

A study on agricultural drought vulnerability at disaggregated level in a highly irrigated and intensely cropped state of India

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Received: 7 June 2014 / Accepted: 11 January 2015 / Published online: 26 February 2015
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Abstract Drought is an important global hazard, challenging the sustainable agriculture and food security of nations. Measuring agricultural drought vulnerability is a prerequisite for targeting interventions to improve and sustain the agricultural performance of both irrigated and rain-fed agriculture. In this study, crop-generic agricultural drought vulnerability status is empirically measured through a composite index approach. The study area is Haryana state, India, a prime agriculture state of the country, characterised with low rainfall, high irrigation support and stable cropping pattern. By analysing the multiyear rainfall and crop condition data of kharif crop season (June–October) derived from satellite data and soil water holding capacity and groundwater quality, nine contributing indicators were generated for 120 blocks (sub-district administrative units).

Composite indices for exposure, sensitivity and adaptive capacity components were generated after assigning variance-based weightages to the respective input indicators. Agricultural Drought Vulnerability Index (ADVI) was developed through a linear combination of the three component indices. ADVI-based vulnerability categorisation revealed that 51 blocks are with vulnerable to very highly vulnerable status. These blocks are located in the southern and western parts of the state, where groundwater quality is saline and water holding capacity of soils is less. The ADVI map has effectively captured the spatial pattern of agricultural drought vulnerability in the state. Districts with large number of vulnerable blocks showed considerably larger variability of de-trended crop yields. Correlation analysis reveals that crop condition variability,

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groundwater quality and soil factors are closely associated with ADVI. The vulnerability index is useful to prioritise the blocks for implementation of long-term drought management plans. There is scope for improving the methodology by adding/fine-tuning the indicators and by optimising the weights.

Keywords Agricultural drought · Irrigated agriculture · Vulnerability · NDVI · Disasters · Composite index · CPC rainfall

Introduction

The impact of disasters resulting from natural hazards depends not only on the magnitude and frequency of the event but also on the vulnerability of the affected area or social group (Bohle 2001; Birkmann 2008). Vulnerability is a key link between hazard and risk and forms an important component of disaster risk reduction strategies. Joseph (2012) conceptualises vulnerability as the asymmetric response of disaster occurrences to hazardous events. The need for identification, assessment and ranking of vulnerabilities is being increasingly emphasised since it is a key step towards disaster risk reduction (Maskrey 1993; Bogardi and Birkmann 2004). Drought is the most significant global hazard followed by tropical cyclones, regional floods and earthquakes (Bryant 2005). It is a climatic hazard and is known for its slow and insidious onset. Agricultural drought, caused by reduced soil moisture availability to crops, leads to considerable economic loss worldwide. In the developing countries, long-term/mitigation programmes of drought management are given low priority, and hence, successive droughts are causing serious environmental problems such as land degradation, loss of top soil and overgrazing of grasslands (Bryant 2005). Despite technological developments and achieving self-sufficiency in food grain stocks, the Indian agriculture continues to be affected by droughts, threatening the sustainable development and food security of the nation (Roy et al. 2006). The basic geographic units for formulation and implementation of drought management plans in the country are the administrative units within the districts, known as taluks, blocks or mandals (Department of Agriculture and Cooperation 2009). Drought management includes both short-term and long-term strategies. Currently available drought monitoring systems based on meteorological, hydrological and spectral indices immensely support

short-term or in-season drought management. Long-term drought management is crucial for building drought-resilient agriculture.

Development of generic, realistic and quantitative indicators of drought vulnerability and risk at different scales is an inevitable requirement towards reducing drought risk (UNISDR 2011; Birkmann et al. 2006). Agricultural drought vulnerability is a measure of the capacity of the agricultural area of an administrative unit to cope up with the drought situation. The degree of vulnerability is not uniform within region or district. In India, 120 million ha of geographic area, spread across 1173 blocks, 185 districts and 13 states, was notified as drought-prone, based on slightly revised criteria in 1994 (www.dolr.nic.in). The drought-prone area classification is based on climatic parameters and percent irrigated area. Since there are no parameter-related soils and crops in the classification, the derived drought proneness does not truly reflect the agricultural drought proneness. Climate variability and irrigation infrastructure developments in the recent past have changed the drought vulnerability status of the country strongly suggesting the need to revisit the drought vulnerability classification.

Many techniques have been evolved to quantify hazard, vulnerability and risk related to drought and other natural disasters. Tsheko Rejoice (2003) developed drought risk and vulnerability indicators using rainfall probabilities derived from long-term rainfall data for selected stations. Drought risk is defined as the probability that a given dryness, expressed as accumulated potential evaporation deficit, exceeds in any year (Mullan et al. 2005). Metrics derived from time series Normalised Difference Vegetation Index (NDVI) were used to map drought vulnerability in India (Murthy et al. 2010). Harikishan et al. (2013) analysed crop-specific drought vulnerability at district level through empirical relations between maize yield reduction and Standardised Precipitation Index (SPI). All these studies have been based on a limited number of parameters. Early work on agricultural drought vulnerability assessment using multiple indicators was reported by Wilhelmi and Wilhite (2002). They used four parameters related to climate, soil, land use and irrigation support and evolved a numerical weighing scheme to generate agricultural drought vulnerability index. Eriyagama et al. (2010) carried out preliminary analysis of vulnerability mapping to study the impact of climate change on water resources and agriculture in Sri Lanka, by assigning weights to multiple parameters at district

level. Mrutyunjaya and Mamata (2011) analysed drought vulnerability, coping ability and residual risk in the selected blocks of Bolangir district, Odisha state, India, using a set of bio-physical and socio-economic indicators. Ravindranath et al. (2011) adapted index-based approach for assessing agricultural vulnerability at district level in the NE region of India using the secondary data. The fourth assessment report of IPCC on climate change has envisaged vulnerability assessment should encompass exposure, sensitivity and adaptive components (IPCC 2007). The three-dimensional model of vulnerability to natural hazards was implemented by Xiaoqian et al. (2013), in China.

Existing studies on agricultural drought vulnerability have been based on a limited number of indicators applied at macro and meso scale (Jülich 2015), and hence, the multidimensional nature of agricultural drought has not been effectively addressed. A composite index derived from multiple parameters provides a robust and scientific approach for mapping agricultural drought vulnerability. Further, vulnerability information is required at disaggregated level for developing effective drought management measures. Since vulnerability to disasters is specific to the resources and environment of the area, the need for measuring vulnerability at local level is strongly advocated (Hinkel 2011; Garcia and Fearnley 2012; Vincent 2007). Vogel and O'Brien (2004), observe that disaster vulnerability is multidimensional, scale-dependent and time-specific.

The current study is on the development of a quantitative multidimensional index to represent the current status of agricultural drought vulnerability at sub-district level. A composite index is formed by synthesising the individual indicators. Construction of composite indices for disaster vulnerability and risk is widely recommended (OECD 2008; Jülich 2015). The specific objectives of the study are (1) to generate a composite index of crop-generic agricultural drought vulnerability based on exposure, sensitivity and adaptive capacity indices by using a set of contributing indicators at disaggregated level and (2) to study the current status of agricultural drought vulnerability in the study area using the composite index.

Composite indices are used to classify the regions/sub-regions based on a set of multivariate data to bring out the subtle variations in the vulnerability. Construction and use of composite indices from multidimensional data for measuring spatial differentials in social and economic development issues have been widely practiced (Iyengar

and Sudarshan 1982; OECD 2008). In this study, a composite index of agricultural drought vulnerability was constructed and used to categorise the blocks of the state on the basis of vulnerability score. Analysis of drought events and yield reduction is outside the scope of the current paper. There is no vulnerability function. The composite index of vulnerability is a blended product of many input indicators, and hence, its relationship with any one of the inputs, say, crop yield alone, does not determine its accuracy.

Study area

The study was conducted in Haryana state. Located in the northwest of India (Fig. 1), it is an important agrarian state of the country. The state has 20 districts and 120 blocks within the districts. The state stands second in food grain production in the country. With highly productive lands and dense irrigation network, the state has a very stable agriculture. The state has contributed significantly to the 'Green Revolution' and the nation's self-sufficiency in food grain production. Most of the agricultural land is cultivated in two seasons a year, namely kharif (June–October) and rabi (November–April). The total geographical area of the state is 4.42 million ha; the cultivable area is 3.6 million ha. The gross cropped area of the state is 6.51 million ha and net cropped area is 3.6 million ha with a cropping intensity of 184.91 % (www.agriharyana.nic.in). About 80 % of agricultural area is irrigated. Surface water is the major source of irrigation in the state, followed by groundwater. The surface irrigation network in the state has two main systems—the Bhakra system and Western Yamuna canal—both getting water from snow-fed river systems; hence, these irrigation supplies are not monsoon-dependent. The quality of groundwater varies significantly from marginal to saline, across the state, restricting the supplementary use of groundwater with canal water. In the monsoon season, rainfall supplements the irrigation water requirements to some extent. With arid-semiarid climate, the state receives an average rainfall of about 400 mm.

Major crops in the kharif season are rice, jowar, bajra, cotton and guar, and those in the rabi season are wheat, mustard and gram. Rice-wheat cropping system is dominant in the state. Paddy is the main crop in all the northern districts of Ambala, Yamunanagar, Kurukshetra, Kaithal, Karnal, Panipat and Sonapat. In these districts, the surface

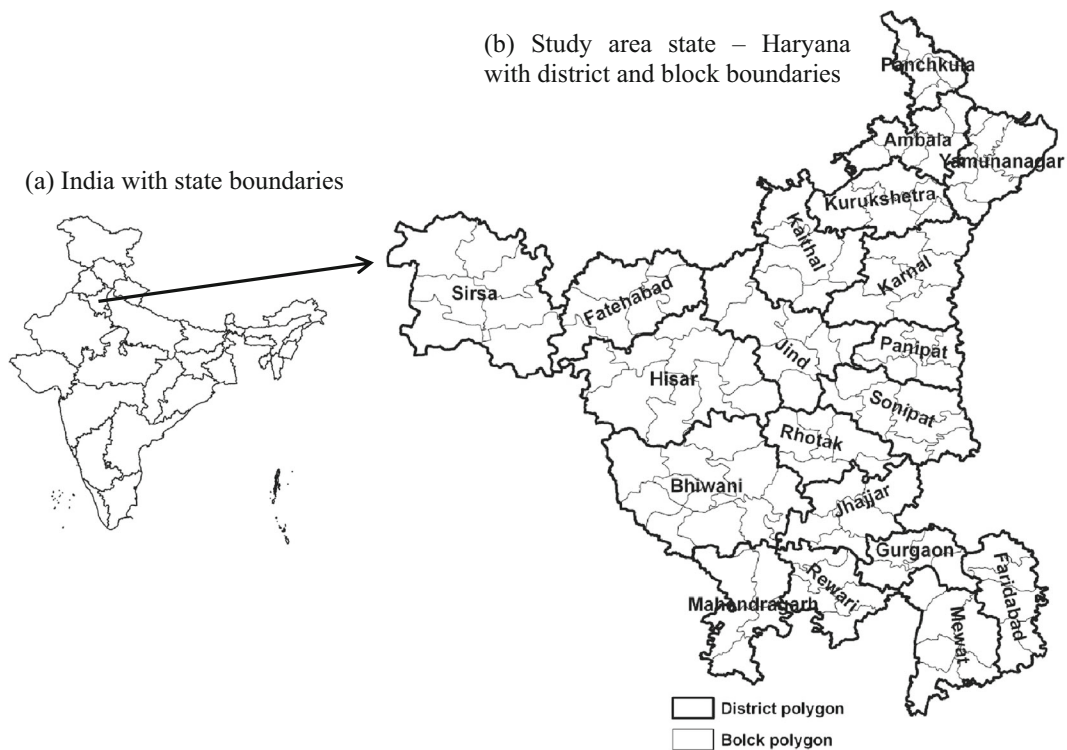


Fig. 1 Study area

irrigation supplies are supplemented by groundwater. Because of good quality of groundwater, the cropping pattern in these districts is dominated by high water consuming crops, such as paddy and sugarcane. Insufficient canal supplies and poor quality of groundwater have resulted in the cultivation of low water requirement crops such as bajra, guar and cotton in the southern districts like Bhiwani, Jhajjar, Mahendragarh, Rewari and Jind (Murthy et al. 2009). Although, cropping pattern is less diversified in Haryana state, significant variability in groundwater quality, soils and crop condition makes it relevant to undertake the drought vulnerability study. Some of the blocks of the state located in the western and southern sides were notified as drought-prone in the country by the Drought Prone Area Programme launched in 1970s and revised in 1990s (www.dolr.nic.in).

Methodology

Exposure, sensitivity and adaptive capacity are the three components of vulnerability. Studies on index-based vulnerability measurements related to disasters and climate change have effectively incorporated these three

components (Birkmann 2008; Xiaoqian et al. 2013; Ahsan and Warner 2014). Crop areas are exposed to hazardous weather like low rainfall and high temperature. The sensitivity and coping ability of the agricultural area, when exposed to drought situation or potentially harmful crop stress situations, determine the vulnerability of the area. Exposure, sensitivity and adaptive capacity together determine the agricultural drought vulnerability which is a relative term and can be represented in a predefined scale. The approach of the current study includes generation of composite index for each of the three components of vulnerability and integration of the individual indices into a single vulnerability index as shown in the broad outline of methodology in Fig. 2. Selection of indicators is guided by their ability to capture the essence of the respective component, data availability, accuracy of the data, etc. Justification for selecting the indicators under each component is described in this section.

The list of input parameters and derived indicators employed in the study is presented in Table 1. Time series data of last 12 years (2001–2012) pertaining to kharif season and map data on soil

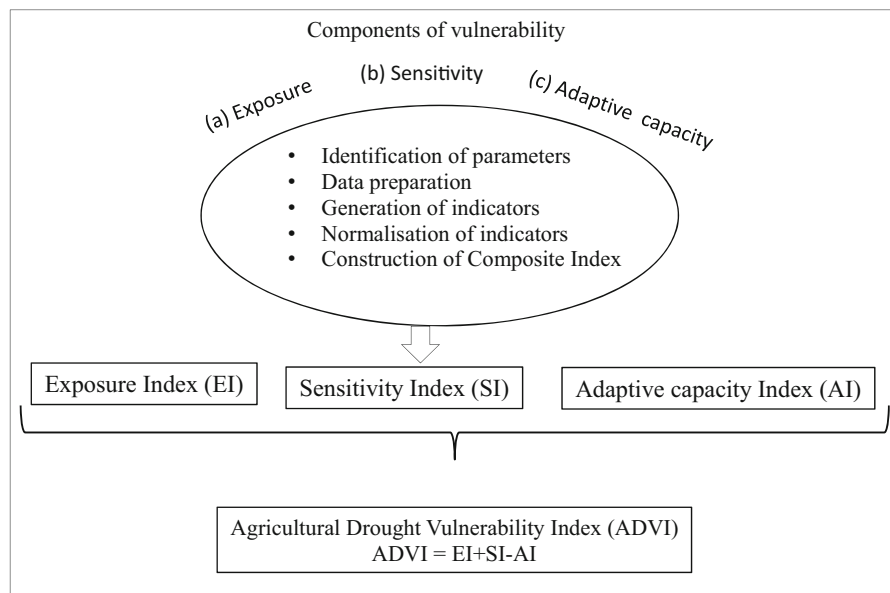


Fig. 2 Study approach

depth and texture and groundwater quality area were analysed. Since Moderate Resolution Imaging Spectroradiometer (MODIS) data is available for 12 years, Center for Climate Prediction (CPC) rainfall data was also taken for the same period to have the same length of time series.

Table 1 Parameters and indicators of different vulnerability components

Parameter	Indicator
A. Exposure component	
1. Total season rainfall	Mean
	Coefficient of variation (CV)
	Drought frequency
2. Total season rainy days	Mean
	CV
	Drought frequency
B. Sensitivity component	
1. Season's Integrated NDVI (SIN)	Range
	CV
	Drought frequency
C. Adaptive capacity component	
1. Soil (depth and texture)	Mean value of soil water holding capacity
2. Groundwater quality	% area under fresh and marginal groundwater quality

Exposure indicates the nature, extent, duration and frequency of drought conditions on the agricultural areas of a region. Meteorological drought is the primary cause of agricultural drought occurrence and its progression in the season over agricultural areas. Xiaoqian et al. (2013) used SPI derived from rainfall time series to represent drought exposure. Ravindranath et al. (2011) used rainfall variability index as proxy to climate change exposure. Satellite-based rainfall estimates are becoming increasingly important due to inadequate network and measurement errors associated with surface gauges (Africa Water Atlas 2010). These spatial rainfall data sets from satellites certainly complement the surface gauge data for early warning on water availability (Verdin et al. 2005).

The US Center for Climate Prediction (CPC) based on several types of satellite measurements merged with ground-based gauge data generates rainfall products. 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 southwest monsoon season (June to September) of the last 12 years (2001 to 2012) was analysed to generate different indicators of exposure. Along with rainfall, data on rainy days was 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 (www.imd.gov.in).

Derivatives from rainfall and rainy days data include mean, coefficient of variation (CV) and drought frequency. The mean and CV of rainfall and rainy days from time series data better represent the average situation of the recent past than that of any single year. Drought frequency indicating the number of years under drought conditions during the 12-year period was computed for both rainfall and rainy days of the season separately. Less than 75 % of normal rainfall was considered as drought situation, as followed by India Meteorological Department (www.imd.gov.in) for computing drought frequency. The Same criteria were extended to rainy days to generate drought frequency based on rainy days. Thus, based on rainfall and rainy days, six indicators of exposure were generated.

Sensitivity is the degree to which the crops are affected by moisture stress due to drought conditions. Sensitivity of crop growing environment to agricultural drought conditions is the strong determinant of the vulnerability of an agricultural area. Sensitivity component in this study is represented by the satellite-derived agricultural vegetation condition during the season. Satellite-derived Normalized Difference Vegetation Index (NDVI) has been successfully used for crop/vegetation monitoring, crop discrimination, stress detection and crop yield estimation. NDVI is widely used for operational drought assessment because of its simplicity in calculation, ease in interpretation and its ability to partially compensate for the effects of atmosphere and illumination geometry (Bannari et al. 1995). Some of the proven examples for successful application of satellite remote sensing for operational drought assessment are Drought Monitor of USA using NOAA-AVHRR data (www.cpc.ncep.noaa.gov), Global Information and Early Warning System (GIEWS) and Advanced Real Time Environmental Monitoring Information System (ARTEMIS) of FAO using Meteosat and SPOT-VGT data (www.fao.org), International Water Management Institute (IWMI)'s drought assessment in Southwest Asia using MODIS data (Thenkabail et al. 2004) and NADAMS drought monitoring in India with IRS-WiFS/AWiFS and NOAA-AVHRR (www.nrsc.gov.in; Murthy et al. 2007) data.

Derivatives from times series NDVI—range, CV and drought frequency, based on standardised NDVI—were used to represent sensitivity component in the current

study. NDVI-derived phenological metrics were used to evaluate the terrestrial ecosystems (Myneni et al. 1997; Lee et al. 2002; Sakamoto et al. 2005; Bradley et al. 2007). Wu et al. (2008) investigated the phenology over crop lands in China using time series NDVI data sets and concluded that significant changes took place in the start of growing season in the past 20 years. Time series phenological parameters over agricultural areas represent the impact of inter- and intra-seasonal variations of climate. Phenological observations measure the response of vegetation to meteorological and environmental factors. Phenological data series indicate the evidence of vulnerability. Chen et al. (2014), using annual mean and standard deviation from NDVI time series, detected the changes in vegetation photosynthetic activity and its trends across the Asia Pacific region.

Terra MODIS 250 m NDVI monthly composites, applied with kharif season agricultural area mask, generated under National Agricultural Drought Assessment and Monitoring System (NADAMS) project of National Remote Sensing Centre (NRSC) (www.nrsc.gov.in), were used. Monthly NDVI composites from four months—July, August, September and October—representing active growing and peak vegetative phase of kharif season, for the time series period of 2001–2012, were analysed. Season's Integrated NDVI (SIN) image was derived for each year by summation of 4-month NDVI. SIN represents cumulative biomass and vigour over the agricultural area. The 4-month period in the summation corresponds to active growing and peak growing periods of standing crops. Using the SIN images of the time series and block boundary vector layer, the block-wise average SIN values were extracted for different years. From the time series SIN data of blocks, two metrics were derived—(a) range and (b) CV. Range is the difference between maximum and minimum SIN values during the time series period. It signifies the amplitude of NDVI change. A higher range indicates more agricultural drought vulnerability and vice versa. CV indicates the average inter-annual variability during the time series. CV is also directly related to drought sensitivity. Both range and CV represent the variability of cumulative biomass/crop vigour between the years. Haryana state has a stable and monotonous cropping pattern, and hence, it is assumed that the changes in NDVI during the time series period are largely attributed to weather effects rather than cropping pattern changes.

SIN-based drought frequency was computed by generating standardised SIN for each year. Based on standardised vegetation index concept of Peters et al.

(2002), Z-scores of SIN distribution were used to estimate the probability of occurrence of SIN for a given block, relative to the possible values of SIN. Through standardisation, SIN deviations were normalised for mean and standard deviation, so that the deviations are comparable across space. Standardised SIN of <0.25 , following Peters et al. (2002), for any year in the time series was regarded as agricultural drought, and the number of such drought years was taken as drought frequency. More details on standardisation are available in Peters et al. (2002).

The coping ability of a block to agricultural drought is explained by soil and groundwater quality parameters. Since more than 80 % of crop area is covered by surface irrigation, the irrigated area factor does not show much variability between blocks and hence not included in the current analysis. Supplementary use of groundwater is widely practiced in the state, and hence, groundwater quality plays a critical role in meeting the crop water requirements (Sakthivadivel et al. 1999). The districts with high irrigation support (surface water plus good quality groundwater) were not influenced by severe meteorological drought of 2002 (Murthy et al. 2009). Therefore, in this study, percentage area under fresh and marginal groundwater quality in each block was taken as adaptive capacity indicator. The groundwater quality map on 1:500,000 scale prepared by Haryana State Ground Water Board was analysed to generate block-wise statistics on percentage area under fresh and marginal groundwater quality.

Soil is an important link between weather and crops and strongly determines the occurrence of agricultural drought. Soil Water Holding Capacity (SWHC) determines the amount of water that can be accommodated in the soil column, and hence, it is directly related to adaptive capacity to drought conditions. Wilhelmi and Wilhite (2002) used SWHC as a drought vulnerability indicator in their study. SWHC in the current study was computed from 1:250,000 scale soil map, by using soil depth and soil texture information under NADAMS project of NRSC (www.nrsc.gov.in). The soil map was originally prepared by National Bureau of Soil Survey and Land Use Planning, Government of India. Using the 1-km-resolution SWHC layer of the study area state, block-wise average AWC values were generated and used as an indicator of adaptive capacity.

Data analysis

The input indicators of the vulnerability model include six indicators of exposure component, three indicators of sensitivity component and two indicators of adaptive capacity component. The data matrix comprising 11 indicators and 120 blocks was prepared for further analysis which includes data normalisation, weights computation and construction of composite indices.

The indicators of the model are in different units, and their functional relationship with respective component index is either positive or negative. Data normalisation was done to normalise the differences in the units of input indicators and their functional relationships with respective component index. Min-max approach was adopted for this purpose (OECD 2008). In case of the indicators that have positive relationship with its respective component index, the normalisation was done using the following formula:

An indicator X over j number of blocks, which is positively related to respective component index, was normalised using the formula

$$X_{i\text{-normalised value}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

If X has a negative relationship with the resulting component index, then its normalised values are

$$X_{i\text{-normalised value}} = \frac{X_{\max} - X_i}{X_{\max} - X_{\min}} \quad (2)$$

After normalisation, all the indicators were ranging from 0 to 1 and their direction of change is the same.

Assignment of weights to the selected indicators is a key issue in the generation of composite indices (Brooks et al. 2005). Wilhelmi and Wilhite (2002) selected weights based on relative contribution of each factor to vulnerability. Li et al. (2006) 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 for all the variables/indicators which is not necessarily correct. In this study, the method given by Iyengar and Sudarshan (1982) to construct a statistically sound composite index from multivariate data was used. Hiremath and Shiyani (2012) used this method for evaluating vulnerability to climate change.

It is assumed that there are N blocks, K indicators and $x_{ij}, I=1, 2, \dots, N; j=1, 2, \dots, K$ are the normalised scores. The composite index of i th block \bar{y}_i , is assumed to be a linear sum of x_{ij} as

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

Where w 's ($0 < w < 1$ and $\sum_{j=1}^K w_j = 1$) are the weights. Here, the weights are assumed to vary inversely as the variance over the blocks in the respective indicators. That is, the weight w_j is determined by

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

Where c is a normalising constant such that

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

By assigning the weights in this manner, 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 was rescaled to 0 and 1 for easy interpretation.

Using this method, three composite indices, namely exposure index (EI), sensitivity index (SI) and adaptive capacity index (AI), were computed. Agricultural Drought Vulnerability Index (ADVI) was computed as under

$$\text{ADVI} = \text{EI} + \text{SI} - \text{AI} \tag{6}$$

The ADVI and component indices reflect relative differences among the blocks, rather than representing specific conditions of a crop growing environment.

The composite vulnerability index thus computed would range from 0 to 1, indicating minimum and maximum vulnerability respectively. Based on the intervals of composite index, blocks are characterised with different levels of agricultural drought vulnerability as shown in Table 2.

Results

Spatial maps of all the 11 contributing indicators scaled between 0 and 1 were generated, though not presented here for the sake of brevity. The distribution of these

Table 2 Vulnerability categorisation based on ADVI

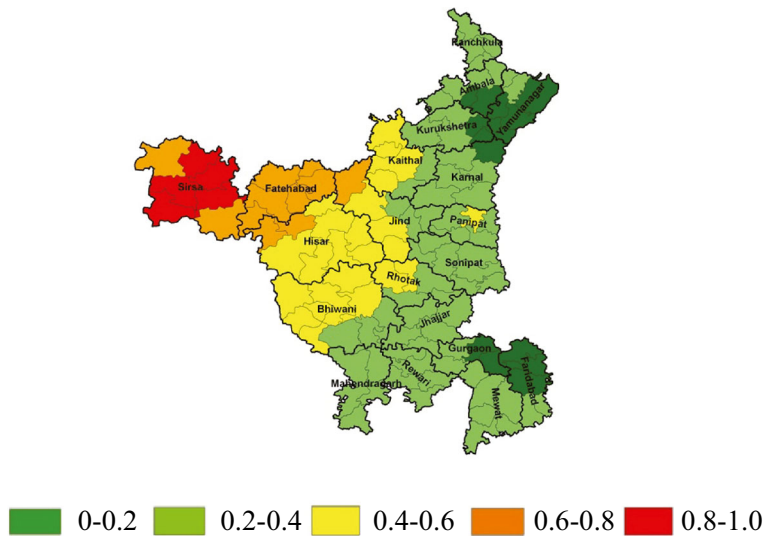
Range of ADVI	Vulnerability class
0–0.2	Less vulnerable
0.2–0.4	Moderately vulnerable
0.4–0.6	Vulnerable
0.6–0.8	Highly vulnerable
>0.8	Very highly vulnerable

ADVI Agricultural Drought Vulnerability Index

indicators in the study area reveals certain interesting patterns. Both rainfall and rainy days are relatively higher in the northeast and southeast part of the state. The western part of the state shows low rainfall, high inter-annual variability and more frequent drought compared to the rest. Rainy days also depict the same trend. Range values of integrated NDVI are more in the blocks of western and southwestern parts of the state signifying higher sensitivity to weather variations. CV of SIN shows lower values in majority of the blocks except in isolated blocks of some of the southern/western districts. Drought frequency based on SIN shows more frequent drought in a few blocks that are not contiguous and located mostly in southern and western parts of the state. SWHC values are relatively higher in the northern and central part of the state. In the southern districts of Bhiwani, Mahendragarh, Rewari, Gurgaon and Jhajjar, lower values of SWHC are dominant. Percent area under fresh and marginal groundwater is significantly more in the northern half of the state. Again, in the southern districts—Bhiwani, Mahendragarh, Rewari, Gurgaon and Jhajjar, the percentage area under fresh and marginal groundwater is less, and this forms a serious limitation for supplementing with canal water.

Composite indices were constructed for each component, and their distribution in the study area state was analysed (Figs. 3, 4 and 5). Distribution of EI (Fig. 3) shows typical pattern with many of northwestern and some of the central districts showing significantly higher exposure levels compared to the rest of the districts. Blocks of Sirsa and Fatehabad districts have higher exposure levels followed by Bhiwani and Hissar districts. High exposure to agricultural drought (EI >0.6) is found in 14 blocks followed by lower exposure (EI <0.4) in 79 blocks and moderate exposure (EI 0.4–0.6) in 26 blocks. Sensitivity to agricultural drought vulnerability also shows skewed distribution to lower side

Fig. 3 Distribution of exposure index



similar to exposure (Fig. 4). Most of the blocks have shown less sensitivity to agricultural drought in the state. The crop condition, crop vigour and its variability between years are stable in many of the blocks. Only 28 blocks are under moderate to very high sensitivity (SI >0.4) category, and these blocks are distributed in the southern and western parts of the state. Adaptive capacity distribution is skewed towards higher side indicating that the coping ability to agricultural drought conditions is more in majority blocks of the state (Fig. 5). About 76 blocks have higher adaptive capacity (AI >0.6) to agricultural drought. There are 19 blocks with less adaptive capacity (≤ 0.4), and these are distributed in the southern districts. In 24 blocks, adaptive capacity (0.4–0.6) is

moderate, and these are located in the southern and western part of the state.

ADVI was generated using the three composite indices, and the blocks of the state were categorised based on ADVI class intervals (Table 2) as shown in Fig. 6, to study the current status of agricultural drought vulnerability in the state. District-wise distribution of blocks under different vulnerability classes is depicted in Fig. 7. It was found that in 51 blocks, the vulnerability status ranges from ‘vulnerable to very highly vulnerable’, of which 17 blocks are under highly and very highly vulnerable situation. Bhiwani district was found to be the most agriculturally vulnerable in the state, with nine blocks under vulnerable to very highly vulnerable

Fig. 4 Distribution of sensitivity index

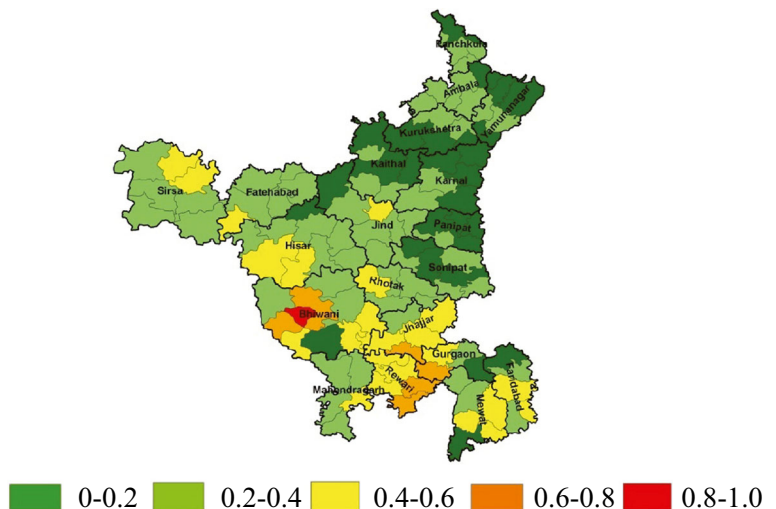
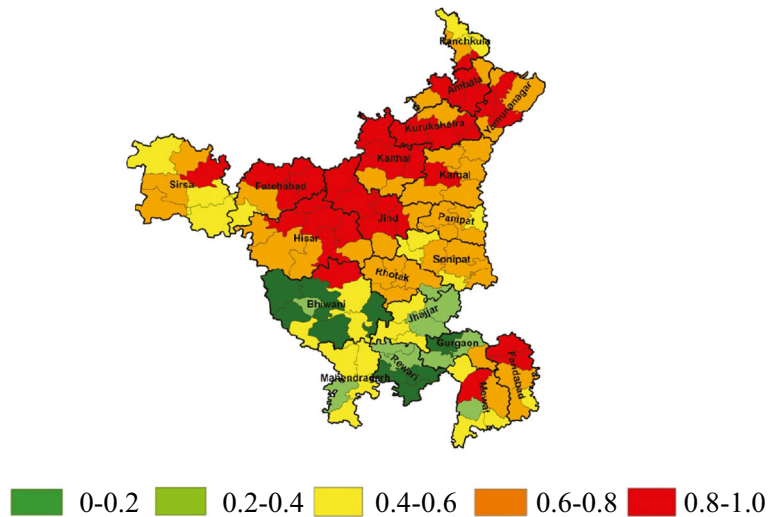


Fig. 5 Distribution of adaptive capacity index



status, followed by Sirsa (nine blocks), Jhajjar, Fatehabad, Mahendragarh (five blocks in each),

Rewari (four blocks), Gurgaon, Hissar and Rohtak (three blocks in each) and Mewat (two blocks). All these

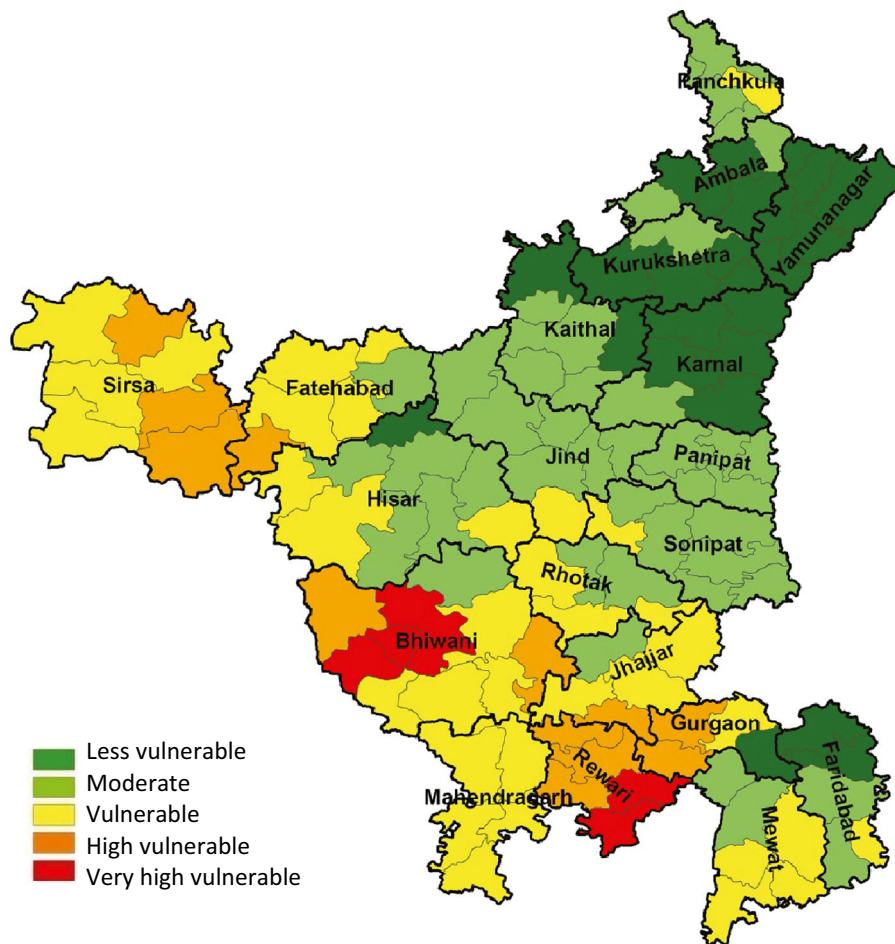


Fig. 6 Spatial distribution of agricultural drought vulnerability based on ADVI

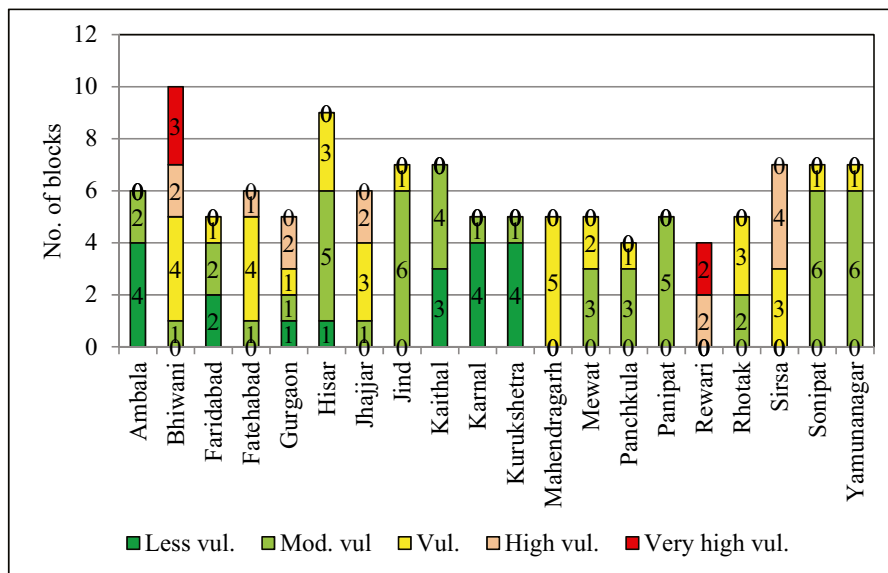


Fig. 7 District-wise distribution of blocks in different vulnerability classes

districts are located in the western and southern side of the state. The rest of the districts with 69 blocks together were found to be less vulnerable. Bhiwani district with four blocks under vulnerable and five blocks under highly and very highly vulnerable status became the most vulnerable in the state. Although Sirsa district has nine blocks under vulnerable status, there are no blocks under very highly vulnerable status in the districts, thereby making it less vulnerable compared to Bhiwani and Rewari. Districts in the northern part of the state, namely Ambala, Yamunanagar, Kurukshetra, Karnal, Kaithal, Panipat and Sonipat, are dominated by less vulnerable blocks.

There is no straightforward procedure to validate the composite indices made up of dissimilar indicators (Vincent 2007). Ahsan and Warner (2014) developed socio-economic vulnerability index and opined that in the absence of direct methods of validation of such composite index, selection of indicators and assignment of weights are the strong determinants of the composite index. The ADVI-derived vulnerability map in this study was validated through an indirect approach by analysing the time series yield data of principal crops at a slightly coarser scale. Empirical evidence on the effects of drought on crop yield and its variability reported by Zhao et al. 2011 and BoubacarInoussa 2012 provide the basis for indirect validation here. In this study, the validation of ADVI map of blocks was done by verifying the association between agricultural

drought vulnerability and crop yield variability. Due to non-availability of crop yield data at block level, district-level yield data was used for validation, and this is the limitation of this indirect approach. The kharif season yields of four principal crops, namely rice, bajra, cotton and guar, at district level for the time series period of 2000–2011 were analysed. Trend analysis of yield was performed by fitting a linear trend for each principal crop in each district separately. After removing trend component, yield figures were computed for each year. The procedure for trend fitting and trend removal was adapted from Cooper and Weeks (1983). The CV of the de-trended yield data was computed for the principal crops in each district. Drought vulnerability and the CV values are assumed to be directly related. Districts dominant with vulnerable blocks—Bhiwani, Sirsa, Fatehabad, Mahendragarh, Rewari, Gurgaon and Hissar—were identified, and their CV values of de-trended yields of cotton, bajra and guar range from 20 to 40 %. The districts dominant with less vulnerable blocks—Ambala, Yamunanagar, Panipat, Jind, Kurukshetra, Karnal, Sonapat, Fatehabad and Kaithal—have CV of <10 %. Thus, the districts dominant with vulnerable blocks showed considerably large variability of de-trended yields of principal crops, and the districts dominant with less vulnerable blocks showed lesser variability of de-trended yields of principal crops. This is only an indicative and not a straightforward method of validation. Another limitation of the

method is that the yield variability need not be entirely due to agricultural drought.

Discussion

The study area experiences lower rainfall at 600 mm per annum compared to many other states in the country (www.rainwaterharvesting.org). The inter-annual variability of rainfall is also less. Relative variations of rainfall among the blocks are not significant. Therefore, drought exposure does not reveal large variability. Only about one third of blocks have relatively higher exposure level. A sharp decline in exposure from west to east side of the state is evident. The cropping pattern is stable, with rice-wheat cropping system being practiced largely. The yield variability is also less. With stable cropping pattern and higher yield levels, sensitivity to agricultural drought is also less in most of the blocks. Only 15 % of blocks are found to be relatively more sensitive to agricultural drought. These blocks are located in the southern part of the state. Adaptive capacity shows more spatial variability with 36 % of blocks having less adaptive capacity, and these blocks are located mostly in western and southern parts of the state.

The index-based agricultural drought vulnerability status can be summarised that majority blocks in the study area are less vulnerable. Out of 51 blocks ranked as vulnerable, only 18 blocks are highly vulnerable. The vulnerable blocks are located on the west and south side of the state. Bhiwani, Mahendragarh, Rewari, Hissar and Sirsa are the prominent districts with more number of vulnerable blocks. All these blocks are dominant with saline groundwater that is not fit to supplement with canal water and the water holding capacity of soils is less. The ADVI map has captured major patterns of vulnerability. It provides objective information on the current status of agricultural drought vulnerability and serves multiple purposes besides aiding vulnerability reduction plans. Correlation between ADVI and contributing indicators revealed that CV of SIN has the highest correlation (0.81) with ADVI followed by groundwater quality (0.69) and SWHC (0.57). Thus, crop condition variability, groundwater and soil-related indicators play a more important role in determining the agricultural drought vulnerability status of the spatial units.

Sakthivadivel et al. (1999) carried out a study on the performance evaluation of the Bhakra irrigation system

which covers much of the northern half of Haryana state with 1.3 million ha of command area. The results indicate that groundwater quality is a crucial factor determining the agricultural performance of the system. Poor quality of groundwater and insufficient canal water supplies caused crop yield reduction as well as large spatial differences in the yields in parts of Sirsa, Hissar and Bhiwani districts. The study by Murthy et al. (2009) in Haryana state revealed that in the districts like Bhiwani, Mahendragarh, Sirsa and Rewari, where canal supplies are insufficient and groundwater quality is poor for supplementary use, the NDVI-based metrics show poor crop condition, signifying the impact of severe drought conditions of kharif 2002. It is interesting to learn that the results of the current study also pointed out the same districts as vulnerable and further reinforced the problem of groundwater quality and its conjunctive use with canal water.

Diagnostic analysis of vulnerable blocks needs to be performed to develop possible action plans. Since groundwater quality and water holding capacity of soils cannot be improved in the immediate future, the possible option is to address the crop and surface irrigation related issues. Improving the distribution of surface water and bringing possible change in cropping pattern and crop calendars could be immediate practical interventions to reduce the agricultural drought vulnerability and to improve the agricultural performance of this largely irrigated and intensely cropped state.

Conclusion

The current study has adopted a three-dimensional model for measuring agricultural drought vulnerability in a highly fertile and a largely irrigated Haryana state of India. The contributing indicators and the composite index of agricultural drought vulnerability are generated at disaggregated level, thereby adding further strength to the study. The spatial information on crop condition, which is closely related to drought sensitivity of crops, is represented by moderate resolution satellite data. The response of agricultural area to drought could be measured objectively by engaging the well-known spectral index NDVI. Rainfall data is also obtained from satellite-derived estimates instead of using manually measured, subjective and inadequately covered conventional rain gauge data. Soil- and groundwater-related indicators are not dynamic, and hence, the recently

available data is chosen. Thus, the input data was selected in a systematic way, and the chances of errors are minimised. The weights of the indicators are generated with recommended procedures in the composite data analysis. The multidimensional composite index thus generated has measured the agricultural drought vulnerability quantitatively, captured the relative differences at disaggregated level and ranked the sub-district level administrative units objectively. The vulnerability map is useful in prioritising the blocks for implementation of drought management programmes. The current study is important to all the drought relevant agrarian countries because (1) drought vulnerability indexing has multiple uses—long-term drought management, crop insurance, climate change, etc.—(2) tools and techniques for vulnerability assessment are available to a limited extent compared to that of operational drought monitoring; (3) the methodology of the study has been demonstrated over a fairly larger geography characterised with considerable variability in respect of soils, groundwater and crop condition, making it fit to other geographies; and (4) it enables the decision makers to measure the vulnerability status from time to time objectively.

The vulnerability index, to be versatile and robust, should be applicable to different agro-ecological regions and crop growing environments such as arid, semi-arid, purely irrigated, purely rain-fed, mix of irrigated and rain-fed, etc. Therefore, extending the study to other agricultural situations is very essential to evolve a sound methodology. There is scope to improve the methodology by increasing the contributing indicators and by exploring the data mining techniques to generate more robust weights to the input indicators. The present study could certainly be an attempt towards evolving an integrated and geospatial approach for making agricultural drought vulnerability assessment more exhaustive, rational, scientific and practical.

Acknowledgments We express our sincere gratitude to Dr. V.K. Dadhwal, Director, National Remote Sensing Centre for his constant encouragement and guidance. Valuable suggestions offered by Dr. P.G. Diwakar, Deputy Director, Remote Sensing Applications, NRSC are sincerely acknowledged.

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