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Identifying prospects and potential areas for introducing pearl millet stress-tolerant cultivars in Rajasthan, India: A geospatial analysis

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A R T I C L E I N F O

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A B S T R A C T

Dryland crops are highly prone to various stresses such as water stress (drought) and heat stress. The identification of stress-prone regions is crucial for effective and efficient implementation of appropriate solutions, such as stress-tolerant crop varieties. This study was conducted in Rajasthan state located in North-western India. Rajasthan is predominantly a rainfed pearl millet ecosystem (>50 % during monsoon season) in India. The pearl millet productivity in Western Rajasthan is the lowest in India with a significant decline in its cultivated area. The present study tried to analyse the pearl millet cropping systems in various ecologies and identified the stress-prone areas by analysing the stress pattern from 2011 to 2020 which helps in targeting the stress tolerant cultivars. The spatial distribution of pearl millet areas was mapped using Sentinel-2 time-series data and spectral matching techniques. The mapped pearl millet areas were well correlated with district-level statistics obtained from secondary sources. Application of geospatial techniques for monitoring changes in pearl millet cropped area proves to be a cost-effective, and reliable approach. It also helps in assessing the cultivated area changes as well as the quantification of yield losses caused by abiotic stresses such as drought and heat. Agricultural research institutes, progressive farmers and line departments from the government can use these findings for better targeting and introduction of climate SMART pearl millet technologies in the state. Introduction of resilient technologies minimize the production risks faced by small and marginal farmer thereby reduces the crop income negative deviations. Scaling-up of such technologies not only protects farmer's livelihoods but also enhances the food and nutritional security in the state.

Introduction

As per 2011 census, Rajasthan was India's largest state, covering around 10.4 % of the country's area and housing nearly 6 % of its population [25]. The state boasts diverse landscapes, with four main regions: the western desert with barren hills, rocky plains, and sandy terrain; the eastern plains with fertile alluvial soils; the Aravalli hills extending from Gujarat to Delhi; and the south-eastern plateau [45]. Rajasthan experiences varying weather conditions and soil types, offering diverse agro-climatic situations [10]. Approximately 65 % of the population, about 56.5 million depend on agriculture which heavily relies on monsoons and canal irrigation. However, the extensive dryland areas pose greater risks and instability to agricultural production [28].

The introduction of drought-tolerant millet cultivars is ideal for protecting the millet cultivation in the state [48]. Millets are cultivated across India, covering around 15.48 m ha [41] (Directorate of Economics and Statistics, GOI), especially in Rajasthan, Maharashtra, and Karnataka states. Among all, sorghum, pearl millet and finger millet, together contribute nearly 88 % of total production. Out of total production in India, Rajasthan alone contribute about 45 % (Statistics at a Glance, GOI, 2019–20). When comparing nutritional values, millet grains stand out with higher amounts of fat, fibre, and minerals compared to cereals like wheat and rice [34]. Millets also have significantly higher protein content than rice. Finger millet have slightly less protein than other millets, but it compensates with its richness in other essential minerals, such as calcium [32]. Therefore, millets are called as "Miracle grains and nutria-cereals" [14].

In Rajasthan, over the past decade, millet cultivation especially pearl millet and sorghum have shown a declining (6.5 m ha to 4.6 m ha) trend until 2012–13. There were no clear trends during 2014–2017, but a

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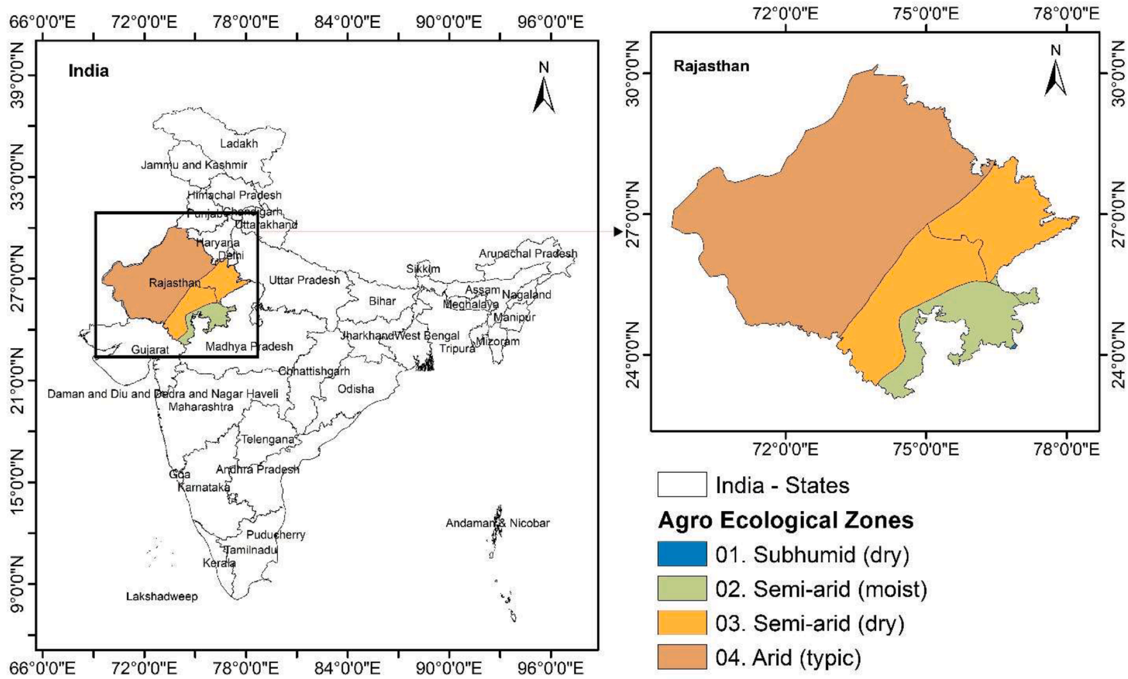

Fig. 1. The state of Rajasthan with agro-ecological zones.

slight upward trend in millet cultivation was observed from 2016–17 to 2019–20. The districts like Churu (0.4–0.25 Mha), Jodhpur (0.63–0.4 Mha) and Bikaner (0.25–0.16 Mha) showed drastic decrease of millet cultivation over time (https://eands.dacnet.nic.in/) [7].

Geospatial information systems are applied to analyse agricultural environments by visualizing the satellite imagery and ground truthing [24]. It has been widely used as an effective and potent tool in detecting land use and land cover (LULC) changes. In agriculture, it is applied in crop identification, acreage estimation, crop health monitoring, yield estimation etc. Multiple techniques were employed to classify crop types and land use/land cover (LULC), with major focus on temporal vegetation-based algorithms [8,29,42,50], classification, regression, decision tree algorithms [11,15,39], Random Forest algorithms [6,35,38,49], supervised and unsupervised classification algorithms for mapping agriculture croplands [12,21], and mapping croplands with time series data [5,13,20]. Therefore, monitoring of croplands at the plot scale using high-resolution methods are important for decision-making and enhancing agricultural productivity. Differentiating major crop types are very complex due to variations of crops sown within and between years [3]. In arid and semi-arid zones, the mapping is quite difficult due to small plot sizes and dynamic variations in cropping pattern and mixed/intercropping patterns [4,22].

Drought is a harsh climatic phenomenon that impacts various climatic zones, particularly in semi-arid and arid regions, which are more susceptible due to their low annual precipitation and high evapotranspiration [33]. To assess drought conditions, researchers have created drought indices like the standardized precipitation index (SPI) using meteorological data and vegetation indices derived from satellite data [2,26,37]. Numerous studies and research have been conducted on quantifying drought through the utilization of diverse indices, models, and water balance simulations [27,40]. Drought indices play a crucial role in monitoring the influence of climate variability on vegetation as they offer a valuable means of identifying and tracking drought episodes spatially and temporally [36]. The complexity of identifying drought events makes these indices essential tools in understanding their impact. The duration of drought can lead to variations in the spatial effects on vegetation, further emphasizing the significance of these indices in assessing drought-induced changes in crop stages [1,30,44].

The International Year of Millets, designated for 2023 by the United Nations, spotlights the vital role of these resilient and nutritious small-seeded grasses in global food security and sustainable agriculture. Millets, cultivated for centuries in various parts of the world, offer a solution to combat hunger, malnutrition, and climate change effects. During the year, initiatives and campaigns will promote millet cultivation, processing, and consumption, emphasizing their nutritional benefits and potential to contribute to a more sustainable food system. It's a unique opportunity for stakeholders to collaborate in addressing these challenges and supporting small-scale farmers.

The major goal of this study is to map the millet areas in Rajasthan using Sentinel-2 and MODIS 250 m 16-day time-series data using machine learning algorithms and spectral matching techniques and identifying the high stress-prone millet areas in the state. Temporal spatial information can be ideal information for millet scientists and planners in developing technologies suited to stress conditions. This information also helps in targeting the right technologies at appropriate locations. Further, the information could be used to develop stress-adaptive measures and technologies focusing on the most vulnerable areas where stress is most severe. It is indeed necessary to introduce and promote stress-tolerant millet cultivars to achieve food security, especially in arid and semi-arid areas. This study also carried out an extensive geospatial analysis for enhancing millet production through monitoring croplands and assessing the drought frequency in selected districts. Finally, the study proposed the assimilation of various drought-tolerant millet cultivars for the target location in the state and estimated their anticipatory economic benefits.

Study area

Rajasthan is the largest state in India located at 23°30′ and 30° 11′ North latitude and 69° 29′ and 78° 17′ East longitude, with an area of 0.342 million sq. km in about 60 per cent is occupied by the Thar Desert. It is surrounded by Pakistan in the west, Punjab in the north, Gujarat in the south, and Aravalli's in the east. Most of the area in the state is in semi-arid and arid zones (Fig. 1). The climate is generally arid or semi-arid with hot temperatures over the year (range of 26–46 °C in spring and from 8 °C to 28 °C during winter). The yearly precipitation reaches

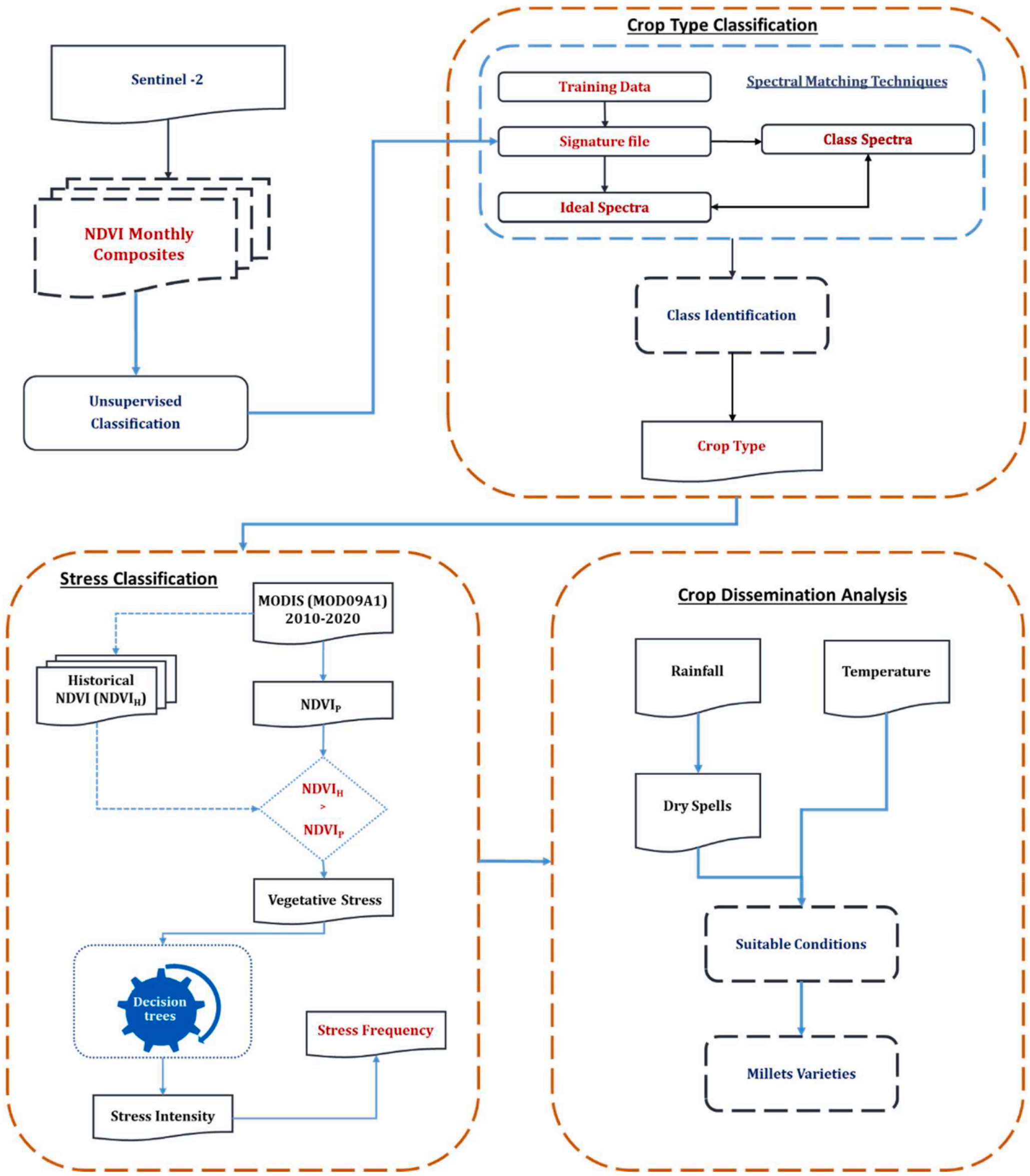

Fig. 2. Methodology used for crop type classification, stress identification and crop dissemination analysis.

100 mm in the western regions and 600 mm in the eastern and south-eastern parts of the state. *Kharif* (rainy) and *rabi* (winter) are two major cropping seasons in the study area [43].

In *kharif*, crops usually sown in June–July and harvested during the months of September and October, whereas the winter crop is sown in October–November and harvested in the months of March–April. The major crops grown in *kharif* are bajra, pulses, jowar, maize and ground nut, whereas in rabi, wheat, barley, pulses and oilseeds are grown [31].

Data and methods

Broadly, the analysis is divided into three major tasks. First is to map out the millet growing areas along with crop intensity; second focused on identifying the stress-prone areas in its cultivation and third exploration of dissemination analysis for its future expansion in the state (Fig. 2).

Crop type map

Sentinel-2, part of the Copernicus Program's Earth observation initiative, is crucial for classifying crops due to its advanced features. The satellite's high spatial resolution, ranging from 10 to 60 meters, allows for a detailed view of different crops and precise monitoring of agricultural fields. Its multispectral imaging tool, with 13 spectral bands covering various wavelengths, helps distinguish between different types of vegetation and provides insights into their health. The twin satellites have 5-day revisit time at the equator which allows monitor crop growth cycles and identify issues like diseases or stress. The free and open access to Sentinel-2 data makes it accessible for researchers, farmers, and policymakers. The satellite's ability to calculate vegetation indices, like NDVI and EVI, is valuable for assessing the health and vitality of vegetation. Level-1C satellite data from Sentinel-2 MSI (Multispectral Instrument) was selected for identifying crop classification through optical data for the crop year 2016–17. Created Normalized Difference Vegetation Index (NDVI)-Maximum with Sentinel-2 B8 (NIR) and B4(RED) bands for every month and stacked into one image for classification. The processing and classification of satellite data imagery was carried out in Google Earth Engine (GEE) platform, which is capable of processing big data [9] and conducting crop types classification. Spectral matching techniques (SMTs) mainly relates ground data with map created spectral signatures to classify different crop types [47].

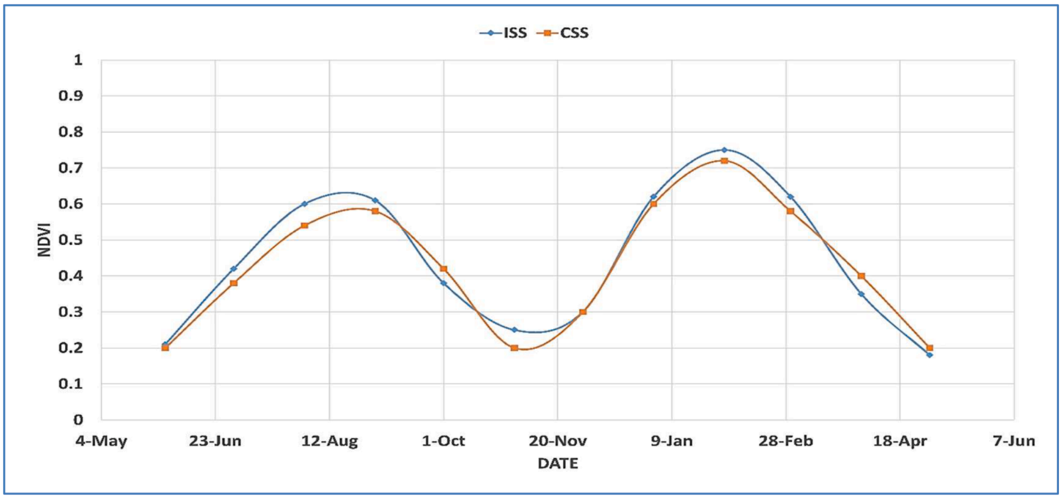

Fig. 3. Sample showing the matching of ISS with CSS.

A. **Ideal spectra signatures (ISS)**

ISS were generated using time-series data of NDVI combined with accurate information about croplands acquired through ground surveys. The ground surveys conducted for generating ISS took into account several crucial considerations to enhance their effectiveness. Emphasis was placed on selecting homogenous areas, each spanning a minimum of 100 × 100 meters (equivalent to 1 hectare), to ensure optimal identification capabilities. These selected areas were characterized by specific attributes, including crop type, availability of irrigation facilities, and soil type etc. The surveys took into consideration of the length of growing periods and adding a temporal dimension to the data collection process. The reference samples obtained from these surveys were carefully classified according to their distinct categories and organized into coherent classes based on factors like cropping intensity, crop types, and cropping systems. This approach ensures that the ISS products provide reliable and comprehensive information about agricultural practices and land use patterns. The spectral signature curve explains crop behaviour over time [46,20].

A. **Class spectra signatures (CSS)**

CSS were generated by employing an unsupervised classification approach on Sentinel-2 time-series data spanning the years 2016–2017, utilizing the K-means cluster algorithm. The outcome of this process yielded a total of 160 classes, each characterized by distinct spectral signatures. For every identified class, detailed spectral profiles were created. This generation not only facilitated the categorization of the crop but also enabled the development of specific and informative spectral signatures for each class.

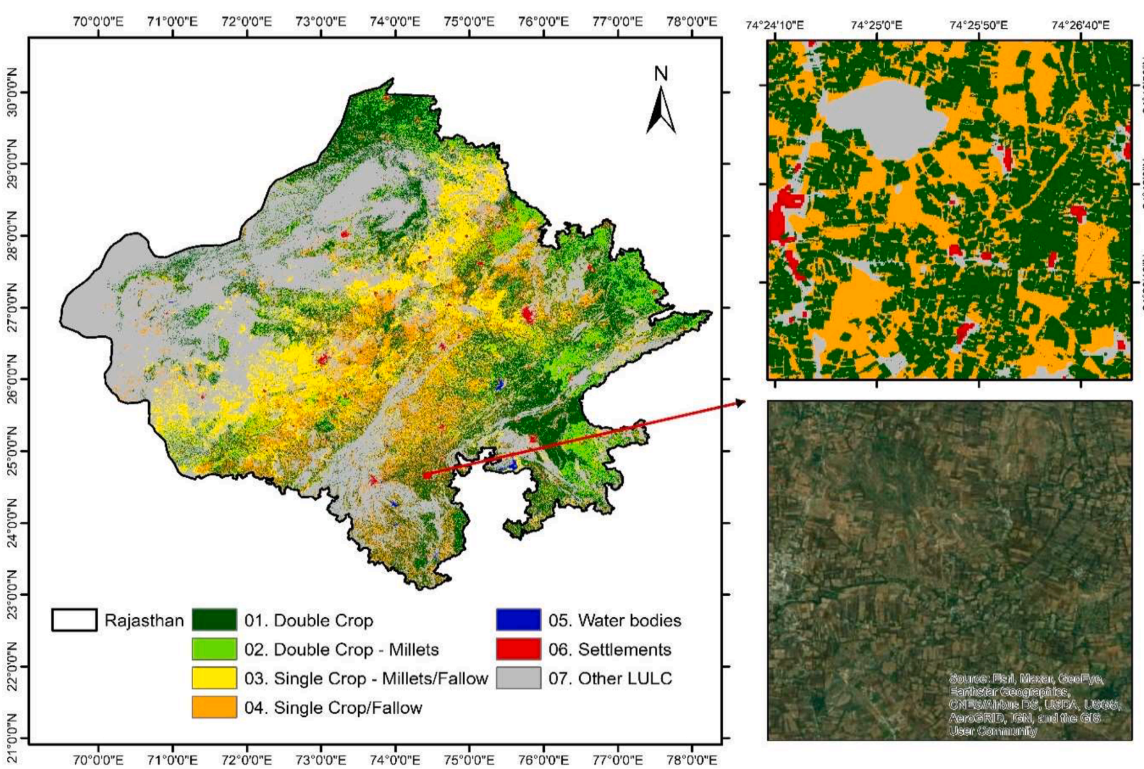

Fig. 4. Spatial distribution of millets growing areas across Rajasthan.

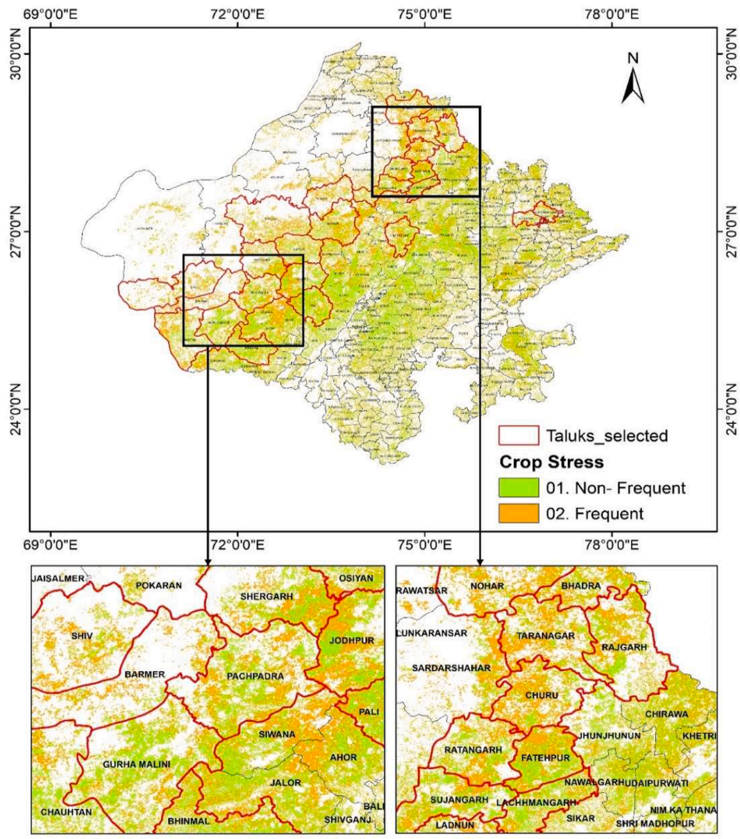

Fig. 5. Spatial distribution of frequency of crop stress across Rajasthan.

A. **Matching of CS with IS**

The identified 160 classes from unsupervised classification (called CS) were combined into a sub-groups based on similarity of spectral profiles [23]. IS profiles that matches with CS and having spectral correlation similarity (SCS) R-square values of >=0.80 is considered as a match and the class name is assigned (Fig. 3). In case of any mismatch, such classes are masked out and reclassification will be carried out [16, 18]. Thus, the millet grown areas are identified using Google Earth high resolution imagery and crop spectral signatures. [19].

Crop stress analysis

Crop stress is certain phenomenon which shows impact on crop production especially in rainfed areas. The NDVI from the Moderate Resolution Imaging Spectro-radiometer (MODIS) holds considerable significance in monitoring crop stress owing to its daily availability. With its ability to provide daily global coverage, MODIS offers a high temporal resolution crucial for capturing rapid changes in crop conditions. The instrument's broad spectral range, covering visible, near-infrared, and thermal bands, allows for the calculation of key vegetation indices like NDVI, enabling the assessment of vegetation health and the timely detection of signs of stress. MODIS's wide swath width ensures the coverage of large agricultural areas in a single pass, providing a comprehensive view of regional or global crop conditions. Its role extends to monitoring drought conditions, aiding in the assessment of moisture stress risks. The free and accessible nature of MODIS data enhances its utility, making it widely applicable in scientific research, agriculture, and resource management. The MODIS NDVI is utilized to map areas of crop moisture stress and changes in cropland. A specific methodology was used to identify crop stress-affected regions by comparing the MODIS-based NDVI with that of a normal year [17]. The comparison involves evaluating the long-term average of NDVI during the rainy (*kharif*) season (June-October) against the current crop year. Any significant deviation from the average will be considered an indicator of crop moisture stress.

Results

Cropland extent

The spatial distribution of millet growing areas showed the significant distribution of millets in Rajasthan. In western and South-western part of Rajasthan, majority of croplands are double crops due to availability of irrigation facilities, in which farmers opt millets as second crop. Whereas in the central and arid part of Rajasthan, most of croplands are under millet cultivation i.e., single crop due to rainfed ecology (Fig. 4).

Often, the single crop is converted to fallow under severe moisture conditions. With the increased access to irrigation facilities and improved water conservation practices, there is significant increase in area under double cropping especially in North, South-west and Western parts of Rajasthan. There is also an existence of single cropped areas cultivating other than millets.

The millet areas estimated from the map are well correlated a R^2 value of 0.75 with the government official statistics (https://aps.dac.gov.in/APY/Public_Report1.aspx). In few districts, there is over and under area estimates due to unavailability of secondary statistics and non-homogenous distribution of millet areas.

Stress

The study has analysed the millet moisture stress areas across Rajasthan from 2010 to 2020 with the help of NDVI time series data and categorised them based on stress intensity using spectral matching techniques. The study also calculated the frequency of stress happened

Table 1
The taluks of Rajasthan with significant crop stress.

S.No	Dist	Taluk	Stress area (ha)	Percent (%)
1	Alwar	Lachhmangarh	69,877	75
2	Alwar	Rajgarh	71,987	77
3	Barmer	Shiv	63,243	75
4	Barmer	Barmer	69,629	77
5	Barmer	Pachpadra	137,180	77
6	Barmer	Gurha Malini	159,417	83
7	Barmer	Chauhtan	195,403	79
8	Bikaner	Nokha	56,004	76
9	Churu	Taranagar	77,672	79
10	Churu	Churu	63,572	78
11	Churu	Ratangarh	58,866	75
12	Churu	Sujangarh	87,411	82
13	Hanumangarh	Nohar	85,427	73
14	Jalor	Bhinmal	79,839	71
15	Jodhpur	Phalodi	107,701	74
16	Jodhpur	Osiyan	75,058	78
17	Jodhpur	Shergarh	117,839	78
18	Jodhpur	Jodhpur	127,628	74
19	Nagaur	Nagaur	111,307	78
20	Nagaur	Parvatsar	74,483	80
21	Pali	Pali	91,498	71
22	Sikar	Fatehpur	77,014	79

from 2010 to 2020 and classified the targeted districts on its frequency (i.e. greater than 5 times in 10 years) (Fig. 5).

Further, the taluk/block level analysis was carried on assessing the moisture stress impact on millets and other single crops production. The taluks with significant stress areas (i.e., >50,000 ha) were selected for further analysis (Table 1).

About 22 taluks identified have more than 70 per cent of their millet cropped area is under moisture stress. The districts such as Alwar, Barmar, Churu and Jodhpur contains significant millet cropland areas as well as their corresponding moisture stresses. Taluks namely Phalodi, Nagaur. Shergarh, Jodhpur, Pachpadra, Gurha Malini and Chauhtan exhibited more than 1,00,000 ha of their millet cropland area under seasonal stress. Hence, the reduction of millet crop yields than its threshold is a regular phenomenon. The repeated moisture stress conditions impacted the millet cropped area significantly. Introduction and promotion of stress tolerant millet improved cultivars in these divisions reduces the production risks of farmers in their millet cultivation. The livelihood and food security of the farmers will be protected by precisely targeting millet resilient technologies in the state.

Stress monitoring

Abiotic stress plays a significant role on millet productivity levels in Rajasthan. It is often comprised of both heat and moisture stresses during the critical stages of crop growth period. Both these parameters were examined critically using geospatial tools during the millet growing period.

Heat stress monitoring

This study evaluated the parameters such as maximum and minimum temperatures for every month across identified taluks. It is observed that there were no major differences in temperatures of individual taluks.

In fact, after the onset of monsoon, the max and min temperatures have come down during the millet growing season (June-Sept). The minimum night temperatures ranging from 20 to 26 °C from May to September whereas there is drop in night temperatures ranging from 8 to 19 °C from October to March.

Moisture stress monitoring

There are major differences in the extent of precipitation distribution across the Rajasthan (https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html). The mean normal rainfall occurred during the millet growing months are - July (60 – 200 mm), August (70–250 mm) and September (30 – 130 mm) across Rajasthan respectively. The millet cropped area in the state are overlaid on rainfall distribution. This clearly visualize that majority of millet cropped area is distributed in the rainfall regime of 400–500 mm followed by <400 mm. This shows that the extent of rainfall received by the millet growing regions are located below <500 mm regime (Fig. 6).

The distribution of rainfall during the monsoon season is critical for achieving optimum productivity levels. To further understand the extent of rainfall distribution, the analysis was further breakdown into month-wise i.e., June to Sept. There are huge variations observed in the month-wise rainfall received among the study taluks in Rajasthan.

The extent of precipation was further scrutinized by day-wise rainfall

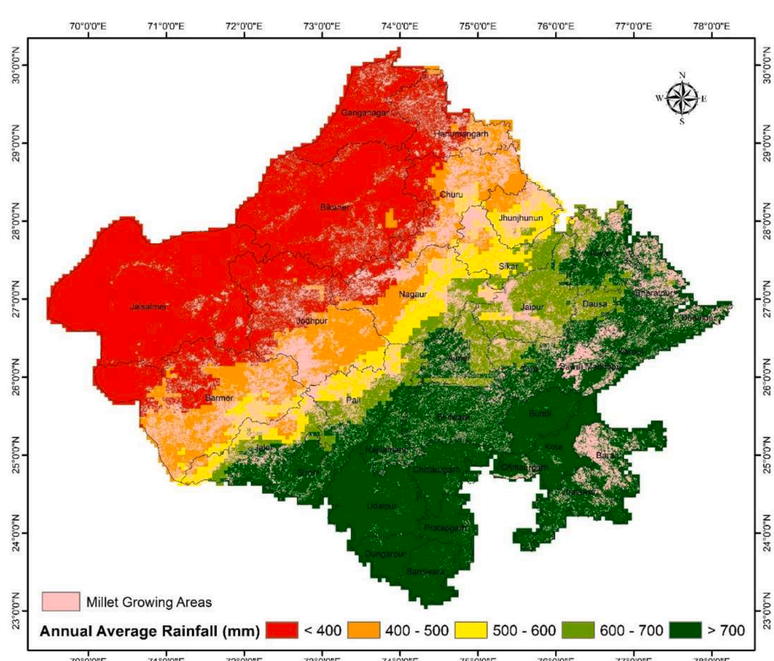

Fig. 6. Moisture stress monitoring in study taluks of Rajasthan.

Table 2
The temperature, rainfall and dry spells values of study taluks.

Sr. No	TALUK	Max. Temp (°C)				Min. Temp (°C)				Rainfall (mm)				Dry Spell (Days)			
		June	July	August	September	June	July	August	September	June	July	August	September	June	July	August	September
1	BARMER	40	36	34	34	27	26	25	24	21	112	171	59	19	11	12	18
2	BHINMAL	39	34	32	33	27	26	25	25	44	305	261	158	17	10	10	15
3	CHAUHTAN	40	36	34	34	27	26	25	25	24	127	190	84	19	11	12	16
4	CHURU	41	37	35	35	28	27	26	26	56	182	124	65	15	8	10	16
5	FATEHPUR	40	36	34	34	28	27	25	25	52	193	147	61	16	9	10	19
6	GURHA MALINI	40	36	34	35	28	27	25	26	28	160	182	78	18	10	11	17
7	JODHPUR	40	36	33	33	28	27	25	25	40	166	159	78	16	9	9	17
8	LACHHMANGARH	40	35	33	34	29	27	26	26	42	220	261	124	17	7	9	16
9	NAGAUR	40	36	34	34	28	27	25	25	27	155	114	54	18	8	10	17
10	NOHAR	42	38	36	36	28	28	26	26	47	112	105	70	13	9	10	17
11	NOKHA	41	37	35	35	28	27	25	25	35	139	82	52	18	9	11	18
12	OSIYAN	40	36	33	33	28	27	25	25	36	166	134	69	17	9	10	17
13	PACHPADRA	40	36	34	34	28	27	26	26	31	157	168	74	17	9	11	18
14	PALI	39	35	32	33	28	27	25	25	45	202	207	101	16	9	8	16
15	PARVATSAR	39	35	32	33	28	26	25	26	37	241	203	92	18	8	8	17
16	PHALODI	41	37	35	34	28	27	26	26	40	130	81	47	17	10	12	19
17	RAJGARH	40	35	33	33	28	26	25	25	41	219	259	121	17	8	9	16
18	RATANGARH	41	37	35	35	28	27	25	25	63	145	131	54	16	9	10	19
19	SHERGARH	40	36	34	34	28	27	25	26	29	149	122	61	18	10	11	18
20	SHIV	41	37	35	35	27	26	25	25	14	99	159	53	22	12	12	18
21	SUJANGARH	40	37	34	34	28	27	25	25	46	152	112	57	18	9	10	17
22	TARANAGAR	41	37	35	35	28	27	26	26	44	145	134	73	15	9	10	18

within a selected month. The extent of moisture stress was captured through the length of dryspell in each selected month. The study assumes that the longer dry spell in a given month, the extent of moisture stress for the crop exposed is rated as high and vice-versa. The detailed break-down of the dryspell analysis was furnished in Table 2. This clearly summarizes the extent of dryspell in each targeted taluk for millet growing period of four months (June-Sept). The extent and length of dry spells identification helps in better planning the sowing dates as well as in predicting the plant growth and productivity levels. The present study have mapped the mean length of dry spells in a targeted month from 2010 to 2020. The pattern and length of dryspells spread across months were plotted in Fig. 7.

The distribution and length of dryspell correspondingly indicates the extent of moisture stress for millet cultivation in the state. It is clearly evident the figures that the months of June and September are critical for millet cultivation as the moisture stress indicated was very high. The extent of moisture stress is very low in the months of July and August when compared with the June and September. The length of dryspell was longer (more than 15 days) in case of June and September months which exactly coincides with the millet crop germination (June) as well as crop maturity (September) stages respectively. Hence the new targeted millet cultivars should have moisture stress tolerance during these stages. Any crop stress during these periods leads to significant productivity losses to the farmers. Hence, the researchers/agronomists should devise suitable moisture stress coping mechanisms/mitigation strategies during these phases of crop. The crop management practices should also be aligned to do a better moisture management practices during these periods. Overall conditions of selected taluks are as shown in Table 2 below.

The moisture stress monitoring analysis was further dis-aggregated within a month to precisely target the new millet improved cultivars in the state. The extent of dry spells was further dis-aggregated in the three parts (1–10, 11–20 and 21–30 days) in each month i.e., given month is divided into three parts. The analysis will further through light on the exact days of dry spells during crop growth period. We perceive that >6 days of consecutive dry spells in any part (1–10, 11–20 and 21–30 days) of the month will critically decline the mean productivity levels (Fig. 8). This kind of knowledge helps the crop improvement scientists to develop cultivars suitable to such situations. Understanding the exact moisture stress period and its nature (stress physiology) during the crop growth period is critical for identifying suitable parental lines for that purpose.

Table 3 clearly visualizes that there is good distribution of rainfall from June second part (11–20 days) to September first part (1–10 days). The crop is experiencing more moisture stress during the first part of June and during the second and third part of the September. This translates to the moisture stress occurring stages of crop growth are during germination and during the crop maturing stages. The millet crop improvement program should focus more on developing cultivars that are moisture stress tolerant during early germination stage and during crop maturing stage. Hence the state government and line departments including agriculture department should focus on pumping new cultivars which has moisture stress tolerant capacity rather than the heat stress tolerant cultivars. The role of heat stress is negligible in Rajasthan while the moisture stress has a significant impact on millet performance in the state.

Anticipated benefits with introduction of stress tolerant cultivars

The spatial analysis has clearly delineated about 22 taluks from Rajasthan which are vulnerable to moisture stress conditions during millet growing period. The cumulated millet cropped area estimated under these taluks are around 20.58 lakh ha. Based on the dis-aggregated analysis, about 77 % of the that total cropped area has the susceptibility to moisture stress conditions due to irregular or delayed monsoon distribution during rainy season. The mean millet productivity levels recorded in the drought prone environments of Rajasthan state is

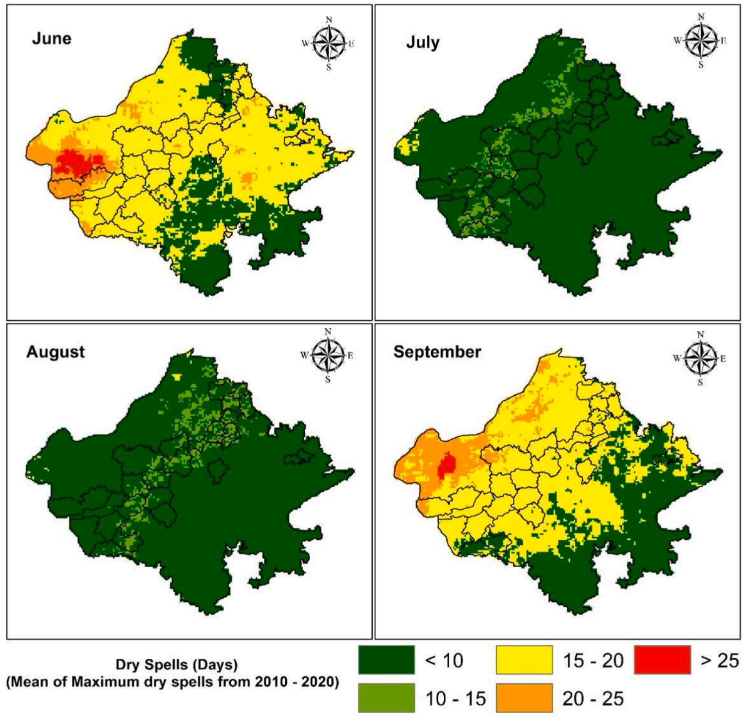

Fig. 7. Mean of Maximum dry spells from 2010 to 2020.

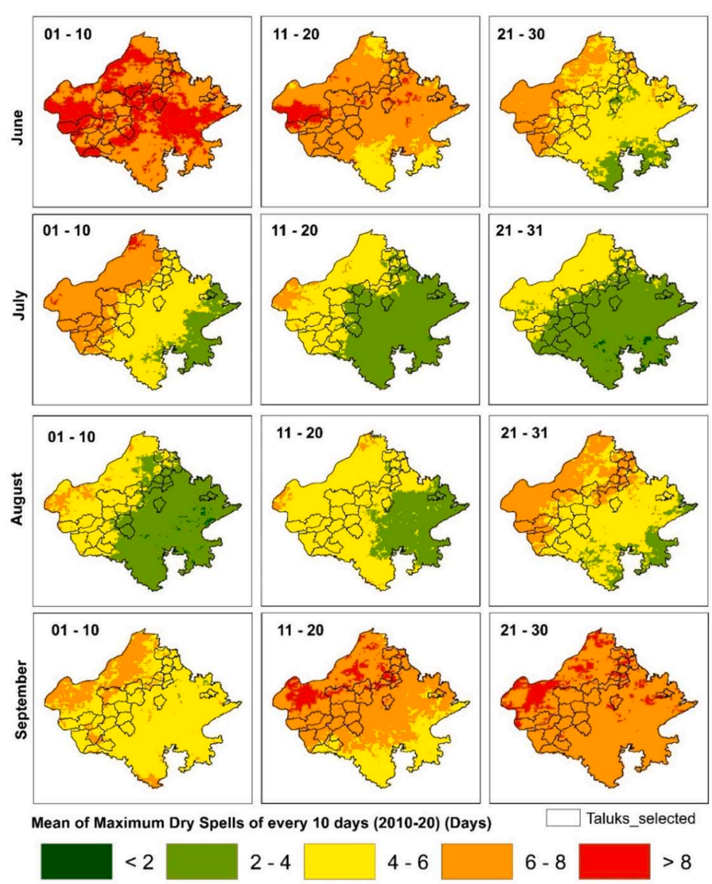

Fig. 8. mean of maximum dry spells in 10-day of June to September of 2010–20.

Table 3
Number of Dry spells in every 10 days from June to September.

S.No	Taluk	June_1	June_2	June_3	July_1	July_2	July_3	Aug_1	Aug_2	Aug_3	Sep_1	Sep_2	Sep_3
1	Nohar	8	6	6	6	4	4	4	5	6	6	7	7
2	Rajgarh	8	7	6	5	4	4	3	4	6	5	7	8
3	Taranagar	8	7	6	6	4	4	4	4	6	5	8	8
4	Churu	8	6	6	5	4	4	4	4	6	5	7	8
5	Ratangarh	7	7	5	6	4	4	4	4	6	6	8	8
6	Fatehpur	7	7	5	5	4	4	3	4	7	6	8	8
7	Nokha	8	7	6	6	4	4	5	5	6	6	8	8
8	Sujangarh	8	7	5	6	4	4	4	5	6	6	8	8
9	Lachhmangarh	7	7	5	5	4	3	3	4	6	5	7	8
10	Phalodi	8	7	6	6	4	4	5	5	6	6	8	8
11	Nagaur	8	8	5	5	4	3	4	5	6	6	8	7
12	Parvatsar	9	7	4	5	4	3	3	4	5	5	8	8
13	Osiyan	8	7	6	6	4	4	4	5	5	6	7	7
14	Shergarh	8	8	6	6	4	3	5	5	6	6	8	7
15	Shiv	9	8	7	7	5	4	6	6	6	6	7	8
16	Jodhpur	8	7	6	6	4	3	4	5	5	6	7	7
17	Barmer	8	7	6	7	5	4	5	6	6	6	7	7
18	Pachpadra	8	7	6	6	4	3	4	5	6	6	7	7
19	Pali	8	7	5	5	4	3	3	5	5	5	7	8
20	Gurha Malini	7	7	6	6	5	3	5	5	6	6	6	7
21	Chauhtan	8	7	7	7	5	4	6	6	6	6	7	7
22	Bhinmal	8	7	5	6	4	3	5	5	5	6	6	7

600–800 kg per ha. These productivity levels can further deline with any moisture stress conditions during the millet growing period. This will impact the livelihoods of the millet growers severely and further pushing them towards chronic poverty in the state. The food and nutritional security of the millet growers are in ambiguity.

The researchers from international, national, and state agricultural universities target to release any pearl millet improved cultivar which has tolerance to moisture stress, especially during the early germination and maturity stage (known as terminal drought tolerance), will provide significant benefit to the millet growers in the state. The introduction, testing and scaling-up of such series of cultivars will significantly benefit the millet growers in the arid region. With careful screening and introduction of any stress tolerant millet cultivar can thrive well under stress conditions and yields the crop normally. This could save at least 20–25 % of yield loss per ha due to the moisture stress in the region. Scaling-up of such cultivars enhances the mean productivity in the region to more than 1000–1200 kg per ha. This is a significant yield gain to millet farmers and wise escaping to moisture stress conditions. Any quick introduction of such cultivars can produce the additional millet production of up to 5–6 lakh tons in the state. This translates to an economic value of about Rs. 1200 crores per annum under conservative scenario. The introduction of such millet cultivars can easily sustain at least a period of 3–5 years in varietal replacement cycle. This in turn estimated the anticipated economic benefits to the tune of nearly 3600–6000 crores to the state government.

Conclusions

The study has effectively proposed a method for spatially identifying pearl millet stress areas, which necessitates the assimilation of stress-tolerant cultivars in the Rajasthan. The study has employed Sentinel-2 data and known spectral signatures to map cropland extent and millet growing areas. Further, the study successfully delineated stress-prone taluks within these millet growing districts in the regions. To aid agriculture researchers in developing improved millet cultivars, the study meticulously analysed variations in temperature, rainfall, and dry spells across taluks and provided crucial analytical inferences. The economical assessment showed that the introduction of stress tolerant millet varieties, especially during the early and late stages of crop growth conditions help in minimizing the millet productivity losses in the state. Introduction of climate SMART millet improved cultivars and scaling-up of those in the targeted taluks significant benefits the millet growers. This in turn will help the state in achieving the food as well as nutritional security. Future research directions will encompass expanding the current study by incorporating additional stress-tolerant cultivars, exploring alternative satellite data sources, and refining spectral signature analysis through machine learning algorithms to enhance the precision of spatial identification. A recommended approach involves conducting a comprehensive multi-year study to evaluate variations in stress areas across different cropping seasons.

CRediT authorship contribution statement

Pranay Panjala: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Venkata Ramana Murthy Reddi:** Data curation, Formal analysis. **Murali Krishna Gumma:** Conceptualization, Methodology, Writing – original draft, Supervision, Writing – review & editing. **Kumara Charyulu Deevi:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Shashi Kumar Gupta:** Formal analysis, Supervision.

Declaration of Competing Interest

No conflict of interest.

Data availability

Data will be made available on request.

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