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A composite index for drought hazard assessment using CPC rainfall time series data

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Abstract Hazard analysis is the first step in any disaster management activity. Drought is a serious environmental hazard strongly limiting the agricultural production in the tropical countries like India. A comprehensive drought hazard map is useful for multiple perspectives such as agriculture, environment and hydrology. In this study, daily rainfall data of the Climate Prediction Centre during the south-west monsoon season (June–September) of 12 years, over India was analysed. Based on rainfall and rainy days, six indicators of drought were generated which were then synthesized into a composite index of drought hazard for every 10×10 km pixel. The weights for the composite index were generated through variance approach. The index has effectively captured the spatial variations in meteorological drought across India by showing a typical pattern with increasing hazardous area from east to west. The drought hazard map also shows considerable agreement with the climate classification map and the drought proneness map reported by other studies. Thus, the current study presents a simple and novel approach for drought hazard analysis, using the routinely available geospatial rainfall data products. The methodology can be extended to other geographies and disasters too. Use of time series data of longer period would improve the reliability of the composite drought hazard index.

Keywords Integrated index · Drought hazard · India · Meteorological drought

Introduction

Drought is recognized as the most disastrous natural hazard affecting the vast geographical area and causing a huge economic impact on human livelihood (Wilhite 2000). Drought originates from the deficiency of precipitation leading to the inadequacy of water to certain activities or groups. Due to the complexities associated with drought occurrence, spread and its impact, there is no single index for drought detection and intensity assessment. Drought management is closely related to sustainable agriculture and food security. The probabilistic seasonal drought forecasts can substantially improve drought early warning systems which can support regions with famine and food crisis (Lobell et al. 2008). Meteorologists, environmentalists, ecologists, agricultural scientists, hydrologists, geologists and socio-economic experts developed different indices to address different aspects of drought (Mishra and Singh 2010). An effective drought monitoring and prediction system should be based on comprehensive and integrated approach that can include multiple drought indicators (Svoboda et al. 2002; Mishra and Singh 2010; Hao and Agha Kouchak 2013). The various data-mining algorithms to build prediction model have vast scope in the field, where physical models are infeasible. There are various application areas like rainfall prediction, storm detection, weather forecasting and other disciples of science and technology where it can be used effectively

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(Kusiak 2000; Li et al. 2008; Fauvel et al. 2008; Marzano et al. 2010; Domenech and Wehr 2011; Kusiak et al. 2013).

Understanding drought at local and regional scales with historical and current perspective is of primary importance for planning and management. A study by Dai (2011) and Otgonjargal (2012) noted that many places in various continents can encounter the significant drying conditions in the coming decades including South-East Asia. There are various studies that have also addressed the regional and global consequences of climate change on the parameters like rainfall and temperature. Addisu et al. (2015) have addressed the issues of climate change on a national and local level by analysing time series temperature and rainfall trends. Their study stated that the rainfall pattern, its distribution, frequency and probability of dry spells in the growing season are key factors and the unusual rainfall amount leads to poor harvest or complete crop failure and famine of pasture and animal feeds. Drought occurrence is strongly determined by a combination of climate hazard and ecosystem vulnerability. Drought hazard assessment is the first step in risk assessment and development of drought management plans. Drought hazard is characterized by location, intensity, frequency and probability of drought. Origin, characteristics and behaviour of hazard constitute the hazard analysis (Nadim et al. 2006). With proactive/mitigation-oriented disaster management being increasingly preferred, hazard analysis has attained greater importance in recent years. Otgonjargal (2012) analysed drought hazard in Morocco using the Standardized Precipitation Index (SPI). Barlow et al. (2006) used weighted anomaly SPI and Persistent Deficits of Precipitation for drought hazard assessment at country level in Asia and recommended sub-country level analysis with multiple indices. Zubair et al. (2006) constructed drought hazard map of Sri Lanka with rainfall data.

Various methods and indices using many drought-causative and drought-responsive parameters like rainfall, soil moisture, surface water levels, groundwater, potential evapotranspiration and vegetation condition have been developed in the recent years, and the strength and weakness of each index have been demonstrated through case studies. Most of these indices such as derived from climate data are applied in non-spatial perspective. Further, these indices are tested in isolation to establish their sensitivity to drought conditions. Since drought is a phenomenon interlinked with multiple processes, use of a combination of indices better captures the drought intensity. For example, although rainfall is the basic cause of drought, use of rainfall and rainy days together better captures the drought conditions (Murthy et al. 2015). This is because rainfall represents the amount of rainfall received at a given location in a given period of time and rainy days represent the temporal distribution of rainfall.

Drought hazard is a multidimensional, spatially and temporally dynamic and scale dependent. Therefore, the real challenge is to evolve a composite index at a disaggregated level. Keyantash and Dracup (2004) recognized the importance of an aggregated index for drought, developed it through the multivariate approach and concluded that the index is superior to different indices used in standalone mode. Hao et al. (2014) provide meteorological and agricultural drought information based on multiple drought indicators using the Global Integrated Drought Monitoring and Prediction System (GIDMaPS). The multiple satellites and model-based input data sets of precipitation and soil moisture are used for a near real-time monitoring and seasonal probabilistic prediction which provide essential information for early warning, taking preventive measures and planning mitigation strategies. The objective of the current study is to carry out meteorological drought hazard analysis through a composite index approach in a geospatial perspective, over India from 2001 to 2012 for south-west monsoon season. Thus, the current study emphasizes the aggregated perspective for drought hazard analysis.

Materials and methods

Study area

The present research work has been carried out over India which is situated in the north of the equator between $8°4'$ and $37°6'$N latitude and $68°7'$ and $97°25'$E longitude with the total area of 3,166,414 km^2 (Fig. 1). India is geographically blessed with a wide variety of climatic conditions ranging temperate and alpine in the Himalayan north to tropical in the south. The south-west monsoon season from June to September is considered the prime rainfall contributor because 75% of annual rainfall is received during this short span of time. India has diverse rainfall zones, crop-growing environments and cropping pattern. The net cropped area is 140 million hectare (mha), and about 60% of it is directly dependent on rainfall. Kharif is the principal crop season, which corresponds to 4- to 5-month period.

Data used

In this study, a composite index of drought hazard was constructed using a set of contributing indicators derived from CPC rainfall time series. The methodology includes analysis of rainfall time series data, generation of input indicators, weights computation, construction of a composite index and analysis of drought hazard patterns as shown in Fig. 2.

Fig. 1 Location map of study area

World

India
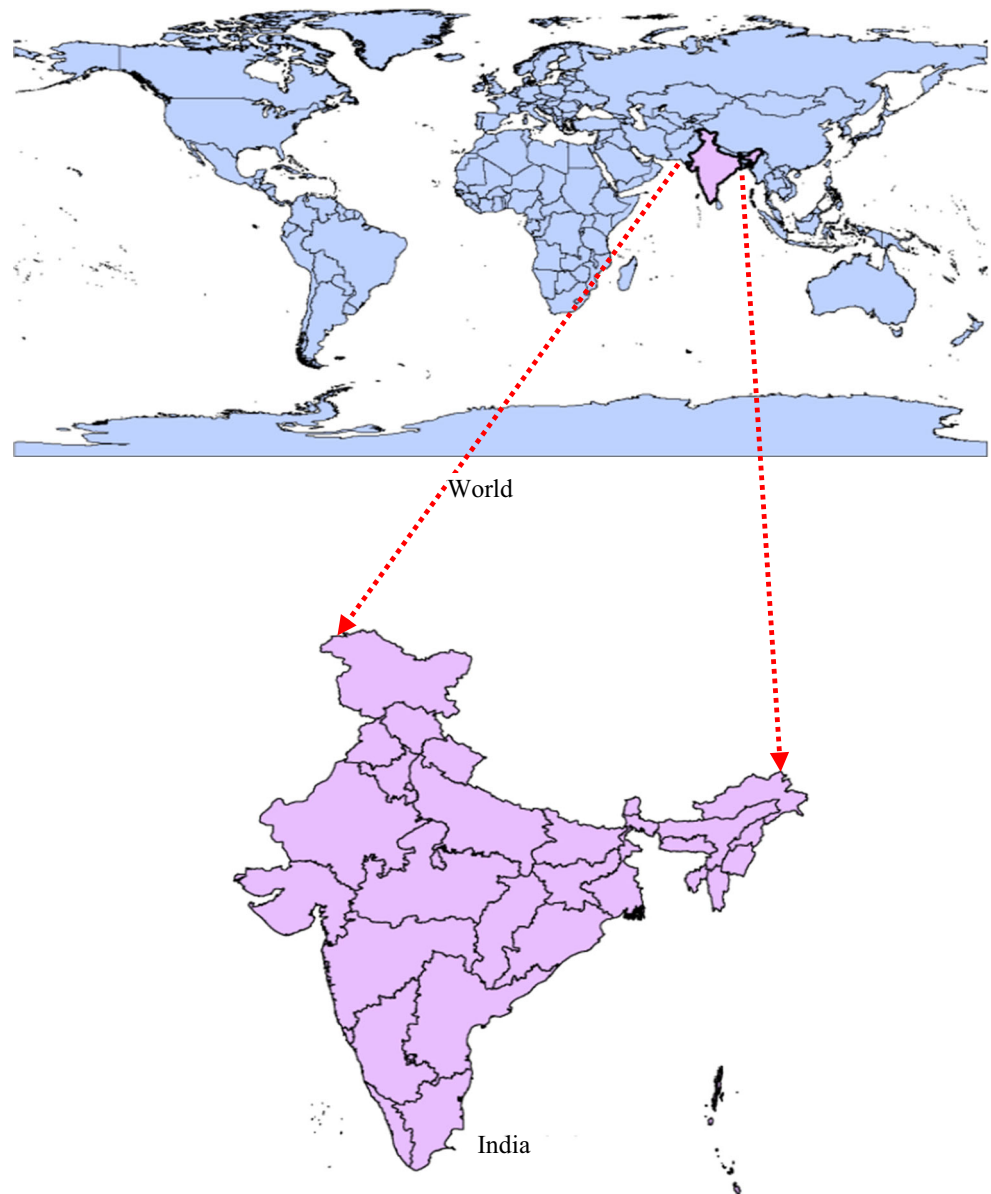
The rainfall database was generated using the CPC daily global precipitation product. The CPC provides South-East Asia to South Asia precipitation data set. The rainfall data for the period of 12 years (2001–2012) and for the duration of four continuous months (June to September, i.e. south-west monsoon) were used for generation of various indices. The spatial resolution of the data set is $0.1° \times 0.1°$. Satellite-based rainfall estimates are becoming increasingly important due to inadequate network and measurement errors associated with surface gauges. These spatial rainfall data sets from satellites certainly complement the surface gauge data for early warning on water availability. Verdin et al. (2005) and Satya et al. (2014) analysed the agreement between TRMM-PR- and gauge-based rainfall and found that the TRMM-PR 3A25 data sets have captured the interannual variability of rainfall over South Asia.

The algorithm used for rainfall estimation is called Rainfall Estimation Algorithm version 2.0, and the products are called RFE 2 estimates (Love et al. 2004; Hermance and Sulieman 2013). CPC rainfall data during the south-west monsoon season (June to September) of the last 12 years (2001–2012) were analysed to generate different indicators of exposure. Along with rainfall, data on rainy days were also considered to account for the distribution of rainfall. The definition of a rainy day is adapted from India Meteorological Department (IMD) which considers any day with greater than or equal to 2.5 mm of rainfall as a rainy day.
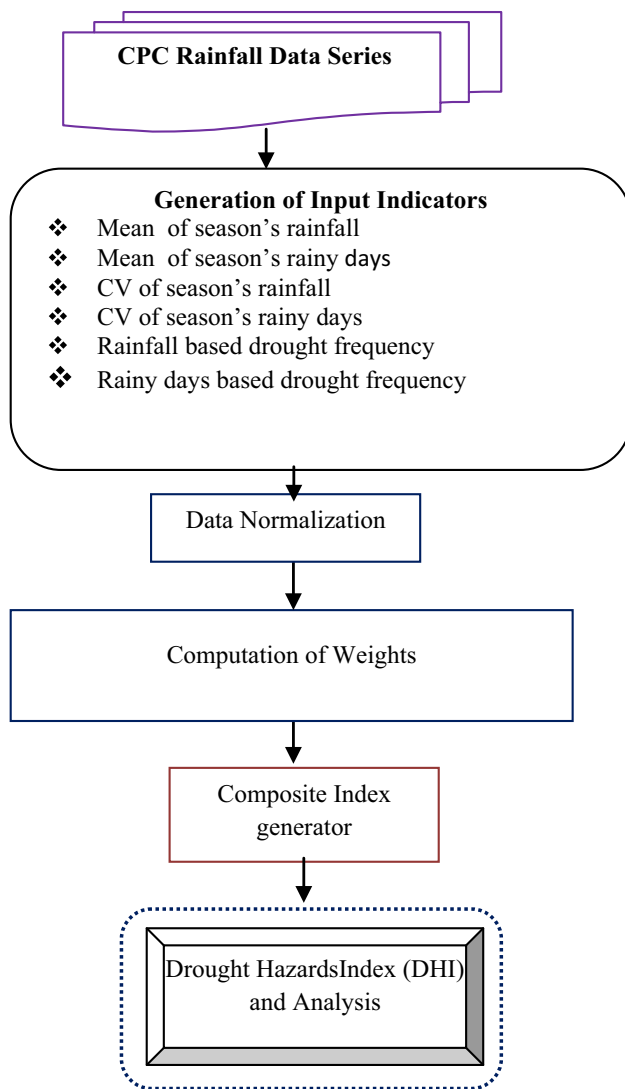
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Int. J. Environ. Sci. Technol. (2017) 14:1981–1988

CPC Rainfall Data Series

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Generation of Input Indicators
- ❖ Mean of season's rainfall
- ❖ Mean of season's rainy days
- ❖ CV of season's rainfall
- ❖ CV of season's rainy days
- ❖ Rainfall based drought frequency
- ❖ Rainy days based drought frequency

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Data Normalization

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Computation of Weights

↓

Composite Index generator

↓

Drought HazardsIndex (DHI) and Analysis

Fig. 2 Methodology framework of the study

From the daily rainfall images of 12 years, two images, namely (1) total season rainfall and (2) number of rainy days in the season, were generated for each year. Rainfall and rainy days together capture the drought situation effectively. Otgonjargal (2012) used both rainfall and rainy days for drought hazard analysis in Morocco. Using total season rainfall time series, three indicators were computed—mean rainfall, coefficient of variation (CV) of rainfall and drought frequency. Drought frequency indicates the number of years under drought conditions during the 12-year period. The criteria for deciding a drought year are an occurrence of less than 75% of normal rainfall (mean of 12 years) in the given pixel for the given period. This criterion of meteorological drought detection has been recommended by IMD in India (www.imd.gov.in). Similarly, from the rainy days time series, the same sets of three

indicators were computed. Thus, there were six indicators of drought constituting the generation of 6-channel image.

Data normalization

The contributing indicators of the model are in different units with different functional relationships with the resultant hazard index. Some of the input indicators are having positive relation with the drought hazard, and some are having negative relation. In order to make these indicators free of their units and to standardize their values, data normalization was done. In the case of the variables that have a positive relationship with its respective component index, the normalization was done using the formula.

$$X_{ij} = \frac{X_{ij} - \mathrm{Max}(X_i)}{\mathrm{Max}(X_i) - \mathrm{Min}(X_i)} \tag{1}$$

In the case of variables that have a negative relationship with its respective component index, the normalization was done using the formula;

$$X_{ij} = \frac{\mathrm{Max}(X_i) - X_{ij}}{\mathrm{Max}(X_i) - \mathrm{Min}(X_i)} \tag{2}$$

where X_{ij} = normalized contributing indicator, X_{ij} = input indicator, $\mathrm{Max}(X_i)$ = maximum value of indicator, $\mathrm{Min}(X_i)$ = minimum value of indicator.

After normalization, all the indicators were ranging from 0 to 1 and have a positive relationship with the drought hazard index where the severity increases from 0 to 1.

Computation of weights

Construction and use of composite indices of multidimensional data for measuring spatial differentials in social and economic development issues have been widely practiced (Iyengar and Sudarshan 1982; Ahsan and Warner 2014). Assignment of weights to selected indicators is a key issue in the vulnerability assessment model. Wilhelmi and Wilhite (2002) selected the weights based on the relative contribution of each factor in the vulnerability. Li et al. (2006) and Chen et al. (2013) used principal component analysis to generate weights for the variables. Brooks et al. (2005) assigned equal weights to each indicator in their study on vulnerability and adaptive capacity assessment at national level. The method of simple averaging gives equal importance to all the input variables which may not be necessarily correct. In this study, the method given by Iyengar and Sudarshan (1982) was used to construct a statistically sound composite index from multivariate data.

It is assumed that there are N spatial units (10 km pixels in the current study), K indicators and x_{ij}, $i = 1, 2,.... N$ and $j = 1, 2,.... K$ are the normalized scores. The level or stage of hazard of ith zone, $\bar{y}_i$, is assumed to be a linear sum of x_{ij} as

$$\bar{y}_i = \sum_{j=1}^{K} w_j x_{ij} \quad (3)$$

where w's ($0 < w < 1$ and $\sum_{j=1}^{K} w_j = 1$) are the weights. In the method suggested by Iyengar and Sudarshan (1982), the weights are assumed to vary inversely as the variance over the spatial units in the respective indicators of hazard. That is, the weight w_j is determined by

$$w_j = \frac{c}{\sqrt{\text{var}(x_{ij})}} \quad (4)$$

where c is a normalizing constant such that

$$c = \left[\sum_{j=1}^{K} \frac{1}{\sqrt{\text{var}_i(x_{ij})}} \right]^{-1} \quad (5)$$

By assigning the weights in this manner (Table 1), the large variation in any of the indicators will not unduly dominate the contribution of the rest of the indicators or distort inter-regional comparisons. The resulting index ranges between 0 and 1, with a 1 indicating the maximum and 0 indicating minimum intensities.

The composite index of drought hazard was generated for each pixel by summing the product of the indicators and respective weights as given in Eq. (3). The DHI was scaled between 0 and 1 representing the minimum and maximum hazard, respectively.

The composite index of drought hazard was generated for each pixel by summing the product of the indicators and respective weights as given in Eq. (3). The DHI reflects relative differences among the pixels, rather than representing specific conditions of drought. Based on the intervals of the composite index, pixels were categorized into different levels of hazard.

Table 1 Weights for the input parameters

S. no.	Variables	Weights
1	Mean of season's rainfall	0.16
2	Mean of season's rainy days	0.13
3	CV of season's rainfall	0.17
4	CV of season's rainy days	0.17
5	Rainfall-based drought frequency	0.18
6	Rainy days-based drought frequency	0.19

Results and discussion

Contrary to single-indicator-based drought hazard analysis reported in various studies, this study, through a novel approach, synthesized a composite index from six contributing indicators. After normalization, all the input indicators range from 0 to 1 with the same direction of change. The spatial distribution of scaled input indicators is shown in Fig. 3.

The mean rainfall distribution shows isolated pockets of high rainfall in north-east, east and west coast regions. CPC rainfall over NE states is considerably less and hence not used for interpretation. North-west India and southern most areas show very low rainfall. CV of rainfall is less in the eastern half of the nation and more in the western part of the nation. The rainfall-based drought frequency is higher in isolated pockets of the western part. Mean of rainy days shows higher dynamic range. CV of rainy days shows smaller variability, with most part of the country having lesser values. Rainy days-based drought frequency does not show larger spatial variability with much of the area having lesser values.

Drought hazard map of India derived from DHI is shown in Fig. 4. DHI class <0.5 indicates less hazardous and that >0.8 indicates highly hazardous area. The DHI classes show a typical pattern with the increasing hazardous area from east to west. Large areas of Rajasthan, Gujarat, Haryana, Punjab and J&K followed by parts of Andhra Pradesh, Karnataka, Maharashtra, Uttar Pradesh and isolated pixels of Madhya Pradesh are under highly hazardous class. CPC rainfall is conspicuously low in the parts of north-eastern region where the rainfall is high in general, and hence, it has resulted in very high hazard index in these areas. The reasons for such a low CPC rainfall need to be investigated.

In Punjab and Haryana states (at s. no. 9 and 10 in Fig. 4), drought hazard does not have serious implications for agriculture because of irrigation support from snow-fed (monsoon independent) irrigation systems. The northern most states of Jammu and Kashmir, Himachal Pradesh and Uttarakhand have very less arable lands, and hence, higher hazard index does not have much impact on agriculture.

Significant area with a higher level of hazard in Tamil Nadu (at s. no. 25 in Fig. 4), the southern state, is due to the fact that rainfall and rainy days of the south-west monsoon season do not have much relevance to the state, since the state is largely influenced by a different monsoon season.

Higher level of hazard intensity in parts of Andhra Pradesh, Telangana, Karnataka, Maharashtra, Madhya Pradesh, Gujarat, Uttar Pradesh and Haryana states affects large tracks of the agricultural area, and hence, it has serious economic implications. Large parts of Odisha,

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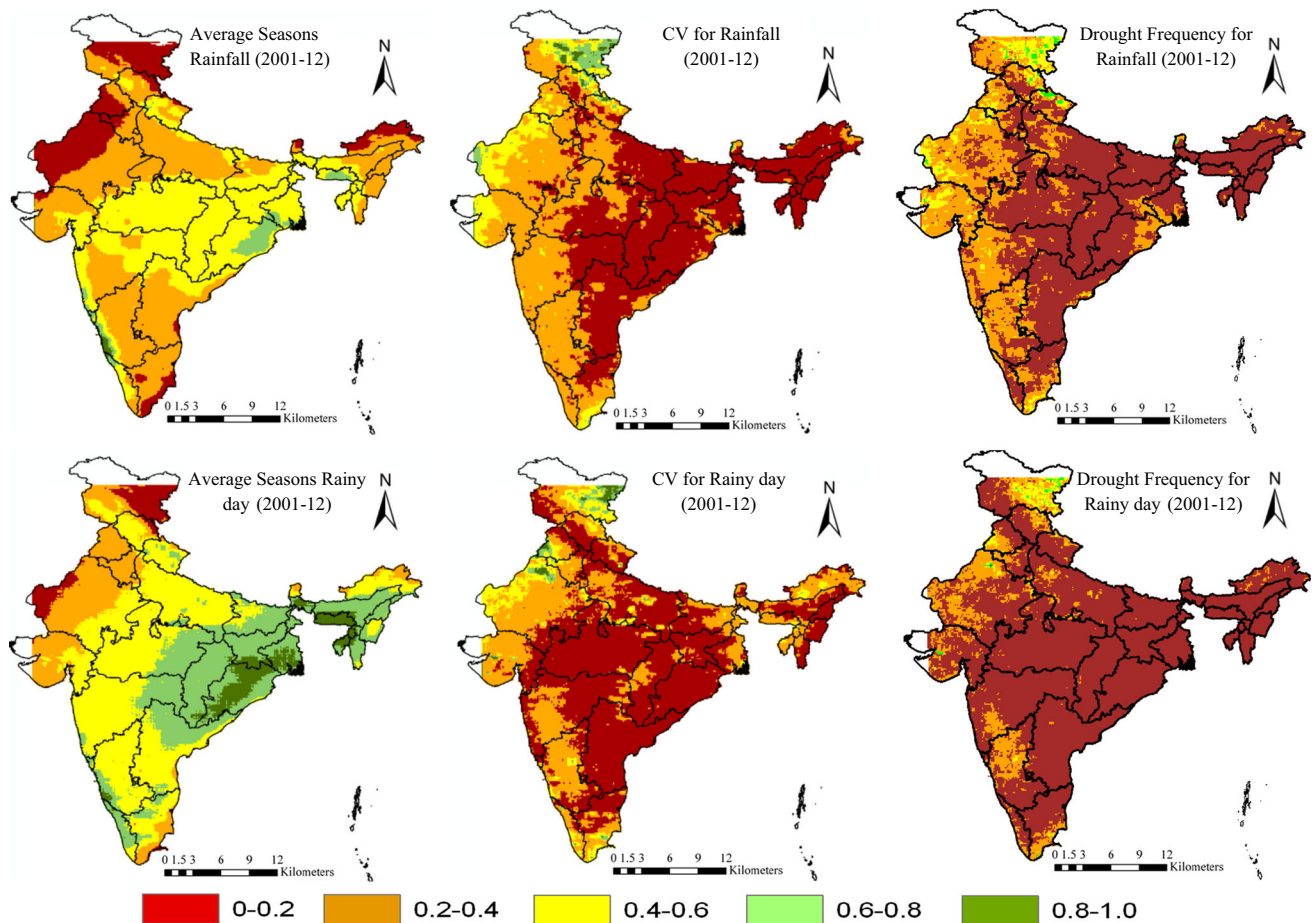Int. J. Environ. Sci. Technol. (2017) 14:1981–1988

Fig. 3 Scaled input indicators of the composite index

Chhattisgarh, Bihar, Jharkhand, Eastern Madhya Pradesh, West Bengal and Assam show much less hazardous area compared to the areas of the western region. Very less hazardous area is limited to other parts of West Bengal, Assam, Jharkhand and Chhattisgarh. The composite index has thus effectively captured the drought hazard patterns in the country.

The drought hazard map of the current study and the climatic classification map generated by Brooks et al. (2005) based on precipitation and potential evapotranspiration has some interesting commonality and class agreements. The climate map contains six classes: arid, semi-arid, dry sub-humid, moist sub-humid, humid and per humid. The arid regions of the map are closely associated with a higher hazard index of >0.8, and these regions are distributed in the western part of the country. The semi-arid region has the hazard index of 0.7–0.8, less than that of arid regions. Parts of the two southern states, namely Andhra Pradesh and Karnataka, contain some pockets of arid areas amidst dominant semi-arid area, and the same is also reflected in the hazard map as pockets of area with index >0.8 in the dominant class of 0.7–0.8 index. The

contiguous distribution of arid and semi-arid areas, west to central India, corresponds to top two hazard index classes. The dry sub-humid area is associated with the hazard index of 0.6–0.7, and their location is almost same in the central and the eastern parts of the country. The moist sub-humid and humid regions show the hazard index of 0.5–0.6, and these are located in the eastern regions. There are some disagreements also between the two classifications, but they are to a very limited extent.

The drought-prone districts map shows significant commonality with the hazard map of the current study. Most of the drought-prone districts have the hazard index >0.7. The spatial patterns in these two maps show interesting agreement over most parts of the country. Thus, the hazard index of the current study goes well with the climatic variability as well as the drought proneness maps of the other studies. Thus, the reliability of composite index generation has been established through the above comparisons. The index can be improved further by adding more variables and fine tuning the variables or by adopting improved techniques for deriving the weights to inputs.
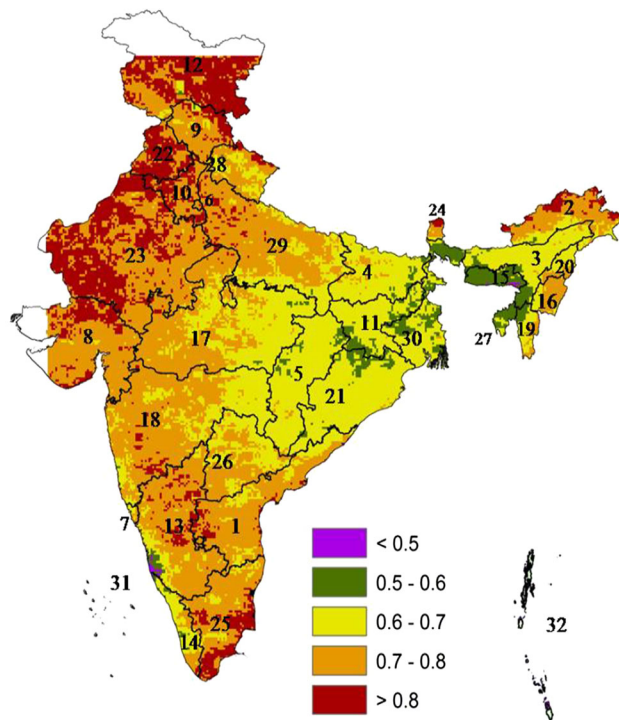
Fig. 4 Drought hazard index map

This study is justified with respect to its relevance and value, and the analysis presented has originality with respect to the technique adopted. The current study was motivated by the ample scope for developing composite indices to address the multidimensional nature of drought hazard, spatial perspective of its variability and scale requirements. Hazard assessment is a crucial component of any disaster preparedness. Construction and use of composite indices from multidimensional data for measuring spatial differentials in social and economic development issues have been widely practiced, and these techniques were explored in the current study for drought hazard mapping. A composite index is formed by synthesizing the individual indicators to summarize the complex and multidimensional realities, and there is no model-independent approach to describe such complex realities. The methodology for measuring and scaling drought hazard in this study is unique: exhaustive inputs, data-driven weights, statistical soundness and application over a large area. The basic methodology can be extended to other regions and disasters.

The uncertainty-related issues in the methodology essentially include the indicator selection and weights generation. While the current study draws the input indicators from rainfall and rainy days, the use of potential evapotranspiration (PET) and rainfall together representing both demand and supply component of water would further improve the hazard map. When data from multiple sources

are used data quality and scale bring uncertainty in the model. Weights generation should follow data normalization. Different methods are used for weights generation. Subjectivity cripples into the model, if appropriate method is not employed. Data-driven methods for weights generation are better than the expert-driven methods.

Conclusion

Meteorological drought hazard analysis was carried out using time series rainfall data at disaggregated level. The methodology has two unique features—composite index approach and geospatial analysis. The routinely available satellite-based rainfall products are effectively used. Combined use of both rainfall and rainy days together is the real strength of the current methodology. Thus, the index presents an aggregated description of drought hazard through a combination of rainfall and rainy days.

The composite index has effectively captured the drought hazard pattern in the country. The drought hazard map shows marked separability. The general agreement of the map with climate classification map and drought-prone map, generated by other studies, is an evidence of the plausibility of drought hazard mapping using the composite index. The 12 years of time series rainfall data are still adequate to represent the current level of average rainfall/rainy days in the study area. Use of long time series data is desirable to make the input indicators more robust. The current study has thus showcased the way for generating hazard index using the currently available geospatial data sets in a simple but novel perspective. The index can be applied to new observational data without any serious limitation. Such indices are potential inputs for primary use such as in disaster management and for secondary use such as in environmental modelling.

References

Addisu S, Selassie YG, Fissha G, Gedif B (2015) Time series trend analysis of temperature and rainfall in lake Tana Sub-basin, Ethiopia. Environ Syst Res 4:25

Ahsan MDN, Warner J (2014) The socioeconomic vulnerability index: a pragmatic approach for assessing climate change led risks-A case study in the south-western coastal Bangladesh. Int J Disaster Risk Reduct 8:32–49

Barlow M, Cullen H, Lyon B, Wilhelmi O (2006) Drought disaster in Asia. In: Arnold M, Chen R, Deichmann U, Dilley M, Lerner-Lam A, Pullen R, Trohanis Z (eds) Natural Disaster Hotspots Case Studies, World Bank Disaster Risk Management Series No.

1988

Int. J. Environ. Sci. Technol. (2017) 14:1981–1988

6. The World Bank Hazard Management Unit, Washington, D.C, pp 1–19

Brooks N, Neil-Adger W, Mick-Kelly P (2005) The determinant of vulnerability and adaptive capacity at the national level and the implications for adaptation. Glob Environ Change 15:151–163

Chen W, Cutter SL, Emrich CT, Shi P (2013) Measuring social vulnerability to natural hazards in the Yangtze river delta region, China. Int J Disaster Risk Sci 4:169–181

Dai A (2011) Drought under global warming: a review. Wiley Interdiscip Rev Clim Change 2(1):45–65

Domenech C, Wehr T (2011) Use of artificial neural networks to retrieve TOA SW radiative fluxes for the EarthCARE mission. IEEE Trans Geosci Remote Sens 49(6):1839–1849

Fauvel M, Benediktsson JA, Chanussot J, Sveinsson JR (2008) Spectral and spatial classification of hyperspectral data using SVMs and morphological profiles. IEEE Trans Geosci Remote Sens 46(11):3804–3814

Hao Z, Agha Kouchak A (2013) Multivariate standardized drought index: a parametric multi-index model. Adv Water Resour 57:12–18

Hao Z, Agha Kouchak A, Nakhjiri N, Farahmand A (2014) Global integrated drought monitoring and prediction system. Sci Data 1:140001

Hermance JF, Sulieman HM (2013) Comparing satellite RFE data with surface gauges for 2012 extreme storms in African East Sahel. Remote Sens Lett 4:696–705

Iyengar NS, Sudarshan P (1982) A method of classifying regions from multivariate data. Econ Polit Wkly 17:2048–2052

Keyantash JA, Dracup JA (2004) An aggregate drought index: assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. Water Resour Res 40:1–13

Kusiak A (2000) Decomposition in data mining: an industrial case study. IEEE Trans Electron Packag Manuf 23(4):345–353

Kusiak A, Wei X, Verma AP, Roz E (2013) Modeling and prediction of rainfall using radar reflectivity data: a data-mining approach. IEEE Trans Geosci Remote Sens 51(4):232–237

Li A, Angsheng W, Shulin L, Shunlin L, Wancun Z (2006) Eco-environmental vulnerability evaluation in mountainous region using remote sensing and GIS-A case study in the upper reaches of Minjiang River, China. Ecol Model 192:175–187

Li X, Plale B, Vijayakumar N, Ramach R, Conover H (2008) Real-time storm detection and weather forecast activation through data mining and events processing. Earth Sci Inf 1(2):49–57

Lobell DB, Burke MB, Claudia T, Mastrandrea MD, Falcon WP, Naylor RL (2008) Prioritizing climate change adaptation needs for food security in 2030. Science 319:607–610

Love TB, Kumar V, Xie P, Thiaw W (2004) A 20-year daily Africa precipitation climatology using satellite and Gauge data. In: 14th conference on applied climatology, Seattle, WA

Marzano FS, Marchiotto S, Textor C, Schneider DJ (2010) Model based weather radar remote sensing of explosive volcanic ash eruption. IEEE Trans Geosci Remote Sens 48(10):3591–3607

Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol 391:202–216

Murthy CS, Jyoti S, Pavan K, SeshaSai MVR (2015) Meteorological drought analysis over India using analytical framework on CPC rainfall time series. Nat Hazards 81:573

Nadim F, Kjekstad O, Domaas U, Rafat R, Peduzzi P (2006) Global Landslides risk case study. Nat Disaster Hotspots Case Stud Disaster Risk Manag Ser 6:21–77

Otgonjargal N (2012) Assessment of drought hazard: a case study in Sehoul area, Morocco. M.S. Thesis submitted to University of Twente, Enschede, The Netherlands

Satya P, Ashis KM, Imran MM, Rajagopal EN, Swati B (2014) Agreement between monthly land rainfall estimates from TRMM-PR and gauge-based observations over South Asia. Remote Sens Lett 56:558–567

Svoboda M, Lecomte D, Hayes M, Heim R, Gleason K, Angel J, Rippey B, Tinker R, Palecki M, Stooksbury D, Miskus D, Stephens S (2002) The drought monitor. Am Meteorol Soc 83:1181–1190

Verdin JP, Funk CC, Senay GB, Choularton R (2005) Climate science and famine early warning. Philos Trans R Soc B Biol Sci 360:155–168

Wilhelmi VV, Wilhite DA (2002) Assessing vulnerability to agricultural drought: a Nebraska case study. Nat Hazards 25:37–58

Wilhite DA (2000) Drought: a global assessment, vols 1 and 2. Routledge, New York, pp 89–104; pp 129–448

Zubair L, Ralapanawe V, Tennakoon U, Yahiya Z, Perera R (2006) Natural disaster risks in Sri Lanka: mapping hazards and risk hotspots. In: Arnold M, Chen R, Deichmann U, Dilley M, Lerner-Lam A, Pullen R, Trohanis Z (eds) Natural Disaster Hotspots Case Studies, World Bank Disaster Risk Management Series No. 6. The World Bank Hazard Management Unit, Washington, D.C, pp 109–136