Geospatial approach for assessment of biophysical vulnerability to agricultural drought and its intra-seasonal variations

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Abstract The study presents a methodology to assess and map agricultural drought vulnerability during main *kharif* crop season at local scale and compare its intra-seasonal variations. A conceptual model of vulnerability based on variables of exposure, sensitivity, and adaptive capacity was adopted, and spatial datasets of key biophysical factors contributing to vulnerability were generated using remote sensing and GIS for Rajasthan State of India. Hazard exposure was based on frequency and intensity of gridded standardized precipitation index (SPI). Agricultural sensitivity was based on soil water holding capacity as well as on frequency and intensity of normalized difference vegetation index (NDVI)-derived trend adjusted vegetation condition index (VCI_{Tadj}). Percent irrigated area was used as a measure of adaptive capacity. Agricultural drought vulnerability was derived separately for early, mid, late, and whole *kharif* seasons by composting rating of factors using linear weighting scheme and pairwise comparison of multi-criteria evaluation. The regions showing very low to extreme rating of hazard exposure, drought sensitivity, and agricultural vulnerability were identified at all four time scales. The results indicate that high to extreme vulnerability occurs in more than 50 % of net sown area in the state and such areas mostly occur in western, central, and southern parts.

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The higher vulnerability is on account of non-irrigated croplands, moderate to low water holding capacity of sandy soils, resulting in higher sensitivity, and located in regions with high probability of rainfall deficiency. The mid and late season vulnerability has been found to be much higher than that during early and whole season. Significant correlation of vulnerability rating with food grain productivity, drought recurrence period, crop area damaged in year 2009 and socioeconomic indicator of human development index (HDI) proves the general soundness of methodology. Replication of this methodology in other areas is expected to lead to better preparedness and mitigation-oriented management of droughts.

Introduction

Droughts are expected to become more frequent and severe in spatial and time scales in the future, with increasing demands, limited and uncertain supplies, and effects of climate change and climate variability (IPCC 2014). Faced with these challenges, decision makers and planners need information to assist for drought preparedness, allocate resources effectively, and reduce impacts. To minimize the likely harm associated with expected frequent and severe droughts, people and society need an accurate assessment of the *vulnerability* of the ecosystem in which they inhabit.

Researchers have analyzed the concept and definition of vulnerability and concluded that vulnerability has three components: (i) the susceptibility of society (i.e., converse of adaptive capacity) which depend upon attributes of society, (ii) exposure to hazard (e.g., water stress), and (iii) coping abilities (Kates 1985; Chambers 1989; Blaikie et al. 1994; Bohle et al. 1994; Downing and Bakker 2000). Vulnerability mapping can be used in all phases of disaster management, viz., prevention, mitigation, preparedness, relief, and recovery. There is an increased attention and urgency to undertake research on assessment and mapping of vulnerability with paradigm shift in approach to disaster management world over from relief and response centric towards preparedness, prevention, and mitigation centric (Fontaine and Steinemann 2009). Vulnerability assessment is a foremost step to prepare the contingency plans for a hazard.

Vulnerability of a system is a relative and dynamic measure; it changes due to change in behavior of society, their adoption to technology, practices, and policies. It varies at different temporal and spatial scale, even varies inter-seasonally from extreme crisis to complete safety (Downing and Bakker 2000; Wilhite 2000). The very purpose of assessing vulnerability is to identify and prepare appropriate strategy to reduce the impact of potential damage by a hazard. Over the previous years, the need for vulnerability assessment has been highlighted by many researchers over extant approaches (e.g., impact assessment) and its methodology (e.g., Ribot 1996; Klein et al. 1999; Smit et al. 1999; Klein and Maciver 1999; Downing et al. 2001; Kasperson 2001; Walker et al. 2002; Eastman et al. 1997; Hewitt 1997; Keenan and Krannich 1997). However, vulnerability assessments are commonly subjective because of the intricacy of the issue of vulnerability and vary between regions and hazards.

Drought is most complex and least understood among the all natural hazards, and its vulnerability is not directly observable phenomenon. Because of complexity of system, quantifying the vulnerability to drought is a challenging task. Many factors affect vulnerability to drought, but their inclusion depends on data availability and local study context. In spite of constraints and limitations, resource manager or planner could aid by regional scale drought vulnerability assessment to take proper adaptation and mitigation steps before the next drought event and lessen the impacts of that event (Wilhelmi and Wilhite 2002).

Different spatial scale vulnerability assessment has now become possible with the recent advances in remote sensing and GIS integrating various spatial data, but there are still methodological problems in implementing model at larger scale. Various drought studies necessitated the use of GIS environment for integrating data from different sources (De Jager et al. 1997; Ghosh 1997; Reed 1993; Matthews et al. 1994). Wilhelmi and Wilhite (2002) presented a methodology of GIS-based agricultural drought vulnerability in Nebraska using biophysical factors, viz., climate, soils, and social factors, viz., land use, and access to irrigation. Similarly, Prathumchai et al. (2001) carried out a study to evaluate criteria for identifying drought risk areas using weighted linear combination of input factors of topography, soil drainage, ground water, irrigation area, annual evaporation, rainfall, and rainy days. Slejko et al. (2009) presented GIS-based methodology for drought vulnerability assessment for the agriculture for the west part of Slovenia using environmental factors, viz., solar radiation, soil water holding capacity, irrigation areas, agricultural land use, and reference evapotranspiration.

Most of the reported studies have methodological drawbacks. The analysis is carried out at a scale of administrative unit (generally district) at which inputs data are readily available though the planners need vulnerability rating at sub-district scale for prioritizing resources in local context. Very few studies have made use of long-term availability of satellite-derived crop sensitivity parameters to capture sensitivity at a finer scale. Further, no study has reported how to assess intra-seasonal variations in vulnerability for devising and implementing effective contingency plans.

In view of above, this study was undertaken to demonstrate and validate a methodology to assess and map biophysical vulnerability to agricultural drought in Rajasthan State of India at local scale (i.e., about 10×10 km^2 area grid size). It aimed at adopting a conceptual framework of vulnerability, generating spatial datasets of key biophysical factors contributing to vulnerability using remote sensing and GIS, and then generating classified map of agricultural drought vulnerability. A novelty of this study is that it not only assessed seasonal vulnerability but also assessed and compared intra-seasonal vulnerability for early, mid, and late periods of *kharif* (June–October) season.

Materials and methods

Study area

The study was conducted for the state of Rajasthan, situated in the northwestern part of India exhibiting

diverse climates in different parts (Fig. 1). The climate of Rajasthan ranges from the semiarid to arid on the west of Aravallis and semiarid to subhumid on the east of Aravallis. Rainfall in this region occurs mainly during June–September through the monsoon. The mean annual rainfall in the west varies from 100 to 400 mm, while it ranges between 550 and 1000 mm in the east with annual average of 570 mm for whole state. During south west monsoon (June to September), the highest monthly rainfall occurs during July and August. Rajasthan has a predominantly agrarian society, with nearly 70 % of its population depending on agriculture and allied activities. The total cultivated area of the state encompasses about 20 million hectares, and out of this, only 20 % of the land is irrigated (State Government of Rajasthan: http://www.krishi.rajasthan.gov.in). The state has principally two crop seasons, viz., *kharif* (June to October) and *rabi* (November to March). The *kharif* crop season corresponds to monsoon period and major crops grown during it are pearl millet, sorghum, pulses, maize, and groundnut.

Vulnerability assessment framework

Many approaches have been proposed for vulnerability assessment (Cutter, et al. 2003; Hayes et al. 2004); however, there is no universally applicable metrics for vulnerability or its components (Schroter et al. 2005). Many researchers (Turner et al. 2003; Schroter et al. 2005; Fontaine and Steinemann 2009) have emphasized to describe vulnerability to be a function of three overlapping elements: exposure, sensitivity, and adaptive capacity. Such conceptual description not only helps in identification of vulnerability but also helps in identification of specific options for stakeholders to reduce that vulnerability. So in this study we adopted the vulnerability framework based on exposure, sensitivity, and adaptive capacity (Fontaine and Steinemann 2009),
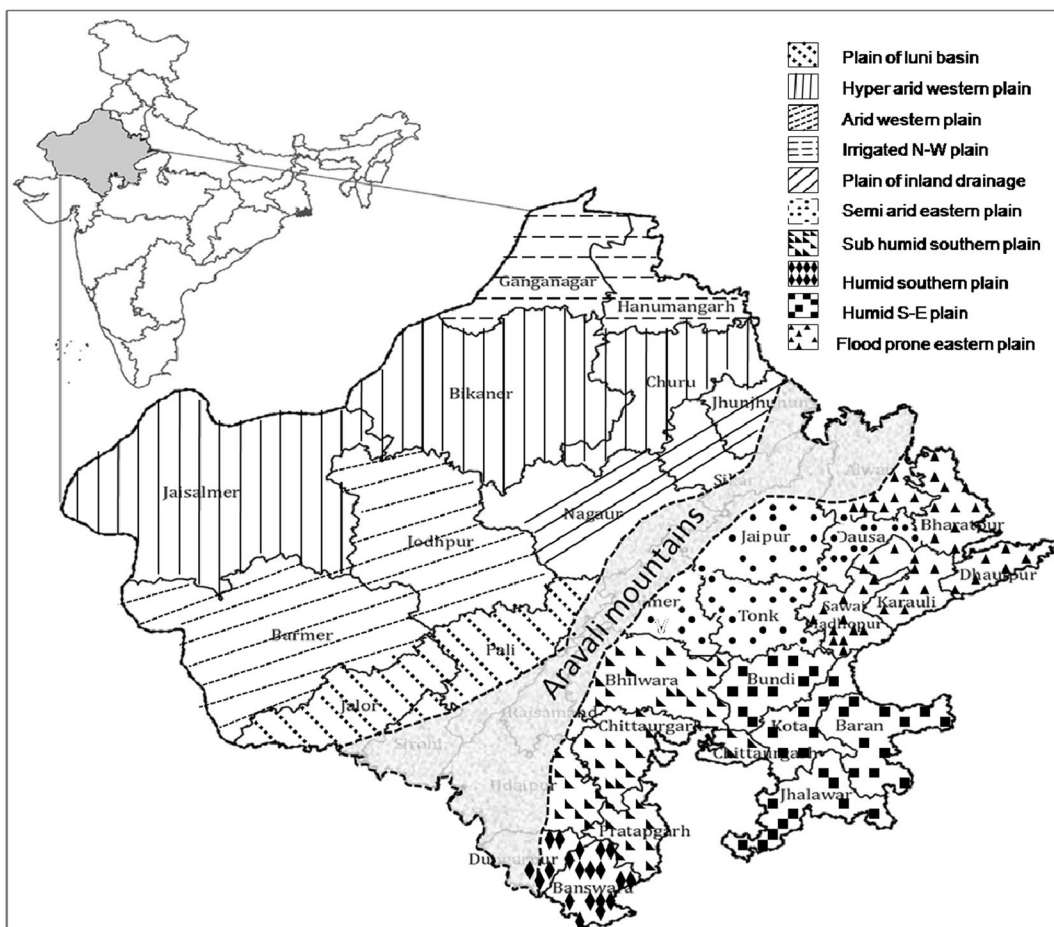

Fig. 1 Geographical location and administrative districts of the Rajasthan State

and accordingly biophysical factors contributing to exposure, sensitivity, and adaptive capacity were chosen. We used frequency and intensity of standardized precipitation index (SPI) as measures of exposure to hazard (i.e., rainfall deficit). Soil water holding capacity and frequency and intensity of vegetation condition index (VCI) based on satellite-derived NDVI were used as measures of sensitivity of cropping system. Percent irrigated area was used as a measure of adaptive capacity.

Spatial datasets

SPI

Drought is primarily caused by precipitation deficit, while secondary factors such as high temperature and high wind can contribute to amplify its intensity. The severity of drought depends upon the duration and degree of moisture stress and, to lesser extent, the size of affected area. Agricultural drought is a manifestation of meteorological drought moderated through soil moisture. SPI (McKee et al. 1993) was chosen to quantify precipitation deficit for different time scales because SPI substantially outranked among 14 indices of precipitation anomaly for their robustness, tractability, transparency, sophistication, extendibility, and dimensionality as reviewed by Keyantash and Dracup (2002). Mathematically, SPI for period i is calculated based on equation:

$$\text{SPI}_i = (X_i - X_{\text{mean}}) \big/ \sigma \qquad (1)$$

where X_i is transformed rainfall of station for period i, and X_{mean} and σ are long-term mean and standard deviation of transformed rainfall for the same period. Since precipitation is not normally distributed, the long-term precipitation record was first fitted to an incomplete gamma probability distribution, which is then transformed into a normal distribution.

The study used gridded monthly precipitation time series data constructed by Climatic Research Unit (CRU TS 3.0) at a spatial resolution $0.5 \times 0.5°$ for 1951–2006 time period (New et al. 2000; Mitchell and Jones 2005). SPI was computed spatially (gridwise) at four time scales during the main *kharif* season, namely, tri-monthly SPI_JJA (June, July, August), bi-monthly SPI_AS (August, September), bi-monthly SPI_SO (September, October), and penta-monthly SPI_JJASO (June to October) corresponding to early, mid, late, and whole periods of crop season, respectively.

Trend adjusted vegetation condition index (VCI$_{Tadj}$)

VCI was originally proposed by Kogan (1995). VCI has proven to be a useful means for measuring the drought intensity, duration, and impacts (Ji and Peters 2003; Kogan 1995). VCI separates the effect of ecology and weather on vegetation growth, while VCI$_{Tadj}$ also separates the effect of production technology. With the change in crop production technology, the VCI may also show a trend and hence shall be normalized. So, VCI$_{Tadj}$ represents better the effect of weather on vegetation vigor and proved to be an improved indicator for agricultural drought. Further details, merits and formula of VCI$_{Tadj}$ are given in Dhakar et al. (2013).

Time series of 16-day maximum value composite NOAA-AVHRR GIMMS normalized difference vegetation index (NDVI) dataset from 1982 to 2006 was used. The time series of NDVI data were filtered for residual noise. The crop phenology parameters such as start of the season (SOS), end of early season (EOES), time for the mid of season (MOS), start of late season (SOLS), end of the season (EOS), and length of the season (LOS) were computed for agricultural area during *kharif* seasons using TIMESAT (Jonsson and Eklundh 2004) to determine the timing of early, mid, late, and whole *kharif* season. Using pixel-wise phenology parameters, NDVI was integrated for early, mid, late, and whole *kharif* seasons and was used for the computation of VCI$_{Tadj}$ for corresponding season over the 24 years. The details of NDVI pre-processing, computation of phenology parameters, and VCI$_{Tadj}$ for early, mid, late, and whole periods of crop season are given in Dhakar et al. (2013).

Available water holding capacity of soils (AWHC)

The soil maps of Rajasthan at 1:500,000 scale published by National Bureau of Soil Survey & Land Use Planning (NBSS&LUP) were digitized, cleaned, mosaiced, and geocoded using ArcGIS 10.0. Soil mapping units were assigned unique *ids* and were linked to attributes of landform, texture, depth, etc. AWHC of soil was computed for each depth of the horizon in a particular soil series by the formula:

$$\text{AWHC} = (\text{FC} - \text{PWP}) \times \text{BD} \times L \times 10 \qquad (2)$$

where AWHC is available water holding capacity (mm/m) for depth L, FC is percent water retention by mass at 33 kPa equivalent to field capacity, PWP is percent

water retention by mass at 1500 kPa equivalent to permanent wilting point, BD is bulk density of soil (g/cm³), and L is depth of soil horizon (m).

AWHC values were computed for depth up to 1 m by summation of AWHC values computed for different depths and those soil series having depth less than 100 cm, the AWHC value was computed up to available depth in that series. Finally, AWHC map was converted to raster format and classified (Fig. 2).

Percent irrigated area

This study utilized the FAO Global Map of Irrigation Areas (GMIA) version 4.0.1 having spatial resolution of 5′ × 5′ (Siebert et al. 2007). Each cell of the map depicts the area equipped for irrigation as percentage of cell area around year 2000, but for India, it refers to area actually irrigated. A more detailed description of the dataset, development, and validation is given in Siebert et al. (2005). The map of percent irrigated area for Rajasthan is shown in Fig. 3.

Scoring of indicators

Because of the different scales upon which criteria are measured, it is necessary that indicators be standardized before combination in equations and that they be transformed, if necessary, such that all indicators are positively correlated with vulnerability. Voogd (1983) reviewed a variety of procedures for standardization, typically using the minimum and maximum values as scaling points and then dividing them linearly into a fixed number of classes. The use of five class division (very low, low, moderate, high, and extreme) is most common in vulnerability assessment studies (Prathumchai et al. 2001; Fontaine and Steinemann 2009). In this study also, each indicator was classified into five uniform classes using its minimum and maximum value to assign the score (Table 1). A five-point ordered scale was used to rank each factor from very low to extreme value. The value 0 was left in scaling to define mask value. Thus, each factor was having an equivalent measurement basis or scale before any weight was applied. The score was assigned to the indicators according to their functional relationship with vulnerability, i.e., if the indicator was directly related to vulnerability, higher ranks were given for higher values. However, in case the indicator was inversely related, lower ranks were given for higher values.

Drought hazard exposure

Methodology flow chart for the computation of drought hazard exposure map is shown in Fig. 4. SPI was used as

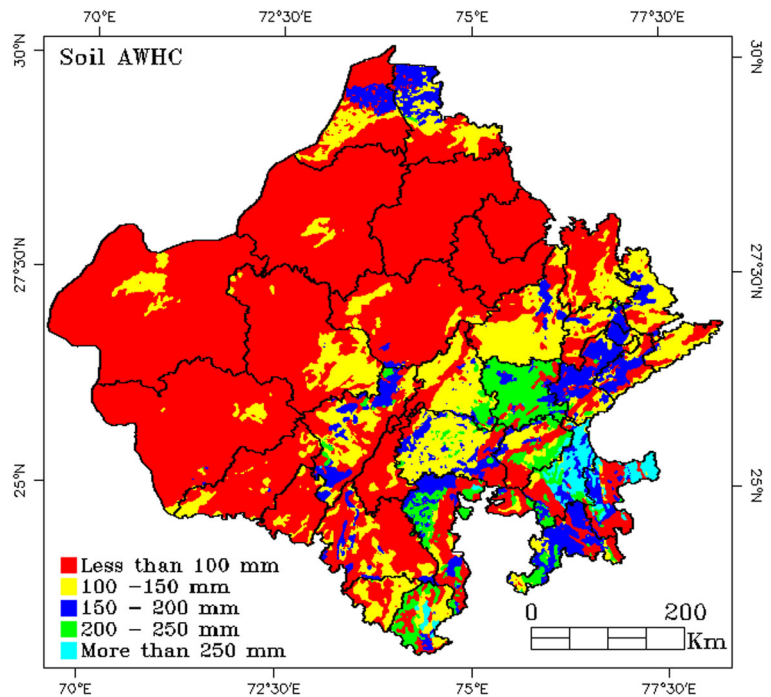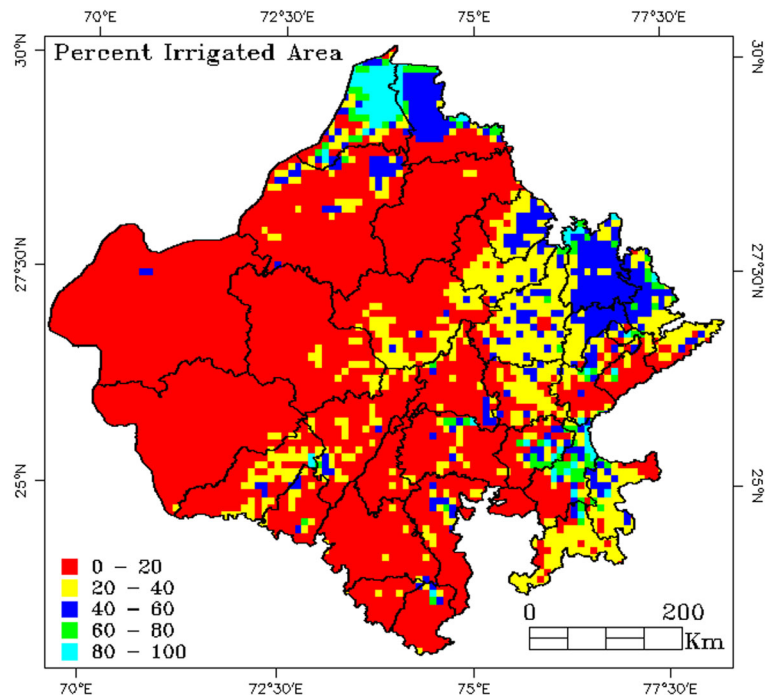Fig. 2 Map of available water holding capacity (AWHC) of soil of Rajasthan

Fig. 3 Map of percent irrigated area for Rajasthan

an index of meteorological drought (McKee et al. 1993). The drought hazard exposure was computed as a weighted sum of meteorological drought frequency and intensity during the 56-year period from 1951 to 2006. The frequency denoted probability of rainfall deficit, while intensity denoted severity of rainfall deficit. A five-point scale (very low, low, moderate, high, and extreme) was used to standardize the two components (Table 1). The component scores were combined as given below to generate drought hazard exposure rating.

$$H = w \times F + (1-w) \times I \qquad (3)$$

where H is the score of drought hazard exposure, F is the score of meteorological drought frequency, I is the score of meteorological drought intensity, and w is the weight.

Meteorological drought frequency was calculated as number of years when value of SPI reached −1 or below during the 56-year period. Similarly, meteorological drought intensity was calculated as a sum of SPI values when it reached −1 or below during the 56-year period. Frequency and intensity were calculated gridwise separately for early, mid, late, and whole *kharif* seasons. Equal weights were assigned to drought frequency and intensity to compute hazard exposure score. The output drought hazard exposure score also varied between 1 and 5, from very low to extreme.

Agricultural drought sensitivity

Flow chart describing steps followed in computation of agricultural drought sensitivity map is shown in Fig. 5. Agricultural drought sensitivity was computed as a weighted sum of agricultural drought frequency and intensity during the 24-year period from 1982 to 2005. The agricultural drought was identified in terms of VCI_{Tadj} computed using integrated NDVI over crop period. The frequency denoted the probability of agricultural drought, while intensity denoted severity of agricultural drought, both indicating sensitivity of crops to stress. The values of agricultural drought frequency and intensity for each rating scale and their scores for vulnerability assessment are given in Table 1. The component scores were combined as given below to generate agricultural drought sensitivity rating.

$$S = w \times P + (1-w) \times A \qquad (4)$$

where S is the score of drought sensitivity, P is the score of agricultural drought frequency, A is the score of agricultural drought intensity, and w is the weight. Frequency of agricultural drought was calculated as number of years out of total valid years when VCI_{Tadj} reached below 50 %. The normalized intensity of drought was calculated as a sum of VCI_{Tadj} divided by number of total valid years. A year was deemed valid for a pixel when VCI_{Tadj} could be calculated

Table 1 Vulnerability scoring system showing ranking scale, value, and score of each variable used

Variables	Ranking scale	Value	Score
Soil AWHC	Very low	<100 mm	5
	Low	100–150 mm	4
	Moderate	150–200 mm	3
	High	200–250 mm	2
	Extreme	>250 mm	1
Percent irrigated area	Very low	0–20 %	5
	Low	20–40 %	4
	Moderate	40–60 %	3
	High	60–80 %	2
	Extreme	80–100 %	1
Hazard frequency	Extreme	>11	5
	High	10–11	4
	Moderate	8–9	3
	Low	6–7	2
	Very low	≤5	1
Hazard intensity	Extreme	< −16	5
	High	−16 to −14	4
	Moderate	−14 to −12	3
	Low	−12 to −10	2
	Very low	≥ −10	1
Agricultural drought frequency	Extreme	>0.65	5
	High	0.55–0.65	4
	Moderate	0.45–0.55	3
	Low	0.35–0.45	2
	Very low	≤0.35	1
Agricultural drought intensity	Extreme	≤35 %	5
	High	35–45 %	4
	Moderate	45–55 %	3
	Low	55–65 %	2
	Very low	>65 %	1

for it. Because for some pixels phenology could not be identified by TIMESAT in all the 24 years, so as to normalize the count and sum of VCI_{Tadj}, the count and sum were divided by the total number of years for which VCI_{Tadj} could be calculated. So, in effect, frequency was represented by proportion of years, while intensity was represented by mean value of VCI_{Tadj}. Equal weight was assigned to agricultural drought frequency and intensity to compute drought sensitivity because both have equal relative importance. The output agricultural drought sensitivity score also varied between 1 and 5, from very low to extreme.

Agricultural drought vulnerability

Flow chart describing steps followed in computation and mapping of agricultural drought vulnerability is shown in Fig. 6. The vulnerability maps of agricultural drought were generated separately for early, mid, late, and whole *kharif* seasons for Rajasthan State compositing score maps of six factors: (1) frequency of drought hazard exposure, (2) intensity of drought hazard exposure, (3) frequency of agricultural drought, (4) intensity of agricultural drought, (5) available water holding capacity of soils, and (6) percent irrigated area. All the six factors were brought to same spatial scale and geographical extents using polynomial warping and nearest neighbor resampling.

Generally, two main issues are faced during compositing of factors: (a) removing biasness of scale among factors and (b) determination of weights for each of the factors. In our case, the five-point ordered scale ranking removed the biasness among scales. For calculating weights of individual factors, multi-criteria evaluation (MCE) with linear combination weighting system (LCWS) was implemented (Saaty 1980) using IDRISI GIS software (Eastman et al. 1995). The software module named WEIGHT in IDRISI GIS was used to generate pairwise comparison matrix and calculate its principal eigenvector directly to produce best fit set of weights as shown in Table 2. Expert judgment was used to define the pairwise importance of each of the two indicators. The degree of consistency that has been used in developing weights is indicated by an index called "consistency ratio" (Saaty 1977). A low consistency ratio of 0.01 obtained indicates that weights were not generated randomly (Table 2). Once the scores were standardized and weight established for factors, weighted linear combination method was applied to develop the drought vulnerability map for early, mid, late, and whole *kharif* seasons, varying from 1 to 5 (1 = very low, 2 = low, 3 = moderate, 4 = high, and 5 = extreme).

Validation of drought vulnerability rating

Crop productivity, human infrastructure, and socioeconomic conditions (e.g., health, income, education, and nutrition) are fairly linked with drought vulnerability (Wilhelmi and Wilhite 2002). As there was no way of directly measuring the drought vulnerability rating at local scale, it was validated indirectly at district scale by comparing it with independent datasets of food grain
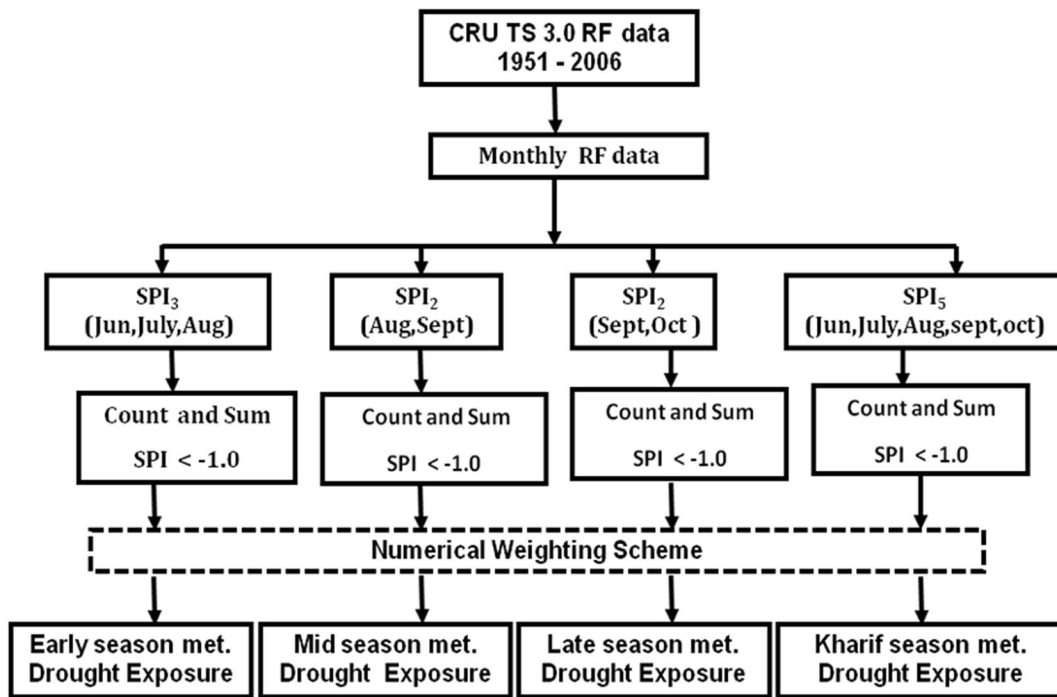
Fig. 4 Flow chart showing steps for computing drought hazard exposure

productivity, socioeconomic indicator of human development index (HDI) (UNDP 2009), recurrence period of drought, and percent damaged crop area in drought year 2009. The districtwise food grain productivity values between 2003 and 2006 were taken from the published reports of the Directorate of Economic & Statistics, Department of Agriculture, Government of Rajasthan,

Jaipur. The HDI is computed as a mean value of three broad socioeconomic variables: income, education, and health status and the underlying assumption is that area with high drought vulnerability shall lead to poor socioeconomic conditions of its population. Districtwise HDI values pertaining to 2000s were taken from the Human Development Report published by Institute of

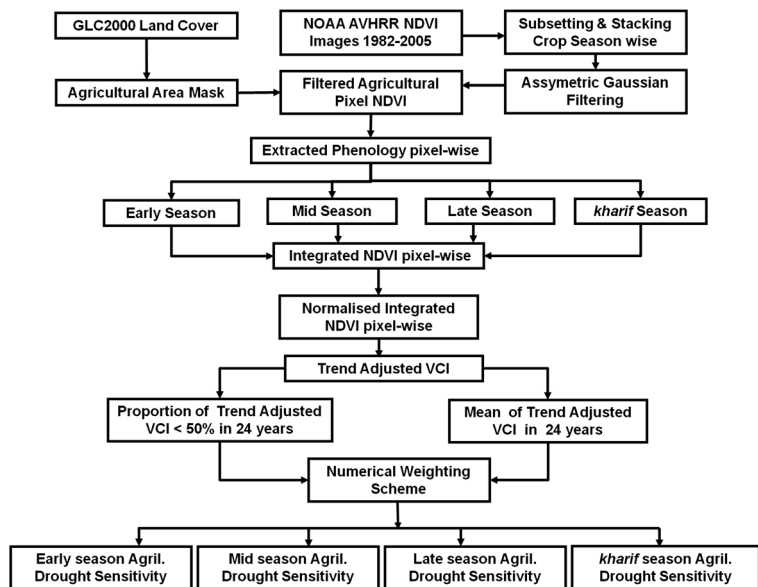**Fig. 5** Flow chart showing steps for computing agricultural drought sensitivity
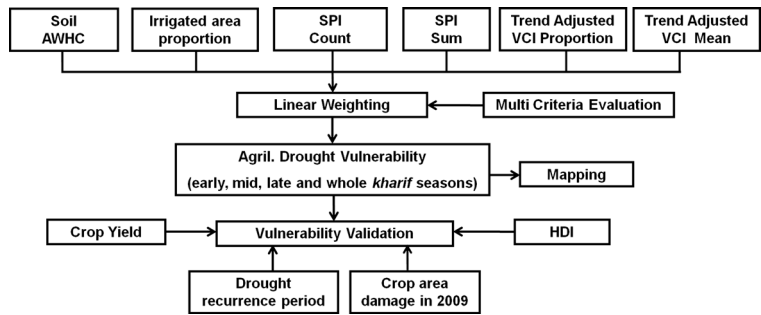
Fig. 6 Flow chart showing computation of environmental drought vulnerability

Development Studies, Jaipur for Government of Rajasthan. The drought recurrence frequency (in years) was taken from the website of Disaster Management & Relief Department, Government of Rajasthan, which is computed based on historical drought events (http://www.dmrelief.rajasthan.gov.in/index.php/irrigation-calender/frequency-of-drought). The percent damaged crop area in drought year 2009 was also taken from the website of Disaster Management & Relief Department, Government of Rajasthan (http://www.dmrelief.rajasthan.gov.in/documents/ext2066.xls). So, the average districtwise vulnerability rating was computed for each of the four seasons and statistically correlated with all the four independent datasets.

Results

Available water holding capacity of soils

The reclassified map of AWHC of soils in Rajasthan is shown in Fig. 2, and it indicates that majority of soils of Rajasthan have very low to low water holding capacity. Very low, low, moderate, high, and extreme classes of

Table 2 Weights derived by calculating the principal eigenvector of the pairwise comparison matrix

Factors	Weights
Soil AWHC	0.0474
% irrigated area	0.3350
Hazard frequency	0.1112
Hazard intensity	0.1112
Agricultural drought frequency	0.1976
Agricultural drought intensity	0.1976

Consistency ratio = 0.01 (< 0.1 is acceptable, Saaty (1980))

AWHC account for 67.6, 18.26, 8.23, 4.49, and 1.41 % area of state, respectively. The AWHC of soils, in general, is increasing from western to eastern districts.

Percent irrigated area

The reclassified map of percent irrigated area, shown in Fig. 3, indicates wide variations in the state. Out of total geographical area of state, 69.7, 17.0, 9.0, 2.1, and 2.1 % area are having 0–20, 20–40, 40–60, 60–80, and 80–100% irrigated area, respectively. This signifies that majority of area is either unirrigated or partially irrigated, mostly spread across western, central, and southern parts. The irrigated area is mainly concentrated in northern districts of Sriganganagar and Hanumangarh, eastern districts of Alwar, Dausa, and Bharatpur, and southeastern districts of Kota and Baran.

Drought hazard exposure

Drought hazard exposure varied from 1 to 5, and higher score means higher is the drought exposure resulting in higher vulnerability. The drought hazard exposure maps for early, mid, late, and whole *kharif* seasons are shown in Fig. 7. They indicate that majority of the region experience moderate to low exposure during early season, late season, and whole season, whereas majority of the region experience moderate to high drought exposure during mid season. There is a clear east–west divide in drought exposure across the Aravalli ranges (Fig. 1) in early season with generally lower values in east and higher in west. During early season, extreme to high exposure is observed in northern and southwestern districts. During mid season, most districts are showing high to extreme drought exposure. During late season, reverse trend is seen in eastern districts with extreme to
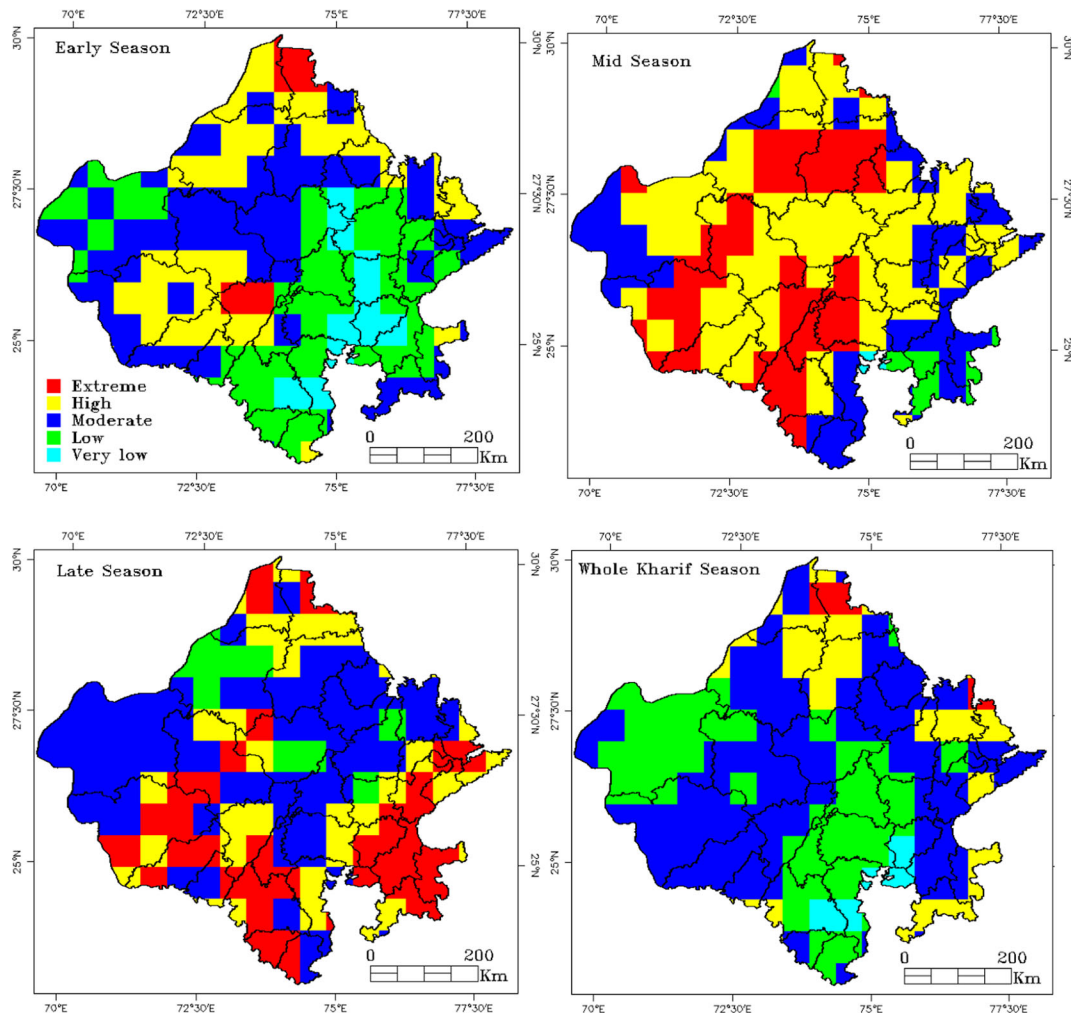
Fig. 7 Drought hazard exposure maps for early, mid, late, and whole *kharif* seasons

high exposure. During whole *kharif* season, most districts fall in moderate category of drought exposure.

Table 3 shows the percent of state area under each class of drought exposure in the four seasons. The results indicate that drought exposure is low to moderate in whole season but high to extreme exposure is occurring in significant areas in early, mid, and late seasons.

Agricultural drought sensitivity

Agricultural drought sensitivity varied from 1 to 5, and higher score means higher is the drought sensitivity resulting in higher vulnerability. The agricultural drought sensitivity maps for early, mid, late, and whole *kharif* seasons are shown in Fig. 8. Wide variations are observed in drought sensitivity in all the districts in four

seasons, but the spatial patterns are similar in early, mid, and whole seasons. Figure 8 shows domination of moderate to high sensitivity during early, mid, and whole seasons but domination of high to extreme sensitivity during late season. Occurrence of high to extreme sensitivity is seen in areas which are at the transition of eastern semiarid to western arid regions in early, mid, and whole seasons. The late season, in comparison to other seasons, shows higher occurrence of moderate to low sensitivity in eastern districts, while high to extreme sensitivity dominates in all other regions.

Table 4 shows the percent of net sown area under different classes of agricultural drought sensitivity in the four seasons. Overall, it indicates that substantial areas of about 50 % experience extreme to high drought sensitivity in all the four seasons.

Table 3 Percent of net sown area experiencing different drought hazard exposure during early, mid, late, and whole *kharif* seasons

Drought exposure	Percent of net sown area of State			
	Early season	Mid season	Late season	Whole season
Very low	7.79	0.25	1.44	3.16
Low	28.56	5.20	30.59	30.78
Moderate	36.52	43.45	33.63	51.06
High	23.61	28.58	22.34	13.32
Extreme	3.52	22.52	12.02	1.69

Agricultural drought vulnerability

Agricultural drought vulnerability maps are shown in Fig. 9. Higher score means higher drought vulnerability.

Wide variations are observed in drought vulnerability in all the districts in four seasons, but the spatial patterns are similar in early, mid, and whole seasons. The maps indicate that the agricultural drought vulnerability is increasing from eastern to western parts of state in all the four seasons. High vulnerability rating is occurring in maximum area in all the four seasons, and the next dominant rating class is extreme vulnerability. The low vulnerability is mostly occurring in districts having high percent irrigated areas, such as Sriganganagar and Hanumangarh in northwest, Alwar, Bharatpur, and Dausa in east, and parts of Kota, Baran, and Jhalwar in southeast. Moderate vulnerability is mostly occurring in districts lying east of Aravalli ranges, such as Ajmer, Jaipur, and Sikar, having about 20 to 40 % irrigation. High and extreme vulnerability is occurring in areas mostly west of Aravalli ranges and in southern plain
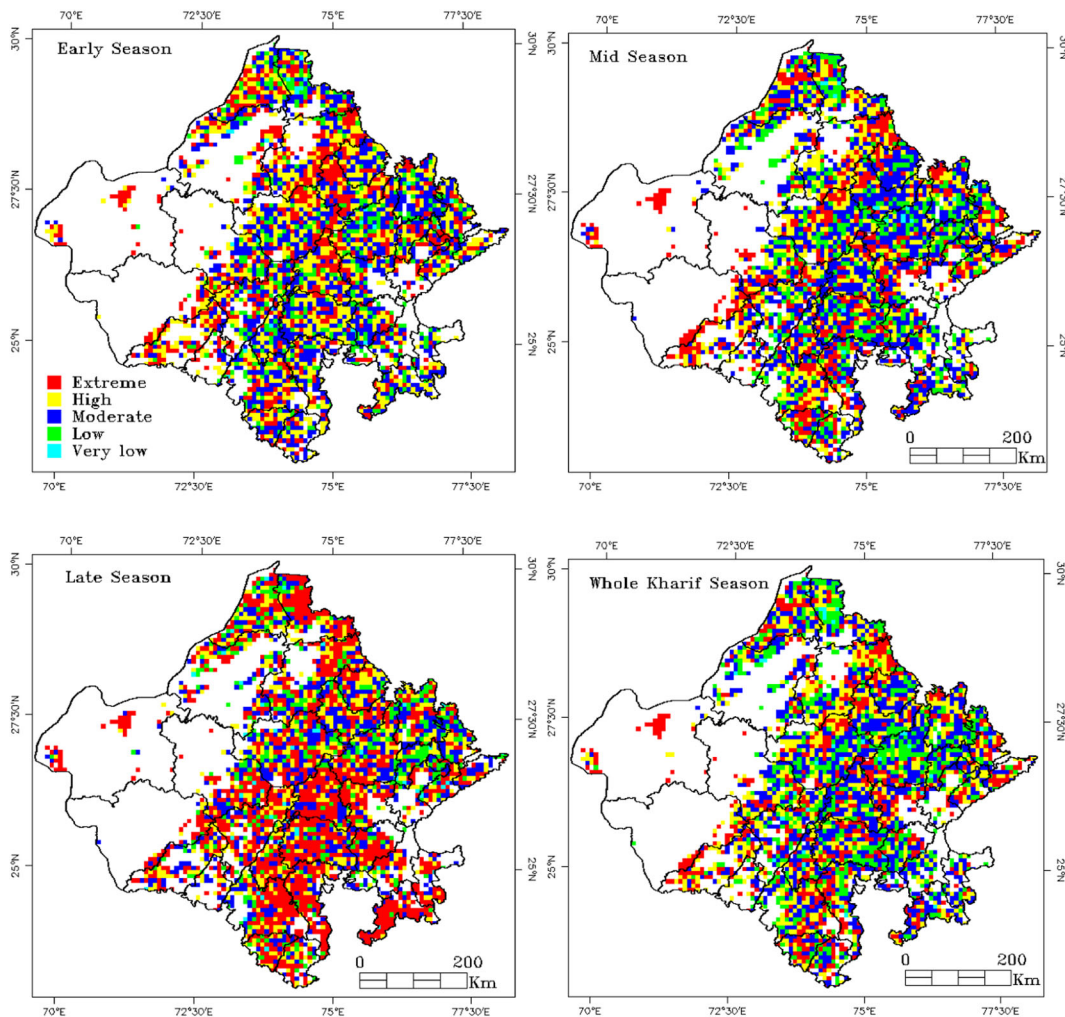

Fig. 8 Agricultural drought sensitivity maps for early, mid, late, and whole *kharif* seasons

Table 4 Percent of net sown area experiencing different agricultural drought sensitivity during early, mid, late, and whole *kharif* seasons

Agricultural drought sensitivity	Percent of net sown area of State			
	Early season	Mid season	Late season	Whole season
Very low	0.74	0.68	1.22	0.98
Low	12.70	17.25	12.00	19.76
Moderate	31.48	34.06	23.10	32.24
High	29.61	24.68	20.27	24.71
Extreme	25.48	23.33	43.42	22.31

districts. These western districts are Churu, Nagaur, Bikaner, Jodhpur, Pali, Jaisalmer, Barmer, Jalore, Sirohi, and Jaisalmer, while southern districts are Dholpur, Karauli, and Sawai Madhopur.

During early season, extreme vulnerability is occurring in Churu, Jhunjhunu, Pali, Jodhpur, Barmer, Jalore, Bikaner, and Jaisalmer districts, while low to very low vulnerability is occurring in parts of Kota, Bundi, Baran, and Tonk districts. Many areas which were showing high vulnerability in early season were showing extreme vulnerability in mid season especially in southern districts. The districts showing extreme vulnerability in mid season are Churu, Nagaur, Jodhpur, Barmer, Jaisalmer, Jalore, Udaipur, Dungarpur, Sirohi, Rajsamandh, and Ajmer. During late season, like mid season, high to extreme vulnerability dominates but during this season even south eastern districts of Kota, Baran, Bundi, and Jhalawar are showing extreme vulnerability. Low
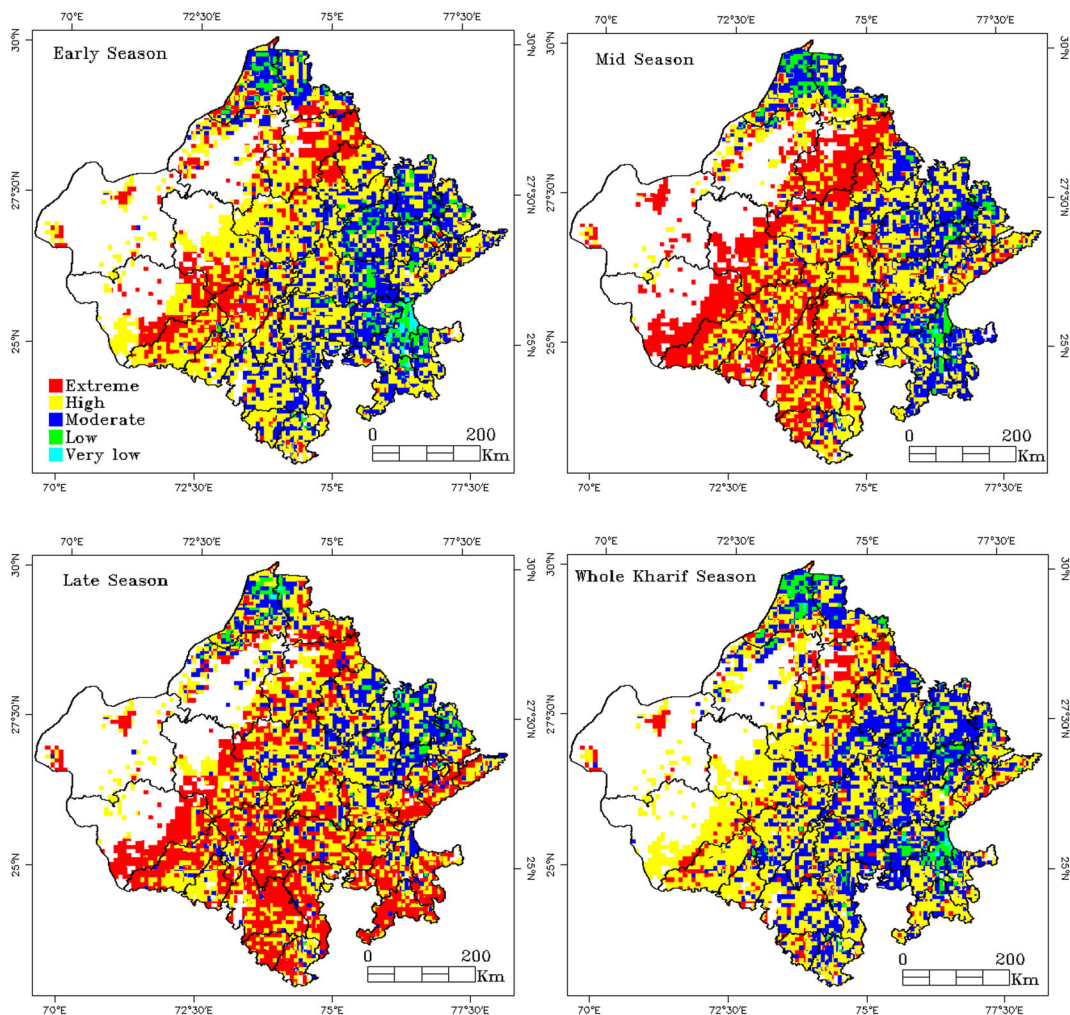

Fig. 9 Agricultural drought vulnerability maps for early, mid, late, and whole *kharif* seasons

vulnerability is seen in few areas, mostly concentrated in northern and north eastern districts, having sufficient irrigation. During whole *kharif* season, the spatial pattern of vulnerability has similarity to early season vulnerability, but many extreme vulnerability class areas in early season shifted to high vulnerability class areas. The extreme vulnerability is mostly scattered in districts of Churu, Jaisalmer, Barmer, and Jalore. High vulnerability is occurring in many districts of western, central, southern, southeastern, and eastern parts of state comprising of districts of Churu, Jhunjhunuh, Sikar, Nagaur, Bikaner, Jodhpur, Barmer, Pali, Jalore, Sirohi, Udaipur, Dunagrpur, Dholpur, Karauli, Sawai Madhopur, Jhalawar, and parts of Kota and Baran.

The percent of net sown area under different classes of agricultural drought vulnerability in four seasons for Rajasthan State is shown in Fig. 10. It indicates that substantial agricultural areas experience extreme to high drought vulnerability in all the four seasons especially during mid and late seasons. Percent of net sown area under different agricultural drought vulnerability ratings for four seasons was also calculated districtwise by overlaying district agricultural area mask of each district. Table 5 shows the list of top five and lowest five vulnerable districts in early, mid, late, and whole *kharif* seasons.

Validation of agricultural drought vulnerability rating

The vulnerability rating showed significant negative correlations with food grain productivity, with HDI, and with drought recurrence period in all the seasons at district level (Table 6). It indicates that districts showing higher vulnerability have lower food grain productivity, shorter drought recurrence period as well as lower HDI and vice versa. A significant positive correlation was observed between vulnerability rating and damaged crop area indicating that in drought year 2009, more crop area was impacted in districts with higher

vulnerability and vice versa. The correlation coefficient with food grain productivity was generally highest, followed closely by damaged crop area. The correlation was comparatively lower with drought recurrence period and least was with HDI. In general, the correlation was higher for early and mid season and lowest for late season, except for HDI. The correlation coefficient with HDI was nearly same over all the seasons.

Discussion

This study was carried out with the main aim of assessing and mapping biophysical vulnerability of agriculture crops to drought in Rajasthan at local scale, i.e., much below a block level. Most of the studies reported in literature either assessed vulnerability at national/regional scales (Fontaine and Steinemann 2009) or at district scale (Wu and Wilhite 2004; Shahid and Behrawan 2008). Recently, Murthy et al. (2015) have assessed drought vulnerability at block scale (subdistrict administrative unit) but not at finer scale. The assessment and mapping of vulnerability at finer scales have more relevance to agencies which are formulating and implementing mitigation schemes at ground level. In order to achieve fine resolution, it was imperative to use drought impact indicators at that resolution which necessitated the use of remote sensing-based indicators of drought. We made use of high spatial resolution remote sensing and other datasets of biophysical factors in a GIS environment so that fine scale assessment could be made and presented as maps. Brooks et al. (2005) have also emphasized the need to use locally contextual indicators to yield full picture of vulnerability because hazard events operate at local levels also. Most of other studies have demonstrated use of GIS for integration of various layers for vulnerability assessment (Wilhelmi and Wilhite 2002; Prathumchai et al. 2001; Slejko et al. 2009), but very

Fig. 10 Percent of net sown area of State under different categories of biophysical agricultural drought vulnerability for early, mid, late, and whole *kharif* seasons
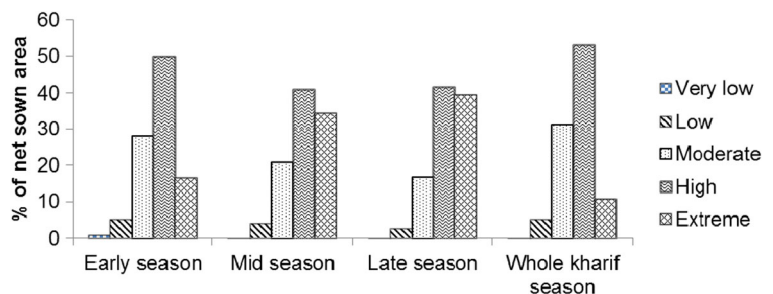
Table 5 List of top five and lowest five vulnerable districts of Rajasthan to agricultural drought in early, mid, late, and whole *kharif* seasons

Season	Top five vulnerable district	Lowest five vulnerable districts
Early	Barmer, Churu, Jalore, Jaisalmer, Pali	Jaipur, Alwar, Tonk, Bundi, Kota
Mid	Barmer, Churu, Jaisalmer, Jodhpur, Rajsamand	Jhalawar, Sriganganagar, Baran, Dausa, Kota
Late	Barmer, Dungarpur, Udaipur, Rajsamand, Jhalawar	Bharatpur, Sriganganagar, Dausa, Alwar, Kota
Whole	Jaisalmer, Churu, Barmer, Jalore, Sirohi	Alwar, Sriganganagar, Bundi, Dausa, Kota

few have used satellite remote sensing data for deriving factor for use in vulnerability assessment as has been the case in this study.

Since the primary focus of this study was to understand the impact of drought on agricultural sector in Rajasthan, we undertook vulnerability assessment not only for main *kharif* season but also assessed its intra-seasonal variations, i.e., during early, mid, and late seasons. Intra-seasonal variations are important because each crop stage has its own sensitivity to water availability/stress. Such vulnerability assessment should better help in formulation of area-specific appropriate crop contingency plans depending on which part of the crop season is impacted more by drought (Srinivasarao et al. 2015). Though many other studies have reported assessment of vulnerability to agricultural drought (Wilhelmi and Wilhite 2002; Slejko et al. 2009), only one study by Wu and Wilhite (2004) has demonstrated phenological stagewise crop-specific drought risk assessment. So, this study on intra-seasonal vulnerability assessment may be among the firsts in this direction.

Drought exposure in this study refers to the probability and severity of water scarcity due to natural causes during crop season and thus takes care of precipitation deficit effects on crops. Because climate of Rajasthan State is arid to semiarid with mean annual rainfall of 570 mm, the deficiency in precipitation is the most important factor to account for exposure to hazard.

Drought exposure was quantified in terms of frequency and intensity of SPI over the 56-year period. To compute drought exposure for early, mid, late, and whole seasons as per the study objectives, SPI was the natural choice because it can be computed over different time scales (McKee et al. 1993). Shahid and Behrawan (2008) have also made use of SPI in GIS for computing drought hazard in different time steps spatially for western part of Bangladesh. Wu and Wilhite (2004) demonstrated a model of crop-specific drought risk based on phenological stagewise computation of SPI.

Sensitivity of agriculture to drought impacts in this study has been captured by two factors: (a) water holding capacity of soils and (b) frequency and intensity of VCI_{Tadj}. The soil water holding capacity was used to identify soils with different abilities to buffer crops during periods of deficient moisture. A soil with lower water holding capacity results in higher vulnerability to drought. Many other studies have used soil water holding capacity or its properties to assess drought vulnerability (Wilhelmi and Wilhite 2002; Prathumchai et al. 2001). In Rajasthan, majority of soils have low to moderate water holding capacity mainly on account of sandy texture and mineralogy thus contributing to enhancing the impacts of droughts on crops. The satellite vegetation index essentially captures the health/greenness of crops and thus can account for the affect of water stress on crop growth till that point in time. So, crop or

Table 6 Correlation coefficients (r) of agricultural drought vulnerability rating with district-level average food grain productivity, human development index (HDI), drought recurrence period, and percent crop area damaged in 2009

Season	Food grain productivity	HDI	Drought recurrence period	Damaged crop area in 2009
Early season	−0.74[b]	−0.34[a]	−0.53[b]	0.65[b]
Mid season	−0.70[b]	−0.42[b]	−0.46[b]	0.68[b]
Late season	−0.40[b]	−0.46[b]	−0.23	0.36[a]
Whole season	−0.62[b]	−0.45[b]	−0.38[b]	0.71[b]

[a] Significant at 0.05 level ($N = 32$)

[b] Significant at 0.01 level ($N = 32$)

vegetation condition index was used as an indicator for sensitivity of crops to drought in an area. Remote sensing data-based VCI_{Tadj} efficiently captures the impact of water availability on crop growth (Dhakar et al. 2013). So, an index based on frequency and intensity of VCI_{Tadj} in 24-year period was chosen as an indicator of agricultural drought sensitivity.

Adaptive capacity is the property of a system to adjust its characteristics or behavior, in order to expand its coping range under varying climate conditions. Adaptive capacity of farmers to drought depends on a range of factors, such as improved technological intervention of crop production, policy framework of incentives for adaptation, access to financial instruments of risk transfer, early warning and preparedness system, etc. In this study, we used the percent irrigated area biophysical factor as a measure of adaptive capacity to offset the harmful effects of water shortage on crops. There is no unanimity among the researchers whether irrigation decreases or increases vulnerability to drought (Opie 1989; Jackson 1991). During the long-term and/or severe droughts, farmers may be inflicted with higher charges of water and energy for irrigation and may cause higher cost of crop production for them. However, in general, during a short-term drought, protective irrigation insulates the farmers from total crop loss and thus reduces the vulnerability to drought (Wilhelmi and Wilhite 2002). In this study, the assumption that area equipped with irrigation is negatively related to agricultural drought vulnerability was based on the fact that irrigated areas have better adaptive capacity to cope with a short-term drought conditions relative to dryland/rainfed areas. The non-significant correlation observed between SPI and VCI_{Tadj} for irrigated areas proved that irrigation significantly mitigate the impact of drought on crops in Rajasthan (Dhakar et al. 2013). In Rajasthan State, though irrigation is available through a variety of sources, majority of areas are either unirrigated or marginally irrigated. Only northern districts of Hanumangarh and Sriganganagar, eastern districts of Alwar, Dausa, and Bharatpur, and southeastern districts of Kota and Baran practice irrigated agriculture. So, lack of irrigation is one of the main reasons of dependence of crops on rainfall thus contributing highly to their vulnerability to drought.

The drought vulnerability maps showed that vulnerability of crop areas to drought is increasing from eastern to western parts of Rajasthan. This may be on account of low to moderate drought hazard and

sensitivity, comparatively moderate to high soil water holding capacity, and higher percent of irrigation in eastern region than in western region. More than 60 % of net sown area showed extreme to high vulnerability in the state across all the seasons. These are the areas which need immediate attention of policy makers for introduction of suitable drought mitigation measures and budgetary provisions. Only less than 5 % of net sown area in state has low vulnerability to drought. Such areas may have low vulnerability and better prepared for short-term droughts but may also suffer negative impacts in long term or severe droughts as was the case in 2002. The study showed that moderate drought vulnerability is occurring in 17 to 31 % of net sown area, in proximity of areas with low vulnerability. Unlike areas showing extreme to high vulnerability where introduction of new drought measures are suggested requiring financial provisions, the areas with moderate drought vulnerability only require suitable modification of existing mitigation measures without incurring extra cost.

In all the seasons, very low to low vulnerability class occurred mostly in southeastern, northwestern, and few pockets of northeastern regions but accounts for less than 5 % of net sown area. For the most part, this class follows the pattern of irrigated areas with scattered patches in southwestern districts of Kota and Baran where soils have high water holding capacity also. The presence of irrigation and clay loam type soils with higher water holding capacity provides a good buffer for crops during periods of deficient moisture. Such areas may have low vulnerability and better prepared for short-term droughts but may also suffer negative impacts in long-term droughts. Even though northern districts of Ganganagar and Hanumangarh have high to extreme drought exposure and moderate to low water holding capacity of soils, they show very low vulnerability class in all seasons mainly because they are intensively canal irrigated with 80 to 100 % area under irrigation.

The moderate class of vulnerability which accounts for 17 to 31 % of net sown area generally occurred close to low vulnerability areas in eastern, central, and southern districts in patches where water holding capacity is between 100 and 150 mm and percent irrigated area is between 20 and 40 %. Besides, the low to moderate drought exposure and sensitivity in this area may be contributing to moderate vulnerability. The moderate sensitivity of crops may be on account of partial access

to irrigation and growing of millets and pulses which have better tolerance to water stress.

The high to extreme vulnerability classes accounted for maximum proportion of net sown area. The high class area ranged between 41 and 53 %, while extreme class area ranged between 11 and 39 %. More area showed extreme vulnerability during mid and late seasons than early and whole seasons. It may be on account of higher exposure during mid season and higher sensitivity during late season. High and extreme vulnerability classes occurred mainly in western, central, and southern regions of state which have soils of low water holding capacity (less than 100 m) with coarse texture, little access to irrigation, high to moderate drought exposure, and high sensitivity of crops. These are the areas which need immediate attention of policy makers for introduction new locally suitable adaptation and mitigation measures.

Schroter et al. (2005) have emphasized the need for validation of vulnerability ratings by comparing the results with the institutions of stakeholders, historical examples of exposure to stress, or using data based on observations. The scope of this study did not allow for undertaking any of the suggested methods, but we validated our vulnerability rating vicariously at district level by comparing them with independent datasets of average food grain productivity, recurrence period of drought, crop area damaged in 2009 drought year, and socioeconomic indicator of HDI. Statistically significant correlations with all indicators, both environmental and socioeconomic, during all the seasons indicated the general soundness of the methodology demonstrated in this study. The vulnerability rating relating significantly with even future drought impacts further supports the selection of vulnerability indicators and applicability of methodology.

Conclusions

This study demonstrated a methodology to assess and map agricultural drought vulnerability of Rajasthan State for main *kharif* crop season. It also showed the importance and way of accounting for intra-seasonal variations in vulnerability. The methodology only assessed biophysical/environmental vulnerability not accounting for socioeconomic factors contributing to drought vulnerability. Use of remote sensing-derived indicators of crop sensitivity to drought helped in producing vulnerability ratings at local scales which have

better relevance to agencies involved at ground level in drought adaptation and mitigation.

The map of agricultural drought vulnerability may be a first objective assessment of drought vulnerability in Rajasthan at locale scale. The maps synthesized a variety of biophysical data as indicators of drought hazard exposure, sensitivity, and adaptive capacity. The output vulnerability maps helped in identification of agricultural areas having high to extreme vulnerability in early, mid, late, and whole season thus needing immediate attention of policy makers and stake holders.

An important insight gained through this study is that agricultural drought vulnerability has within season variations, and the whole season vulnerability may be moderated due to time scale considered thus underrepresenting extreme vulnerability areas. In Rajasthan, it has been observed that mid season agricultural drought vulnerability is higher than in early, late, and whole seasons. Such information helps in prioritizing crop contingency planning to better prepare for drought situation.

Even though the study has limitation of not including socioeconomic factors in vulnerability assessment, but comparison of vulnerability rating with human development index based on income, education, and health status showed a general applicability of vulnerability rating in accounting for some of the effects of socioeconomic factors on drought vulnerability. The significant correlation of vulnerability rating with food grain productivity, recurrence period of drought, and damaged crop area in a future drought year validated the methodology. Overall, this study on drought vulnerability is expected to lead to replication of proposed methodology to other agricultural areas of the world in same or improved format so that better preparedness and mitigation-oriented drought management could be attempted.

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