estimate the historical frequency and intensity of drought to characterise the different drought-stresses in rice growing areas. Given the accuracy of the map, the method should be explored further to map recent historical frequency and intensity of drought in rice-growing areas, but it does not predict or map

**Table 5.** A comparison between the state-wise rice area ( $\times 1000$  ha) calculated using the MODIS classification and the state-wise census data (NA = data not available).

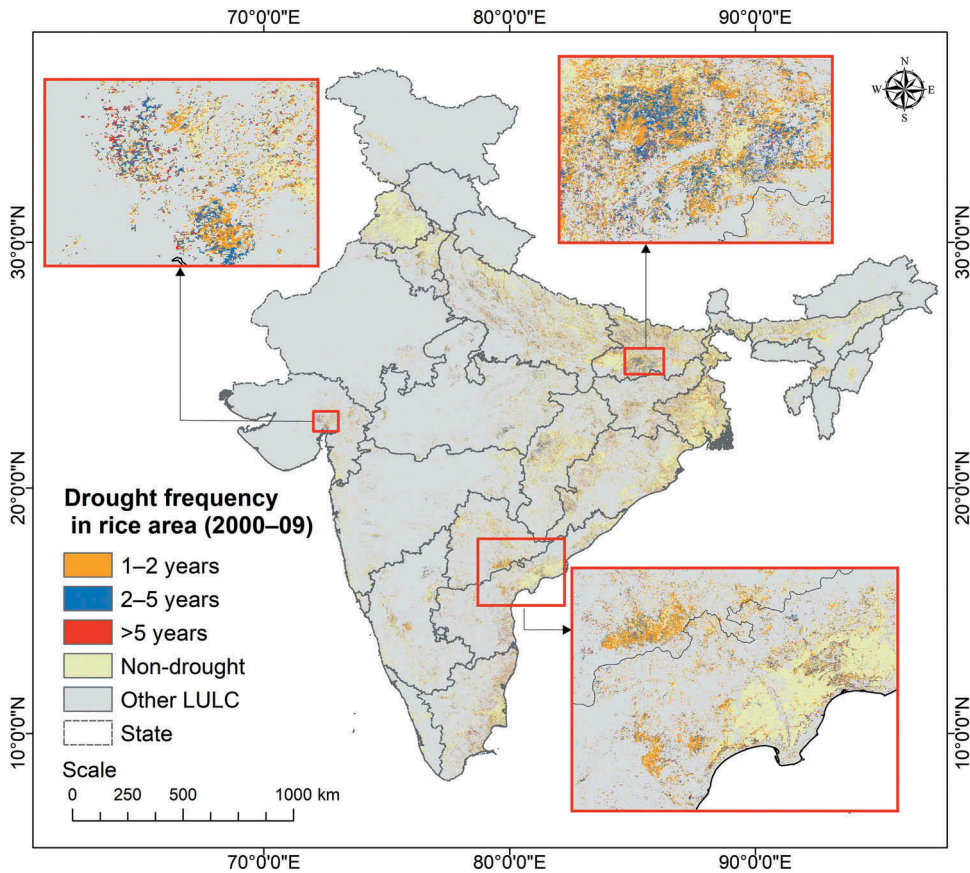
State	MODIS rice area (2000)	MODIS rice area (2002)	Sub-national statistics (2000)	Sub-national statistics (2002)
Andhra Pradesh	3 764.4	3 119.4	3 956.3	3222.0
Arunachal Pradesh	126.4	122.7	108.2	122.9
Assam	2 252.5	2 154.3	2 646.2	2541.0
Bihar	3 453.7	3 184.2	3 656.2	3584.9
Chhattisgarh	3 713.4	3 183.2	3 794.1	2983.5
Goa	56.7	53.0	68.0	56.2
Gujarat	722.1	566.4	634.6	580.0
Haryana	1 016.8	829.9	1 049.0	906.0
Himachal Pradesh	97.4	92.7	- NA -	- NA -
Jammu and Kashmir	280.1	258.2	244.1	92.2
Jharkhand	1 437.4	1 296.8	1 463.7	1383.2
Karnataka	1 298.5	1 134.9	1 481.4	1154.5
Kerala	360.6	351.7	346.6	314.1
Madhya Pradesh	1 705.4	1 312.0	1 699.0	1374.1
Maharashtra	1 463.7	1 237.3	1 511.5	1389.5
Manipur	192.4	185.6	212.4	170.0
Meghalaya	109.2	107.2	106.8	107.7
Mizoram	48.5	48.4	67.2	30.6
Nagaland	140.6	140.0	150.5	150.0
Orissa	4 062.0	3 537.3	4 437.3	3873.6
Puducherry	20.5	15.2	28.0	23.9
Punjab	2 688.1	2 379.3	2 611.0	2530.0
Rajasthan	163.5	124.0	166.1	83.6
Sikkim	0.4	0.4	- NA -	25.6
Tamil Nadu	2 231.6	1 821.2	2 113.3	1510.0
Tripura	105.3	102.5	241.2	255.3
Uttar Pradesh	5 830.0	4 977.5	5 817.5	4919.9
Uttaranchal	242.5	232.5	285.5	282.8
West Bengal	4 790.3	4 525.5	5 041.4	5081.6

**Table 6.** District-wise area cropped to rice ( $\times 1000$  ha) calculated using the MODIS classification, compared with district-wise census data and figures reported in other studies for Nagarjuna Sagar command area.

District	District census		Biggs, Gangadhara Rao, and Bharati 2010		MODIS estimates	
	2000–2001	2002–2003	2000–2001	2002–2003	2000–2001	2002–2003
Krishna	394	246	354	225	374	222
Guntur	306	206	329	204	301	216
Nalgonda	262	132	165	125	272	112
West-godavari	472	332	400	349	466	332

drought occurrence on a real or near-real-time basis. While the time series can be updated every year, it is not a tool for in-season management or drought mitigation.

SMTs have been previously used to monitor crop lands for different purposes, such as mapping and classifying irrigated areas, detecting land use/land cover changes, and detecting different rice systems and rice crop intensities (Thenkabail et al. 2007; Gumma et al. 2015a, 2011a, 2014, 2016). We have demonstrated its ability to discriminate between levels of drought stress. The matching of class spectra with ideal spectra leads to quick identification and labelling of classes.



**Figure 10.** Identification of drought stress-prone areas (severe and moderate drought) and number of years in which stress occurred between 2000 to 2009 (LULC = land use/land cover).

SMTs require substantial field plot data to develop accurate sets of ideal spectral signatures (Gumma et al. 2016). Uncertainties and/or inaccuracies in ground data will result in class labelling errors leading to uncertainties in classes that are interpreted and mapped. The field data were collected following a protocol which has been used in past studies (Gumma et al. 2011a, 2014; Thenkabail et al. 2009) and were checked for completeness and consistency. Photographs and interviews with local partners helped ensure the quality of the field data.

Some studies have used 8-day and 16-day data to study drought using NDVI along with LSWI, NDWI, LST (Gu et al. 2007; Wan, Wang, and Li 2004). However, it is also possible to identify drought classes using monthly NDVI and LSWI, since there the monthly maximum value composite results in less cloud contamination than shorter composites. This is important in areas such as South Asia where cloud cover can be pervasive. Given the longer duration of drought stress relative to other stresses such as submergence, this lower temporal resolution was deemed appropriate to detect drought stress in rice growing regions. Eight-day composites were however used during class identification and ideal spectra generation.

**Table 7.** Rice-growing areas prone to drought stress, per state, for three categories of drought frequency during the 10 years (during 2000–2009), compared with total rice areas derived from remote-sensing data for year 2000–2001.

State	MODIS rice area (×1000 ha): year 2000	Drought frequency during 2000–2009 (×1000 ha)		
		1–2 Years	2–5 Years	>5 Years
Andhra Pradesh	3764	1177	384	155
Arunachal Pradesh	126	13	8	6
Assam	2252	403	124	45
Bihar	3454	1265	492	127
Chhattisgarh	3713	627	272	131
Goa	57	5	2	1
Gujarat	722	199	95	39
Haryana	1017	197	88	33
Himachal Pradesh	97	11	4	2
Jammu and Kashmir	280	35	15	9
Jharkhand	1437	491	175	103
Karnataka	1299	328	144	62
Kerala	361	24	8	3
Madhya Pradesh	1705	424	213	86
Maharashtra	1464	263	100	43
Manipur	192	16	3	1
Meghalaya	109	9	3	1
Mizoram	48	0	0	0
Nagaland	141	1	0	0
Orissa	4062	891	303	159
Puducherry	21	5	2	1
Punjab	2688	240	83	32
Rajasthan	164	53	26	12
Sikkim	0	0	0	0
Tamil Nadu	2232	632	243	161
Tripura	105	11	2	1
Uttar Pradesh	5830	1277	545	276
Uttaranchal	243	29	8	2
West Bengal	4790	1274	342	121

While NDVI is often used to indicate drought stress, it may not be sensitive enough to detect the difference between a drought-stressed crop and a normal crop in the very early stages of the growing season when vegetation cover is low and where there is a stronger soil component in the signal. In such cases, a Soil Adjusted Vegetation Index (SAVI) may be more sensitive (Huete 1988).

Our comparison of NDVI time series across years, where the deviation in any one year against a mean is indicative of drought, implies that the seasonality is consistent from year to year. However, it is possible that a different crop, or no crop is grown in any given year. It is also possible that a farmer would delay crop establishment until there has been sufficient rainfall. Those decisions may be management responses to drought, and could lead to a difference in NDVI from the mean NDVI that could be interpreted as a crop response to drought by this method. Thus, there is a risk that our method overestimates the frequency and intensity of drought in rice growing areas. The use of 500 m resolution MODIS data may mitigate this somewhat, since the NDVI signal represents an average signal from many smaller fields, and such management decisions would need to be taken coherently and consistently over a large area for them to have a significant impact on the area estimated to be affected by drought. To reduce this risk further, the method could be improved by analysing the NDVI curve for any temporal shifts from year to year and their relationship with temporal shifts in accumulated



rainfall, and by detecting any abrupt changes in the NDVI time series using methods such as BFAST (Breaks for additive seasonal and trend) (Verbesselt et al. 2010).

TRMM rainfall estimates have been previously validated with station data for the study region (Kneis, Chatterjee, and Singh 2014; Nair, Srinivasan, and Nemani 2009). Nair, Srinivasan, and Nemani (2009) conducted a study in the western part of India for seven monsoon seasons and concluded that there was some over- and under-estimation, but the timing of rain events as estimated by satellite coincided very well with station observations. Future improvements could include the use of other remotely sensed rainfall estimates with higher accuracies and higher spatial resolution than TRMM such as Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS) (CHIRP 2016).

We observed a large difference between the rainfall in the 2002 *kharif* season and the average *kharif* season rainfall for 1998–2010 and these were mapped to reveal rainfall anomalies that could be associated with drought conditions (Figure 7). The lower rainfall reported by TRMM during this time corresponded with official reports (Pandey and Bhandari 2009). No rainfall was observed (July 2002) in the severe drought rice-growing areas. Though not much variation was observed in moderate drought areas, during the peak season (in July 2002) 196 mm was recorded in the drought year, compared with 281 mm for the 13-year July mean. Yet in July 2002, some areas in the coastal regions were affected by flood.

In addition to abiotic stresses, rice production in eastern India can be influenced by increasing labour costs, declining rice subsidy programmes, and groundwater depletion (Mohanty and Yamano 2017). However, drought remains an important factor which needs to be monitored closely because of its unpredictability and potential impact on rice production.

There have been several studies on drought within India (Murthy et al. 2009; Chandrasekar et al. 2010; Singh, Roy, and Kogan 2003; Bhuiyan, Singh, and Kogan 2006; Biggs, Gangadhara Rao, and Bharati 2010; Thenkabail, Gamage, and Smakhtin 2004). NDVI is the most commonly used index for monitoring changes in vegetation growth (Anderson et al. 2011; Steven et al. 2003). NDVI time series information is useful to create temporal profiles and identify crop signatures in rice systems (Gumma et al. 2011b, 2011a). The main advantage with VCI is that it is more sensitive during the wet season (November to January) and TCI is more sensitive in the dry season or during months with high temperature. VHI is an enhancement of TCI and VHI has a combination of VCI and TCI and it provides better comprehension about drought occurrence (Amalo and Hidayat 2017; Bhuiyan, Singh, and Kogan 2006). Since EVI is more sensitive to canopy variations, abiotic stresses and changes related to drought (Anderson et al. 2010), it is very useful for monitoring vegetation. Murthy et al. (Murthy et al. 2009) conducted a study in Haryana state using NDVI from NOAA AVHRR data and rainfall data for the year 2002. Results were compared against a normal year 2004. Their results correlate well with ours where a significant reduction in rice area during 2002 was observed (Table 5). Chandrasekhar et al. (Chandrasekar et al. 2010) also conducted a study for the same year in the state of Andhra Pradesh using MODIS data. That study derived LSWI characteristics and related them to a more conventional NDVI based drought assessment. Biggs et al. (Biggs, Gangadhara Rao, and Bharati 2010) studied a major irrigation system and focused on the response to water supply shocks in irrigated areas. While there is general agreement between the findings of these studies and ours, at least in cases where

we were able to make a quantitative comparison, we believe that ours is the only one to date to look at the drought-affected rice area on a national scale.

## 6. Conclusions

Drought was mapped and characterised in the major rice growing season of 2002–03 (a major drought year) in India, using seasonal and monthly MODIS derived NDVI MVCs, with an overall accuracy of 83% and accuracy ranging from 67% to 93% across the drought classes. The characterisation was rice and season specific and may not apply to other crops or regions. The observed spatial patterns in the drought-affected rice area corresponded with reported state-level reductions in rice area between 2000–01 and 2002–03. They also corresponded well with the against a limited amount of previously published municipal level drought area estimates. Furthermore, there was good correspondence between the drought-affected areas and differences in TRMM rainfall between the year 2002 and the 1998–2010 average providing further evidence that the approach is valid for estimating drought affected rice area across India in the *kharif* season. On the basis of this, the method was applied to nine years of NDVI data to map spatial and temporal patterns of drought occurrence (i.e. location and severity of drought) in the *kharif* season, though this was not validated.

These results suggest that our methods can be applied for large-scale mapping of drought in rice-growing areas of India. Further adaptation of the method may be required for other crops and regions and also reducing the risk of misclassification due to changes in crops or delays in crop establishment. Given the continuing availability of temporal remote sensing data, the method could be used to characterise the frequency and intensity of drought to support the targeting of technologies to boost productivity in drought-susceptible regions. However, care should be taken while working with dryland ecosystems where drought is a common phenomenon, as the thresholds and limits set for rice may not hold true for rainfed crops. Further studies need to be conducted in the drylands and arid regions to define drought in the appropriate agro-ecological context.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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