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Mapping farmer vulnerability to target interventions for climate-resilient agriculture: science in practice

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ABSTRACT

Farmers in dryland regions are highly vulnerable to rainfall variability. This vulnerability is unequal, as it is mediated by biophysical and social factors. Implementing policies for climate resilience requires the ability to identify the farmers who are most vulnerable to extreme events like dry spells. We develop a novel approach by conceptualizing dry spell vulnerability in terms of monsoon crop water deficit at the farm scale. Using inputs of weather, terrain, soil properties, land-use-land-cover, crop properties, and a cadastral map, our tool models an hourly soil water balance at 30 m $\times$ 30 m resolution and maps the crop water deficit under rainfed conditions. This is a good indicator of the relative sensitivity of farmers to dry spells and allows prioritization of interventions within the focus region. Our tool, developed and deployed within the Maharashtra State Project on Climate-Resilient Agriculture, is iteratively calibrated and refined. We present the result of one such iteration in which 72% of cases were found to have an agreement between the modelled output and farmers' perception of dry spell-induced crop water stress. Our work demonstrates how vulnerability to climate hazards may be mapped at micro-scales to assist policy-makers in targeting interventions in ecologically fragile regions with high rainfall variability.

Key words: Climate-resilient agriculture, Crop water stress, Dry spell, Protective irrigation, Transdisciplinary research, Vulnerability

HIGHLIGHTS

- Vulnerability of rainfed farmers to dry spells is unequal.
- Mapping farm-level vulnerability is important to target interventions for climate-resilient agriculture in ecologically fragile regions.
- We conceptualize farm-level dry spell vulnerability as a function of biophysical and social attributes and extend the concept to practice in the form of a tool that is embedded in the state process.

1. INTRODUCTION

The Indian summer monsoon provides close to 85% of the annual rainfall to the Indian subcontinent. It crucially supports food production and livelihood security for a large population. Climate change impact is causing a shift in the rainfall pattern (Singh *et al.*, 2014) seen in the form of delayed onset of monsoons, long dry spells, and destructive floods, resulting in large crop failures and economic losses. The agricultural sector, dominated by marginal and smallholders, is highly vulnerable to monsoon variability. The monsoon (or *kharif*) crop is the most important crop, especially in dryland regions where most smallholders rely heavily on it for their livelihoods and household nutritional security.

Farmer vulnerability to monsoon variability is unequal (Kuchimanchi *et al.*, 2019; Dagdeviren *et al.*, 2021), and is mediated by access to natural, social, and economic resources (Duncan *et al.*, 2017; Singh, 2020). Farmers who have farms with poor soil quality or unfavourable locations within the watershed, and have limited or no access to irrigation are highly vulnerable to dry spell-induced crop losses (Kumar *et al.*, 2018). Depletion of soil moisture during dry spells, especially during key crop growth stages have been shown to have a significant impact on yield (Panigrahi *et al.*, 2005). A systems study of dryland farmers in Northeastern Tanzania has shown how climate-related poverty traps are created as a result of crop losses from frequent dry spells and depletion of soil moisture (Enfors, 2013). Securing irrigation and retaining soil moisture is emphasized as an important strategy to reduce yield gaps caused by dry spells in Africa (Rockström & Falkenmark, 2000; Rockström *et al.*, 2010) and India (Manivasagam & Nagarajan, 2017; Sikka *et al.*, 2018). This has also been extended to watershed-scale supplementary irrigation planning (Imbulana & Manoharan, 2020; Hessari & Oweis, 2021). The ability to identify and map relative vulnerability is therefore desirable in order to target investments for life-saving irrigation access to farmers who are most vulnerable to dry spell-induced crop losses. This is true not only for India but also for dryland rainfed regions all over the world which face increasingly variable rainfall seasons. However, there is a gap in methodology on how dry spell vulnerability may be conceptualized and computed at the unit of a farm and, at the same time, mapped for all farms at an aggregate scale such as a village to support policy implementation.

Vulnerability has been defined and used in many different contexts and disciplines. In the context of climate change, the IPCC's third assessment report provides a commonly accepted definition that frames the vulnerability of a system as a function of its exposure to a climate hazard, its sensitivity to the hazard, and its adaptive capacity. Brooks (2003) refers to this as the biophysical vulnerability, which relates to the combined effect of the physical impact of the hazard (e.g., loss in soil moisture or crop stress) and its eventual outcome (e.g., economic loss). One of the determinants of biophysical vulnerability is the social vulnerability of the system (Brooks, 2003). This is understood as a system's structural property determined by deep-rooted factors such as poverty, inequality, power relations, and access to resources (Ramprasad, 2018; Nyantakyi-frimpong, 2020), which mediate the impact of climate events resulting in outcomes such as economic damage or loss of life.

Studies on climate vulnerability assessments use varied approaches and differ in their objective, scale, and how actionable they are. The purpose of the assessments may be to identify current and potential hotspots to identify entry points for climate adaptation intervention (Kienberger *et al.*, 2016) or to track changes in vulnerability through monitoring of adaptation efforts. The scale of mapping varies from national to village scale, and the unit of mapping varies accordingly. Studies vary in their focus on different components of vulnerability, i.e., exposure to climate hazard, sensitivity, or adaptive capacity. For example, Kadiyala *et al.* (2021) and Kuchimanchi *et al.* (2021) have mapped block-level exposure to variability in climatic elements in the Indian state of Telangana, but do not focus on differences in sensitivity or adaptive capacity. de Sherbinin *et al.* (2019) provide a comprehensive review of different studies for mapping social vulnerability. Social mapping is useful to understand who is structurally the most vulnerable and how this variation in vulnerability results in unequal outcomes of a climate hazard (Kuchimanchi *et al.*, 2019; Swami & Parthasarathy, 2020). However, these studies do not capture the biophysical drivers of sensitivity to climate hazards. Also, de Sherbinin *et al.* (2019) find that while most works emphasize the importance of vulnerability mapping to adaptation planning, not many engage with policy-makers to support decision-making. A variety of indicators and composite indices-based vulnerability assessments have been made by scholars to estimate and compare both social and biophysical vulnerability to droughts and other climate hazards at local or regional level (Lindoso *et al.*, 2014; Keshavarz, 2016; Swami *et al.*, 2018). Kienberger *et al.* (2016) identified and mapped a variety of geo-spatial indicators to spatially assess vulnerability of agricultural and pastoral livelihood systems to climate change in two provinces of Mauritania using a combination of methods including stakeholder engagement, modelling, composite index development, and visual mapping. Remote sensing-based approaches have also been used to capture spatial and temporal aspects for the computation of drought vulnerability indicators at national and sub-national scales (Meza *et al.*, 2021).

In our review of current vulnerability assessments, we do not find one that is developed to identify differential vulnerability to dry spells at the intra-village scale, incorporating biophysical and social drivers. Moreover, none are developed for the purpose of empowering communities for demanding greater accountability from state interventions which may otherwise be appropriated by local political interests. Our paper addresses this gap by not only making a contribution to the scientific literature through our conceptualization of dry spell vulnerability as a measurable and comparable entity but also contributing to the practice of science, by developing a tool to map farmer vulnerability to dry spell hazards at the farm scale in the context of a state implemented project.

Our objective is to conceptualize and map farm-level vulnerability to dry spells to target interventions in regions that face high rainfall variability. This entails conceptualizing dry spell vulnerability, using an appropriate model to capture it, and developing a tool to map it. An iterative cycle of model calibration and tool enhancements is followed to improve the social acceptance of the final outcome. In this paper, we present the model and the results of one such cycle of field application to illustrate the novelty of the approach and the challenges to be overcome. Finally, we reflect on our transdisciplinary approach to inform decision-making for climate-resilient agriculture.

1.1. State response for climate-resilient agriculture

India has a long history of watershed programmes in drought-prone regions which have evolved over time with a gradual change in their goals and implementation methods. Although a watershed-based approach to land management started in the early 1960s, planning of scattered soil and water conservation efforts pre-dated this. The Drought-Prone Areas Programme (DPAP) was one of the early programmes launched in 1972–73 focusing on soil and water conservation in fragile, drought-prone regions. Following the severe drought of 1987, the concept of integrated watershed development was institutionalized in the form of National Watershed Development Programme for Rainfed Areas in 1990–91. There was also a subsequent shift from the programmes being driven by state technical agencies to greater participation of non-governmental organizations.

The state of Maharashtra has been at the forefront of watershed development programmes. Drought-proofing works were already being promoted under the Employment Guarantee Scheme in the 1970s. Also in the 1970s, the Pani Panchayat movement in Maharashtra offered many success stories of people-centred watershed development which became role models for the participatory watershed programmes that emerged in the 1990s. Over the next couple of decades, watershed development guidelines called ‘Hariyali guidelines’ were developed and refined, eventually leading to the Integrated Watershed Management Programme (IWMP) in 2008. *Jalyukta shivar abhiyaan* (JSA), launched in 2014, was a major state-led watershed programme that promised to make all villages in Maharashtra ‘drought-free’ by the end of year 2019. The programme focused on conventional water conservation activities for augmenting water availability, and at the same time introduced steps towards demand-side management. Simultaneously, *Magel tyala shettale* was launched in 2016, which offered subsidy to farmers for constructing private farm-ponds. Programmes such as the JSA typically expended between INR 5 million to INR 30 million in a village. Although there have been success stories (Garg *et al.*, 2020), there have also been criticisms of the programmes by experts, civil society organizations and practitioners regarding the conduct and lack of scientific soundness of the programmes (DTE, 2019; Prasad *et al.*, 2022).

The Project on Climate-Resilient Agriculture (PoCRA) was launched in the state of Maharashtra in 2017. Funded by the World Bank, PoCRA is the first state project on climate-resilient agriculture in the country, being implemented in over 5,000 villages in 15 districts, largely in Marathwada and Vidarbha regions. It aims to address farm-level vulnerability not only to inter-seasonal climate variability but also to intra-season variability. The programme especially focuses on farmer vulnerability to dry spells that occur during the rainfall season. Our work is developed in the capacity of a knowledge partner to the Project Management Unit of PoCRA. One of our mandates is to conceptualize climate vulnerability as an actionable condition that may be mapped and compared within a village and to develop a tool to guide the targeting of state investments. The tool is to support not only the programme implementation agency but also the villagers themselves by bringing greater accountability and transparency in the targeting of state interventions.

2. METHODS

In this section, we begin by first discussing our conceptualization of dry spell vulnerability based on the IPCC definition of climate vulnerability. We then describe the method used to compute and map farm-level sensitivity to dry spells followed by our approach for field-level application of the developed mapping tool.

2.1. Conceptualizing dry spell vulnerability

Based on the commonly accepted IPCC definition of vulnerability, we conceptualize monsoon dry spell vulnerability for a farmer as a combination of three components: exposure to the climate hazard, sensitivity to the exposure, and adaptive capacity of farmer. Specifically, we consider (a) exposure in the form of t occurrence of dry spells within the rainfall season, (b) the crop's sensitivity to dry spells in terms of the water stress experienced by it given the farm biophysical attributes, and (c) adaptive capacity in terms of access to irrigation for the farm plot under consideration. Since the purpose of this exercise is to map relative vulnerability within a village, it may be assumed that exposure to dry spells is not a differentiating factor, as all farm plots at a village scale are likely to experience the same dry spell events. The key differentiating factor is the sensitivity of the plots to a dry spell event and the farmers' adaptive capacities. We conceptualize sensitivity to dry spells in terms of the water deficit faced by the crop on a given farm plot during a dry spell event. This deficit is a function of the available soil moisture relative to the crop water need and depends upon the farm's biophysical properties and farm practices for moisture retention. The sensitivity varies within a village because of the variability in soil moisture retention across plots, which itself is due to the diversity in soil type within a village (Prasad & Sohoni, 2020). For example, farms with thin sandy soils experience greater crop stress than those with deep clayey soils. Hence, the need for life-saving protective irrigation (Jurriens *et al.*, 1996) during dry spells (both quantity and frequency) varies depending upon the biophysical attributes of the farm plot for the same choice of crop. To map this sensitivity, we compute the monsoon crop water deficit (in mm of water) for the predominant *kharif* crop at the unit of a farm plot. Computation of this is an important requirement from our model and our key contribution in incorporating the biophysical drivers of vulnerability. Finally, the adaptive capacity of the farmer is seen as a combination of the capacity to irrigate and socio-economic factors such as access to capital, knowledge, social networks, etc. which determine access to irrigation (Kumar & Saleth, 2018). We use two proxies to capture the adaptive capacity: (a) cropping intensity of the farm as indicated by the land-use map, i.e., if only one rainfed crop is cultivated on the farm or if the farmer can farm in multiple seasons indicating that they have access to irrigation, and (b) socio-economic factors such as landholding size, gender, and caste. Together, these are used to capture farmer vulnerability to monsoon dry spell hazards.

2.2. Estimating dry spell sensitivity

The agricultural calendar has three main seasons – *kharif* (the monsoon crop, from June to September), *rabi* (the post-monsoon winter crop, from October to February), and summer (March–June). For most farmers, *kharif* is the main cropping season for food and income security. Typical *kharif* crops in the regions targeted under PoCRA are soybean, lentils such as *mung*, *urad*, or long *kharif* crops (6–8 month duration) such as *tur* (pigeon pea) and cotton. *Rabi* crops require irrigation and are usually cultivated only on a part of the cultivated area, and by those who have access to irrigation. Unlike other parts of Maharashtra, sugarcane cultivation in the project focus villages is limited due to no access to canal irrigation and unreliability of groundwater availability.

The primary source of water for *kharif* crops is the soil moisture replenished by monsoon rainfall. Variability in rainfall in the form of long dry spells causes soil moisture stress during key crop growth stages and results in crop water deficits. For the same level of exposure, the sensitivity of farm plots to a dry spell (in terms of crop stress) may be unequal. In this section, we first discuss our method to compute dry spell sensitivity at the unit of a farm, and then discuss how this information is aggregated to produce village-level maps.

2.2.1. Computing sensitivity to dry spell at the farm plot unit

To compute dry spell sensitivity, we develop a location-based point model for soil water balance that uses the FAO methodology (Allen *et al.*, 1998) and SWAT methodology (Neitsch *et al.*, 2011) as shown in the upper panel of Figure 1. The input is the rainfall pattern (daily or hourly data for a selected year) and farm-level soil and crop parameters. The model first partitions the rainfall as run-off and infiltration. The soil is considered as two layers, the top layer being the crop root zone for the crop under consideration. The infiltrated water

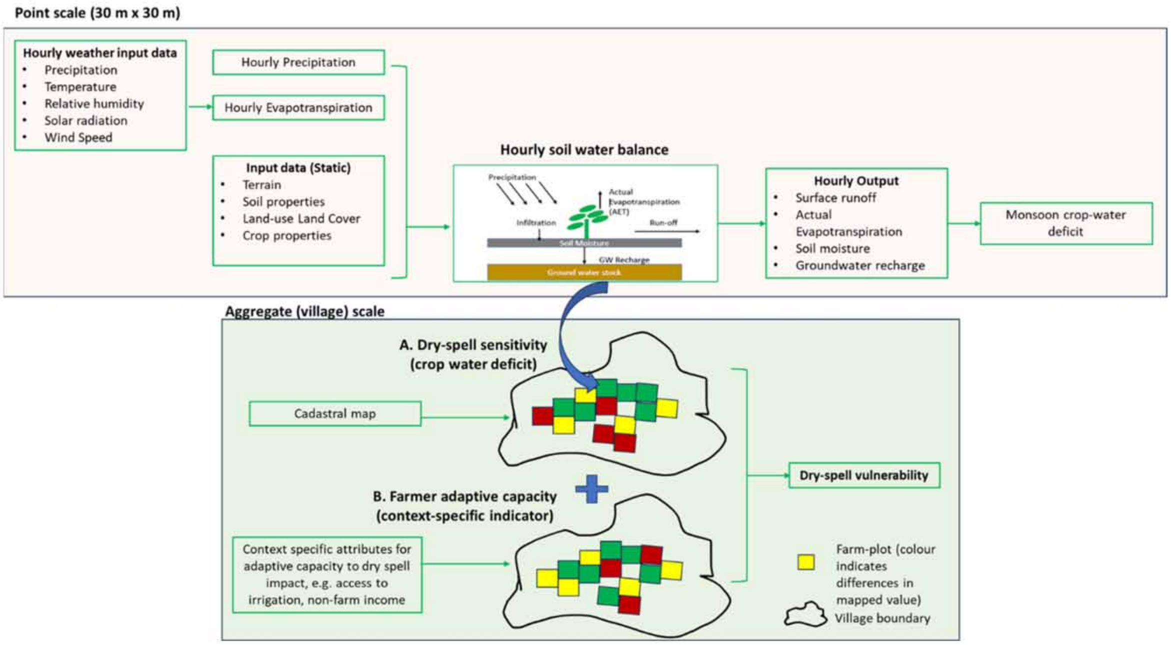

Fig. 1 | Method developed for mapping dry spell vulnerability. An hourly soil water balance is modelled for each point at 30 m × 30 m resolution within the aggregate village boundary and the resultant crop water deficit over the rainfed season is mapped for each point. This creates the dry spell sensitivity map, which when combined with context-specific indicators of farmer adaptive capacity helps to identify farmers who are most vulnerable to dry spells.

replenishes the soil moisture in the two layers and the excess is accounted as deep percolation that ultimately recharges the groundwater. Part of the available soil moisture in the root zone is used by the crop to grow and is thus converted to actual crop evapotranspiration (AET). When there is insufficient soil moisture due to dry spells, the AET falls below the potential crop evapotranspiration (ET) leading to crop water stress. The crop water deficit is computed as the difference between potential crop ET and AET over the rainfed season. Depending upon the stage of crop growth, the impact of crop water stress on crop yield may be substantial. If the farmer is able to access protective irrigation, then it is possible to reduce loss in yield due to this stress. The model thus translates farm-level biophysical parameters and rainfall regimes into quantifiable crop water deficits which can be compared across plots (for the same crop) to identify the farmers who are most sensitive to dry spells.

Application of the farm-level water balance tool to different farm plots allows us to compare their relative sensitivity to monsoon dry spells. Figure 2 illustrates this for two different plots of the soybean crops in Sangamner

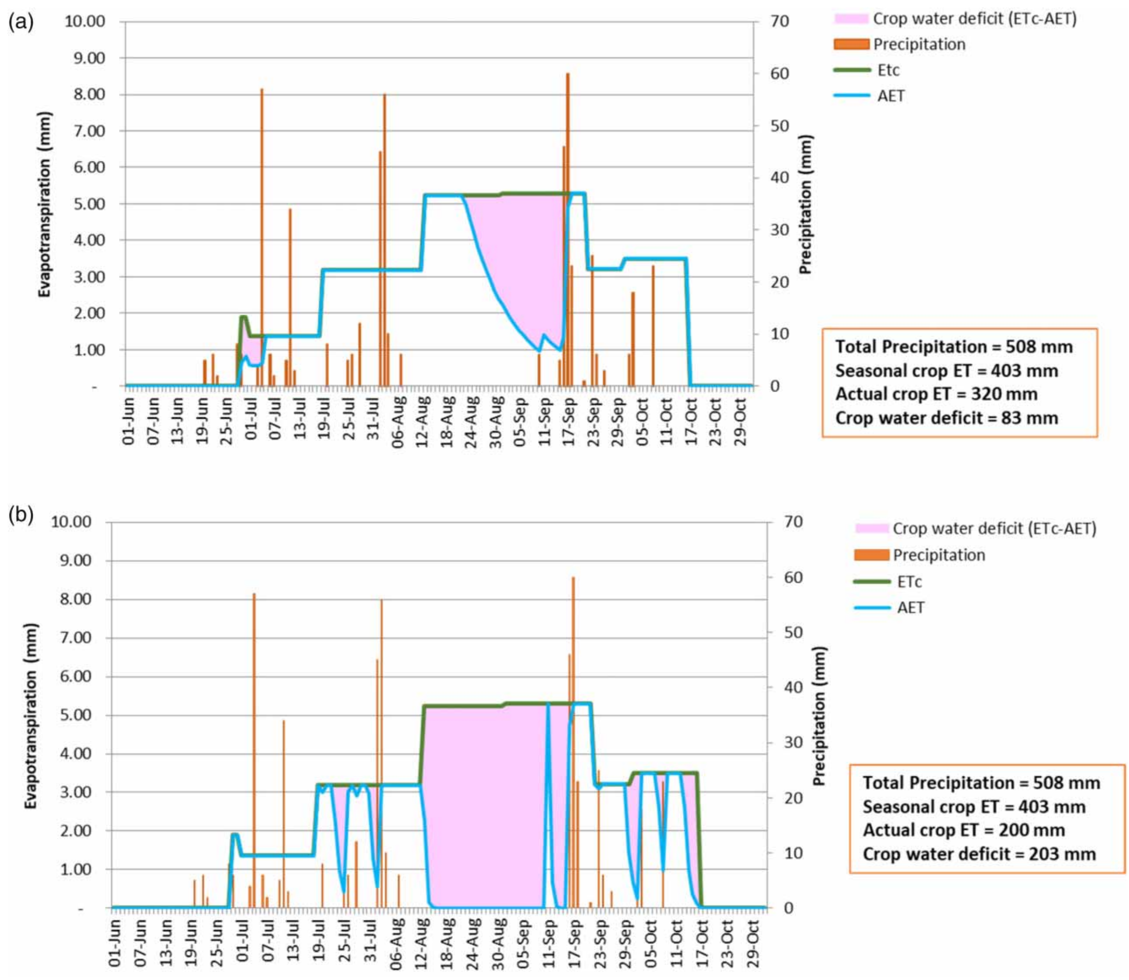

Fig. 2 | Crop water deficit for soybean crop during a 33-day monsoon dry spell modelled for two different farm plots in Sangamner, Maharashtra, for year 2016. (a) Clayey loam soil of 1 m thickness and (b) gravelly sandy loam soil of 40 cm thickness. The shaded area shows the kharif crop water deficit which is computed as the difference between crop evapotranspiration and actual evapotranspiration. For the purpose of illustration, the sowing date is assumed to be the same in both cases.

district of Maharashtra when a 32-day-long dry spell occurred during August and September in the monsoon of 2016. The model shows very significant differences in the impact of the dry spell on the same crop in two different soil types. In the case of deep clayey soil, the soil moisture is built up gradually and is retained longer, but in the case of the shallow gravelly sandy loam soil, the moisture holding capacity is less and the moisture is drained quickly. As a result, we see that when a dry spell occurs, in the case of the deep clayey soil the crop water requirement continues to be met to some degree with the available soil moisture. The crop suffers water stress of about 83 mm, but there is not a single day when the crop receives no water from the soil. On the other hand, in the case of the gravelly sandy loam soil, the same crop suffers 203 mm of water stress which is almost half the crop water requirement. The crop gets no moisture for about 25 days which would lead to a serious reduction in yield if not complete crop failure. This can be avoided if the farmer is able to access protective irrigation. Thus, the farm with shallow gravelly sandy loam soil is significantly more sensitive to dry spell impact than the one with deep clayey soil. Identification and mapping of such farms is an important step in planning interventions for dry spell resilience.

2.2.2. Collating and aggregating sensitivity over the village map

The above section discussed the procedure developed to compute monsoon crop water deficit at a single point. To compare this across all farm plots in a village, we incorporate the model into a tool that maps this value for all points (i.e., 'pixels' at the resolution of 30 m $\times$ 30 m) in the cropped area within the village boundary. This is done using a Python plugin for QGIS, an open-source GIS platform. The plugin accesses GIS input layers, viz., the village boundary, land-use map, digital elevation map, soil depth, and texture map to produce a grid of crop water deficit values (see Figure 1). The crop water deficit values are classified into different categories (e.g., 0–25 mm, 25–50 mm, 50–75 mm, etc.) for visual comparison. The village cadastral map is overlaid on this to obtain a farm-plot level mapping of sensitivity to dry spells. This indicates which farm plots have a greater protective irrigation need than others to be resilient to monsoon dry spells. In the results section, we illustrate this for two selected villages. When this dry spell sensitivity map is seen in combination with farmers' adaptive capacity, it allows us to capture relative farmer vulnerability to dry spells. We illustrate an application of this in the Supplementary file.

2.3. Field application: study area

The outputs of the model, and hence the vulnerability maps, depend on sound data inputs and calibration, especially soil and crop parameters. Thus, an important task is to combine the calibration of the model with the verification of the key input data sets through field application in sampled villages. We made a comparison of the simulated impact of dry spells in preceding years obtained by the model against the farmers' experiences. This was recorded through farmer surveys in more than 20 villages as part of the PoCRA project in iterative cycles. Here, we present the results of one such exercise conducted in two villages.

The two villages are Adgaon in Yavatmal district and Mangrul in Nanded district of Maharashtra (Figure 3). Adgaon is a large village of about 1,400 ha and population of 1,835, compared to Mangrul which is a smaller village of 375 ha and a population of 598. The 5-year average annual rainfall for the villages is 754 mm for Adgaon and 1,081 mm for Mangrul. Both villages have predominantly clayey soils, but also areas with soils that are loamy sand, clay loam, gravelly clay loam, or silty clay loam. The depth of the soil also differs from shallow soils in the upper reaches and deeper soils in lowlands. The predominant crops cultivated in the villages are cotton and soybean. Other crops include lentils (especially, pigeon pea or *tur*) and turmeric in *kharif*, and millets, groundnut, or wheat in *rabi*. There is no access to surface water irrigation, but many farmers have their own private wells and borewells. However, the groundwater availability is unreliable, and many wells are dry between March and July.

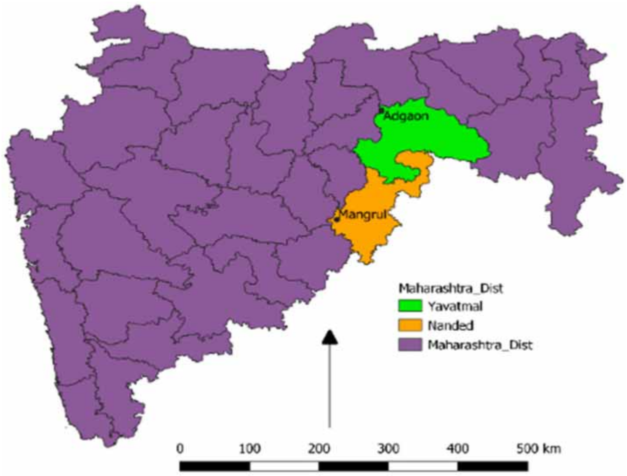

Fig. 3 | Location of field application.

For each village, we developed a model-computed dry spell sensitivity map. We then conducted farm surveys by sampling farm plots to cover a wide geography and hence different soil attributes of the village. Farmers were asked for details such as: farm biophysical properties (soil quality, depth), *kharif* crops sown, dry spell details (if experienced, how long and when), if the crop required irrigation, and if they were able to irrigate. We also asked the farmers their perception about the potential yield loss if they were unable to irrigate. In the next section, we elaborate on the findings.

3. RESULTS

In this section, we present the results of applying the dry spell sensitivity mapping tool to the two selected villages for the monsoon of 2021. We then compare the model output against farmers' own perception of the water deficit faced by their crops during the dry spells.

3.1. Dry spell analysis

We first study the rainfall pattern of 2021 monsoon for the two villages. 2021 was an above average rainfall year. Total rainfall received was 1,613 mm for Mangrul and 990 mm for Adgaon (50 and 31%, above average rainfall, respectively). However, as shown in Figure 4, despite being good rainfall years in terms of the total quantity of rainfall, Mangrul had a long dry spell of 23 days (between 24 July and 15 August), and Adgaon had three shorter dry spells of 12 days (29 June–10 July), 9 days (24 July–1 August), and 11 days (5 August–15 August). Both villages, especially Mangrul, also experienced an intense wet spell during the soybean harvesting time in late September which adversely impacted yields. Sowing of soybean and cotton was done in the early or end of June.

3.2. Dry spell sensitivity map

In order to compute the plot level sensitivity to the observed dry spells, we follow the method discussed in the previous section to prepare monsoon dry spell sensitivity maps. Figures 5(a)–5(f) and 6(a)–6(f) show the spatial input (secondary) data used to do so for the two villages. Figures 5(g) and 6(g) show the output, i.e., the monsoon dry spell sensitivity computed for the predominant *kharif* crop soybean. Since 2021 was a high rainfall year, the crop deficits are seen to be generally small, but the impact of the dry spells can be seen differently in the two

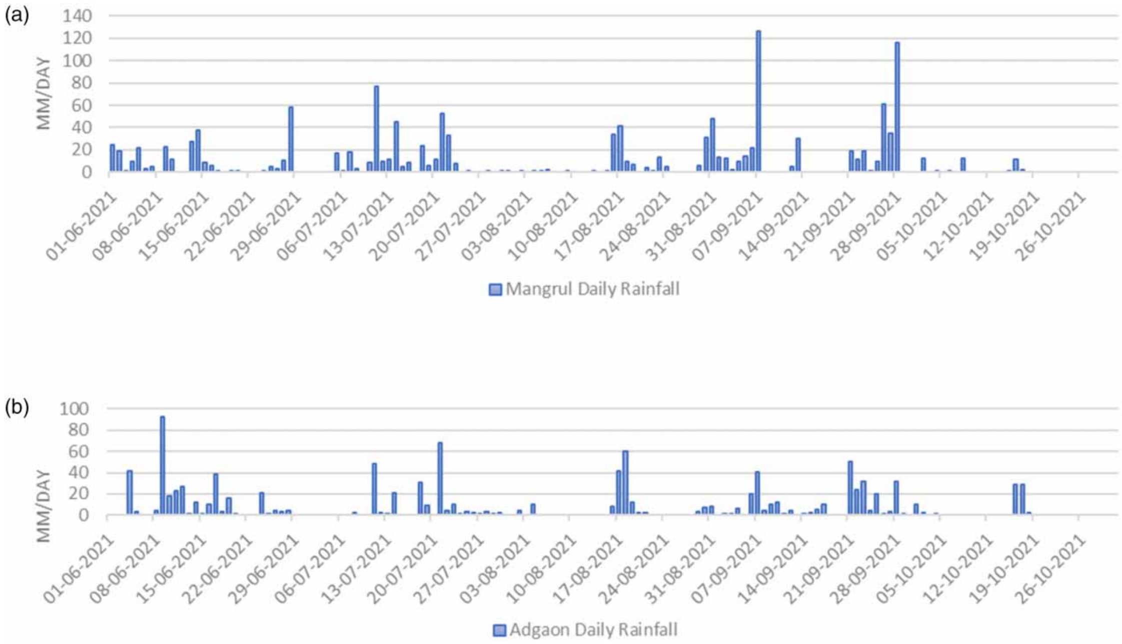

Fig. 4 | Daily monsoon rainfall pattern and dry spells for the year 2021: (a) Mangrul village, Nanded district and (b) Adgaon village, Yavatmal district (rainfall data source: Skymet).

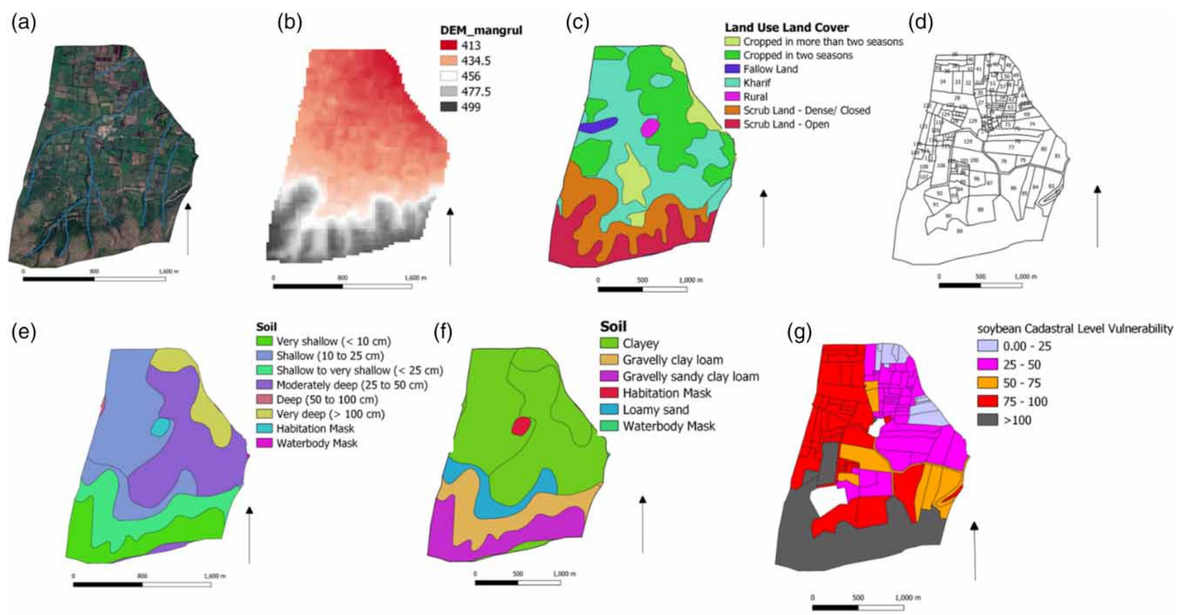

Fig. 5 | Mangrul village maps: (a) satellite map of village from Google Earth, drainage, (b) elevation, (c) land-use and land-cover (LULC), (d) cadastral map, (e) soil depth, (f) soil texture and output sensitivity map, and (g) cadastral level crop water deficit (in mm) for soybean crop in monsoon of 2021. Maps (a)–(f) are input data, which result in the output map (g). LULC, soil depth and soil texture maps based on shape files sourced from Maharashtra Remote Sensing Application Center (MRSAC), cadastral map sourced from Maha-bhulekh.

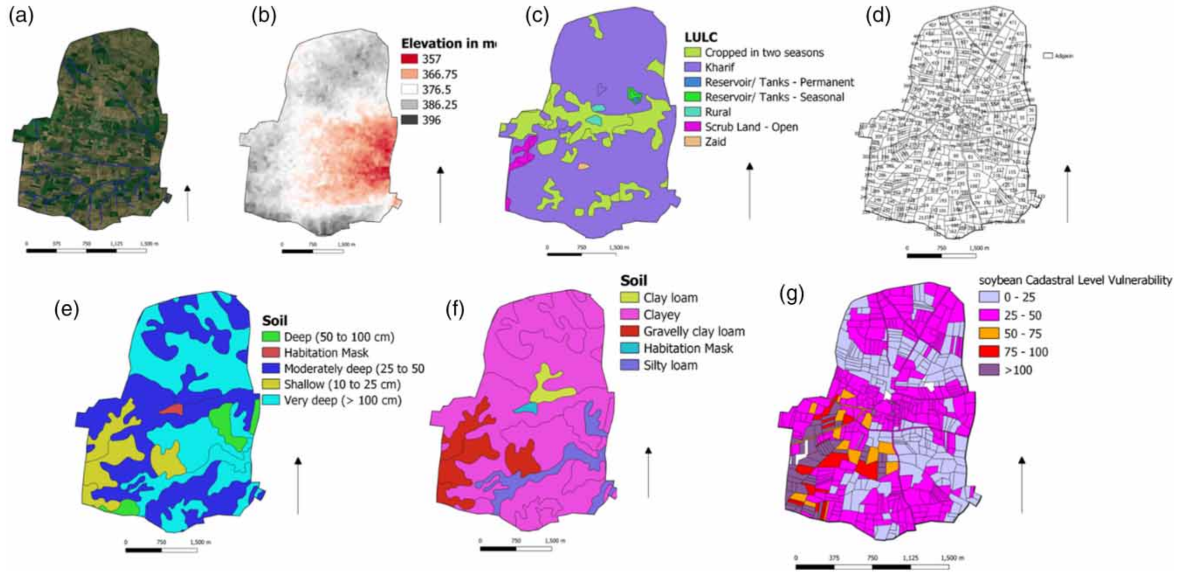

Fig. 6 | Adgaon village maps: (a) satellite map of village from Google Earth, drainage, (b) elevation, (c) land-use and land-cover (LULC), (d) cadastral map, (e) soil depth, (f) soil texture and output sensitivity map, and (g) cadastral level crop water deficit (in mm) for soybean crop in monsoon of 2021. Maps (a)–(f) are input data, which result in the output map (g). LULC, soil depth and soil texture maps based on shape files sourced from Maharashtra Remote Sensing Application Center (MRSAC), cadastral map sourced from Maha-bhulekh.

villages. The map for Mangrul (Figure 5(g)) shows many farms with a crop water deficit of more than 75 mm due to the long dry spell. However, in the case of Adgaon in Figure 6(g), the model shows that most farm plots suffered less than 75 mm deficit due to the shorter, frequent dry spells. Plots with deep clayey soils were able to withstand these dry spells to some degree, but farms with shallow gravelly soils in the upstream region faced a much higher crop water deficit for the same rainfall pattern, thus requiring crop-saving protective irrigation.

3.3. Field interview findings

In this section, we share the comparison of the model output of dry spell sensitivity map with the farmers' perception gathered through surveys conducted at the end of the 2021 *kharif* season. A total of 69 farmers were sampled: 30 in Mangrul and 39 in Adgaon. Surveys revealed that there was a significant mismatch between the remotely sensed MRSAC soil maps and farmers' own description of their soil type and depth. To address this, the crop water stress for the sampled plots was recomputed using primary soil information instead of MRSAC soil maps. As seen in Figure 7, this had a significant impact on the computed deficit for the farm plot and indicated the need for improved input maps.

We now compare the model output of crop water deficit with farmers' perceptions of the need for irrigation using the corrected soil data (Figures 8 and 9). The monsoon crop water deficit was computed for each plot and those which had a computed deficit of more than 15 mm were shown as ones needing irrigation. Figure 8(b) and 8(d) shows the model output for soybean and cotton, respectively, for Mangrul (and similarly Figure 9(b) and 9(d) for Adgaon). They are compared with Figure 8(c) and 8(e) which show farmers' perceptions captured through surveys. We note that farmers often sow multiple crops on the same plot, i.e., some acres may be devoted to soybean and some to cotton. Farmers also inter-crop cotton–soybean or *tur*–soybean. Hence, even though the total number of

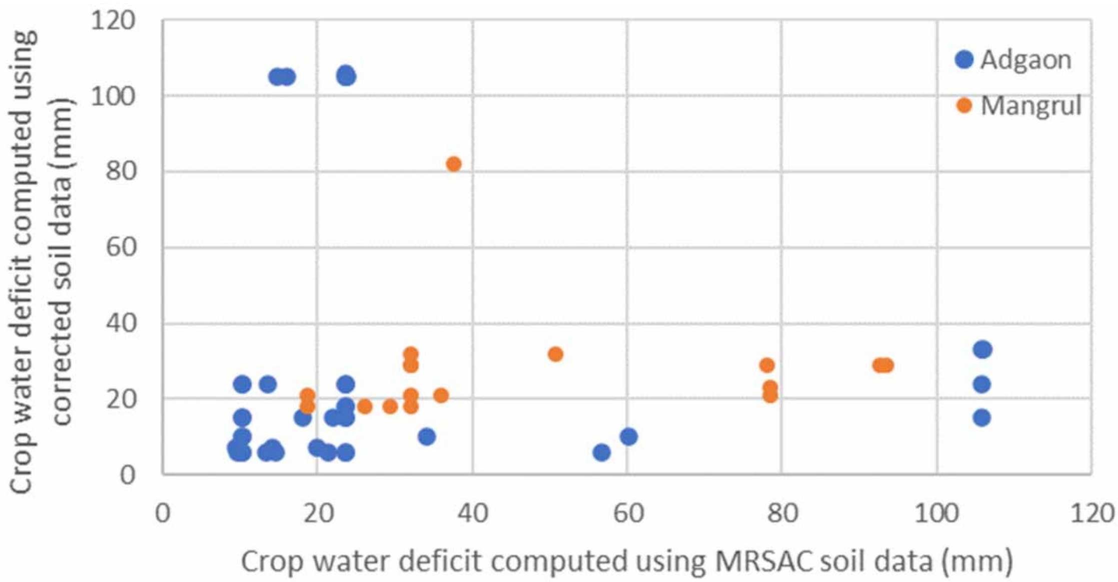

Fig. 7 | Comparison of soybean crop water deficit computed for surveyed plots using two different input data for soil type (state MRSAC data vs. primary field data).

surveyed farmers was 69, several farmers provided dry spell impact data for more than one crop giving us a total of 108 crop-farm plot combinations ranging over five crops. We limit our analysis to the 77 crop-farm pairs for the two dominant monsoon crops: soybean and cotton. Cotton is a long *kharif* crop (6–8 months) which is sown at the onset of monsoon. Those with access to irrigation provide a few irrigations to the crop after the end of the monsoon. The irrigation requirement indicated in the maps refers to irrigation required to meet the water deficit experienced by the crop during the monsoon season (and not in the post-monsoon period of the crop).

As an example, let us consider plot number 129 in Mangrul (Figure 8(a)). There are multiple farmers within the plot and two of them were interviewed. The first farmer cultivates 1.25 acres on this plot and also owns three other plots (numbers 106, 113, and 119) with a total of 7.65 acres across the four plots. The second farmer cultivates 3.7 acres on plot number 129. In the *kharif* season of 2021, the first farmer cultivated soybean while the second farmer cultivated both soybean and cotton. For farm plot 129, the MRSAC data indicated shallow soil depth (between 10 and 25 cm deep). Due to this, the computed deficit in Figure 5(g) is high (75–100 mm for soybean). However, both farmers described the soil depth in their farms to be more than 2 feet (>60 cm). As a result, we recomputed the crop water stress with corrected soil depth for all surveyed plots. With the correction, the model output shows that soybean would face a water deficit of about 30 mm. This agrees with the farmers' view who both indicated that their soybean crop needed to be irrigated. The first farmer was able to provide this by accessing a well, while the second was unable to do so. This was also reflected in the differences in their crop yields for soybean. In the case of the cotton crop on the same plot, the model estimates no need for irrigation due to the larger root zone for cotton from which moisture is accessible to the crop. However, in this, there was a disagreement with the farmer who believed that the crop needed irrigation (although he was unable to irrigate) while the model estimated that it was not needed.

In this way, a plot-wise comparison was made for each crop and farmer. This comparison is tabulated in Table 2, where the rows are the bins for the deficits obtained from the corrected soil parameters, and column

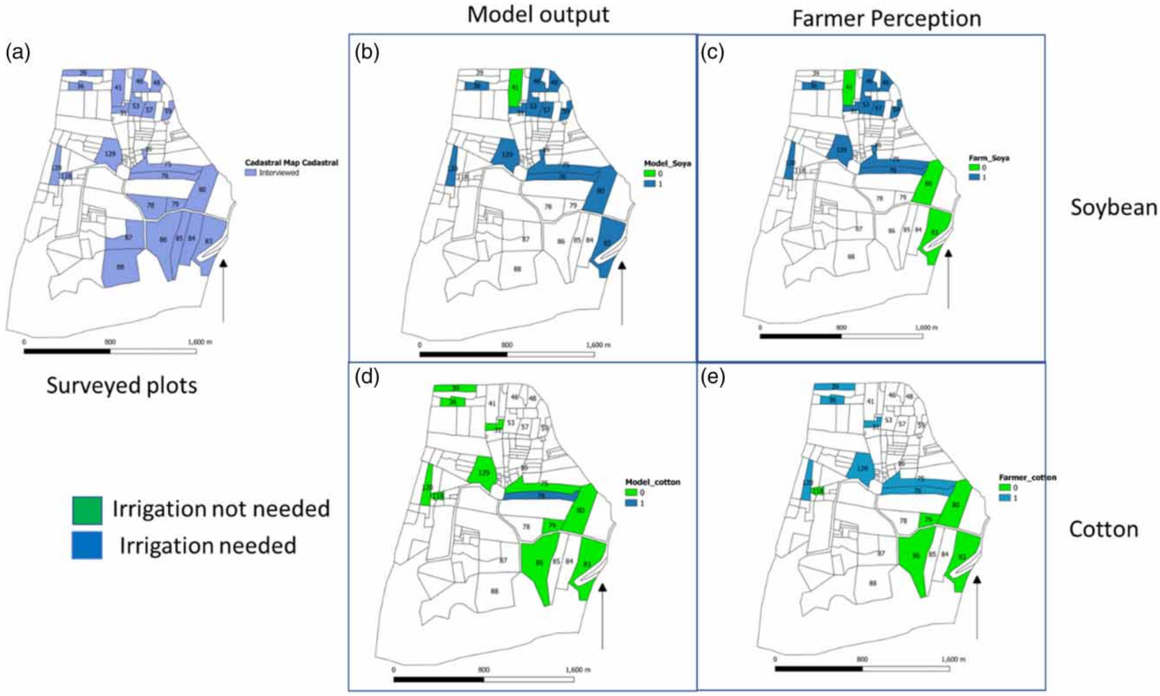

Fig. 8 | Kharif dry spell vulnerability in 2021 monsoon for Mangrul (a) interviewed farm plots, (b and d) dry spell sensitivity map in terms of irrigation requirement for (b) soybean and (d) cotton based on farmer's soil description (assumes irrigation not needed when crop water deficit is ≤15 mm, and irrigation needed when deficit is more than 15 mm), (c and e) farmer's description of whether irrigation was needed in 2021 monsoon for (c) soybean and (e) cotton. (0 = no need; 1 = needed). Cadastral map sourced from the government of Maharashtra Maha-bhulekh.

A is the frequency of that bin. Columns B and C record the farmer's perceptions for comparison. We find that for 72% (i.e., 56 of the 77 farm-crop pairs) of the data points there is an agreement between the model's output and the farmers' perception about their need for irrigation. It was seen that there are several nuances in farmers' perception of when a crop needs irrigation. Some farmers do not feel that there is a need for irrigation unless there is significant crop water stress, i.e., they seek protective irrigation for the crop to avoid a heavy loss of yield. And there are others who believe that irrigation is needed at the earliest signs of stress, i.e., they aim for productive irrigation to maximize crop yields. It is therefore expected that due to the qualitative nature of the questions posed to the farmers, there would not be a perfect match between farmers' perceptions and the model output. However, the model and farmers' perceptions match for plots with high crop water deficit (75 mm and higher) where protective irrigation would typically be required to reduce significant yield loss. Since 2021 was a high rainfall year, there were few plots with high crop water deficits. Another factor that may have contributed to mismatches between the model output and farmer perspective is poor recall of the dry spell impact by the farmers as they were heavily impacted by the destructive wet spell at the harvesting stage.

4. DISCUSSION

Vulnerability is a complex phenomenon, which needs better understanding and conceptualization. Currently, in practice, it is measured through social identities such as caste, class, gender, and their intersections which are

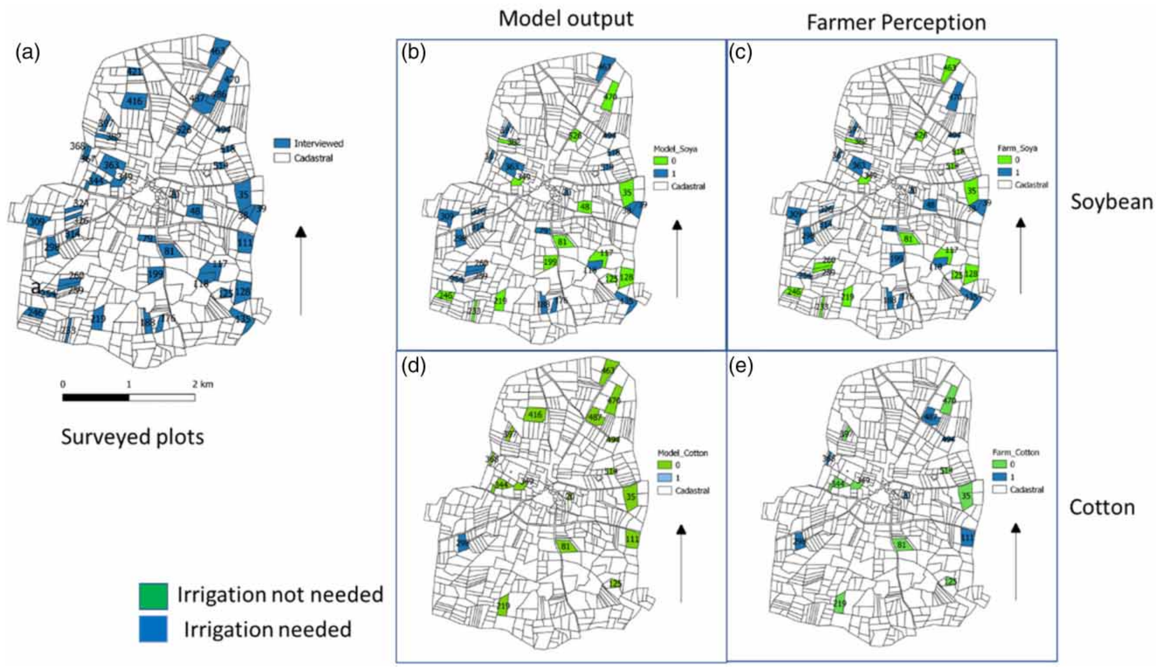

Fig. 9 | Kharif dry spell vulnerability in 2021 monsoon for Adgaon (a) interviewed farm plots, (b and d) dry spell sensitivity map in terms of irrigation requirement for (b) soybean and (d) cotton based on farmer's soil description (assumes irrigation not needed when crop water deficit is ≤15 mm, and irrigation needed when deficit is more than 15 mm), (c and e) farmer's description of whether irrigation was needed in 2021 monsoon for (c) soybean and (e) cotton. (0 = no need; 1 = needed). Cadastral map sourced from the government of Maharashtra Maha-bhulekh.

Table 1 | Computation method for farm-level water balance tool.

Water balance component	**Computation method**	**Reference**
Precipitation	Input from meteorological data	
Reference Evapotranspiration	Hargreaves model	FAO Paper 56 (Allen *et al.*, (1998))
Surface Run-off	SCS Curve number adjusted for slope	SWAT manual (Neitsch *et al.*, (2011))
Crop evapotranspiration (ETc)	FAO methodology for crop ET under standard conditions	FAO Paper 56 (Allen *et al.*, (1998))
Actual crop evapotranspiration (AET)	FAO methodology for crop ET under soil water stress	FAO Paper 56 (Allen *et al.*, (1998))
GW recharge	SWAT methodology	SWAT manual (Neitsch *et al.*, (2011))
Soil moisture	Mass balance	
Monsoon crop water-deficit	Difference between potential Crop Evapotranspiration and Actual evapotranspiration aggregated over the monsoon period	

Table 2 | Comparison of modelled monsoon crop water deficit using corrected soil type with survey output for soybean and cotton farmers, year 2021.

Crop water deficit model output (mm)	(A) Number of farm plots	(B) Farmer perspective: irrigation was not needed	(C) Farmer perspective: irrigation was needed
0	17	10	7
0–15	21	14	7
15–30	27	6	21
30–45	4	1	3
45–60	0	0	0
60–75	0	0	0
75–100	2	0	2
100–125	6	0	6
Total	**77**	**31**	**46**

It is assumed that a modelled deficit of <15 mm requires no irrigation. This is compared with farmers' perception of whether irrigation was needed by the crop.

shown to generally map to different levels of access to material and social assets. When it comes to climate vulnerability, these factors influence the adaptive capacity of farmers. However, crop sensitivity to dry spells is a largely biophysical phenomenon, which has so far not been captured in climate vulnerability literature or in state interventions to address farmer vulnerability. Our key contribution is our conceptualization of dry spell sensitivity in terms of crop water deficit at the unit of a farm and a methodology to map its distribution to allow comparison between farms at an aggregate scale such as a village or cluster of villages. A related quantity that has been considered a good indicator of agricultural droughts is the soil moisture content. However, soil moisture alone is not a good indicator of dry spell sensitivity as it needs to be seen in combination with other variables such as precipitation patterns and type of crop grown. For example, Gao *et al.* (2016) used a distributed hydrological model to capture and map soil moisture for their study area in North China Plain and extended this to map drought vulnerability. This required mapping of four distinct factors: rainfall distribution, available run-off, soil water storage capacity, and crop type, and creating a vulnerability score by weighing them equally. Our method of mapping crop water deficit is an improvement over such an approach as it integrates these related factors into a single physical quantity that captures the stress experienced by the crop during a dry spell. Secondly, crop water deficit is an actionable attribute that suggests the extent of irrigation needed to avoid crop loss. In this way, our proposed map not only presents who is most vulnerable to dry spells but also relates it to the action needed to address it. Preston *et al.* (2011), in their review of approaches to map climate vulnerability, call this an important criterion for placing vulnerability mapping on a robust footing. Thirdly, our approach to mapping vulnerability makes it possible to validate or refute the output, unlike vulnerability mapping approaches which are broader representations of vulnerability and are thus limited in their ability to influence policy and action (de Sherbinin *et al.*, 2019).

With increasing variability in rainfall patterns across the world, especially in rainfed regions of Asia and Africa, identifying and targeting support to farmers facing dry spell vulnerability will be increasingly important. Our method is easily replicable in other geographies. Coupling dry spell sensitivity with appropriate regional proxies for adaptive capacity (such as access to irrigation, and knowledge) leads to a robust way to measure different levels of vulnerability to enable action. In the Supplementary material, we illustrate how our tool assists prioritization and planning of a specific type of investment, i.e., the open dug-well, within the PoCRA project by

Table 3 | Status of input data sets and needs for further improvement.

Input dataset	Current source of data	Scale and resolution	Limitation	Corrective measures needed/ taken
Soil texture and soil depth shape files	Maharashtra Remote Sensing Application Centre (MRSAC)	Scale: 1:50000	Poor accuracy of soil texture and depth	MoU with National Bureau of Soil Survey (NBSS) initiated for generation of more accurate (higher resolution) soil maps
Soil properties (e.g., bulk density, saturated hydraulic conductivity, field capacity etc.) for each texture class	FAO and SPAW (Soil–Plant–Air–Water) model	NA	No state-level database available for local soil properties, no studies undertaken	Extensive field surveys and lab tests required to generate local state-level soil databases capturing organic matter, salinity etc. that impact soil properties
Crop properties such as: root depth, depletion factor, crop duration, growth stages, Kc value	FAO	NA	Kc values may differ from region to region and variety to variety. No state-level data available	Estimation of Kc for few major crops through lysimeter experiments at State Agriculture Universities to be initiated in PoCRA. More local studies required for documenting different crop varieties and their properties
Rainfall and weather data	Skymet automated weather stations	Spatial: Roughly 1 station per 13,000 ha. Temporal – hourly	Problem of some weather stations going down during monsoon season due to power outage or network issues	Significant improvement in data resolution and frequency is already achieved – from yearly district level rainfall data (1998), then daily block level data (1999), followed by daily revenue circle level rainfall data (from 2013). Since 2018, hourly weather data is recorded by Skymet in collaboration with GoM through weather stations in all revenue circles
Curve number	USDA	Available for different land covers and HSGs (Classified as per US conditions)	Researchers have shown differences in curve numbers when computed locally. But no state-wide data available on curve numbers.	Need several local studies for generating local database for Curve Numbers
Digital elevation map	SRTM	30 m × 30 m	Current resolution and quality are sufficient for	1 m × 1 m resolution DEM maps available. May be

(*Continued.*)

Table 3 | Continued

Input dataset	Current source of data	Scale and resolution	Limitation	Corrective measures needed/ taken
			generating slope and drainage maps.	used for better delineation of stream proximity regions in the future
LULC data	MRSAC	Scale: 1:50000 Temporal: once in 5 years	Latest available data is from 2015 to 16. Yearly changes in LULC due to rainfall are important but not currently recorded/ published	LULC map must be updated at least every year but preferably quarterly to capture seasonal cropping
Cadastral data	Maha-Bhulekh and MRSAC	Temporal frequency: Maps updated every 5 years	Changes and divisions of land-parcels not reflected yearly. Quality: several duplicates, overlaps in cadastre polygons, survey plot numbers encountered	Data needs frequent updates, resolution of errors

combining dry spell sensitivity maps with indicators of adaptive capacity. Supplementary material, Fig. S1 depicts the Well Beneficiary module used to create a village scale vulnerability map based on which subsidies for dug wells are prioritized. A sample of the generated output report is shared in Supplementary material, Fig. S2. There are, however, many challenges associated with the approach which we reflect on in the following section.

As seen in our results, the quality of input datasets presents many challenges. For example, significant inconsistency was found between the soil characteristics as indicated by the state-provided MRSAC maps and the soil characteristics described by the farmers. As a result, the project partnered with the National Bureau of Soil Survey and Land-Use Planning (NBSS&LUP) to improve the accuracy of soil maps. Besides this, other challenges in input data sets were encountered, which are tabulated in Table 2. Similar challenges in vulnerability mapping have also been called out by other scholars. Given the inter-sectoral nature of vulnerability assessments, (Kienberger *et al.*, 2016) in their spatial vulnerability mapping in Mauritania emphasize the importance of the availability of data at good spatial resolution and policies for data sharing across sectors.

In addition to efforts on improving input data quality, the model requires many refinements, for example, to improve the calibration and to incorporate the effect of key farm-preparation practices. Although the tool is based on a standard crop water–soil model, there is a need to calibrate it to context-specific practices, e.g., irrigation methods, intercropping practices, etc. for better results. For example, Gao *et al.* (2016) report an error margin of 10% in their mapping of modelled soil moisture when compared to observed values, despite the availability of detailed input data. Some of our ongoing efforts for model improvements are tabulated in Table 3. These demonstrate the challenges in the practical application of science for enhancing climate resilience in agriculture. It requires long-term engagement, extensive fieldwork, and continuous engagement with a large number of stakeholders.

Our experience is consistent with de Sherbinin *et al.* (2019) who caution that developing vulnerability maps should not become an end in itself. The centrality of stakeholder engagement in vulnerability mapping cannot

Table 4 | Ongoing and planned model improvements.

No.	Problem addressed	Model improvement	Remark	Status
1	Model run-off higher than field observation	Change from daily to hourly time-step		Complete. Report published here: https://www.cse.iitb.ac.in/~pocra/Report_a.pdf
2		Shift from using static monthly ET^0 values to weather-based hourly values.	Linked with hourly Skymet data	Complete
3		Calibrating reference evapotranspiration (ET^0) computation	Comparison of ET0 values from three different empirical equations (Hargreaves, Jensen-Haise and FAO-56 Penman Monteith) against measured data from WALMI to select the appropriate one	Complete. Report published here: https://www.cse.iitb.ac.in/~pocra/MoU%20II%20Phase%20II/PET_Method.pdf
4	Different farm practices and their impact on recharge and soil moisture retention	Furrows: Incorporating ponding effect	Ponding constant introduced in the model	Complete. Report published here: https://www.cse.iitb.ac.in/~pocra/Report_a.pdf
5		Impact of intercropping		To be addressed in the future
6	Improvement in groundwater recharge estimates in high rainfall situations	Improvement in groundwater recharge estimation	Incorporating hydrogeological parameters such as aquifer thickness and specific yield for capping GW recharge and accounting excess as surface or base flows	Conceptual prototype recommended and accepted by GoM. The changes can be implemented over the whole state once GSDA publishes/shares better resolution hydrogeological data

be sufficiently emphasized. At the same time, conducting transdisciplinary research with different stakeholders who have different expectations has its own challenges. For example, the government agencies want measurable output within a given timeframe, the scientists look for scientific robustness of the output and the communities expect an outcome that they deem to be relatable and understandable. The desired approaches of each stakeholder are also different. State agencies look for more centralized, secondary data-based processes to plan interventions. The communities have their institutions and structures of power and politics embedded within them which have strong interests in planning interventions. It is these considerations that researchers must negotiate when working together with policymakers and programme implementors.

5. CONCLUSION

All over the world, rainfed agriculture faces growing risk from climate change. Farmers suffer from dry spell-induced crop failures. Implementing policies to enhance climate resilience of farmers within the dryland regions requires ways of identifying and mapping relative vulnerability in order to target investments to the most vulnerable. Vulnerability mapping has been used at coarser scales for problem orientation and policy decisions on which hotspots to focus on. Here, we present a methodology that allows vulnerability mapping at the unit of a farm, which is useful to support targeting of interventions for climate resilience within a project focus area, such as a cluster of villages. This is important since there is wide variation in vulnerability within any focus region.

In India, the Government of Maharashtra's PoCRA is the first state programme in the country that has the mandate to support farmers identified as most vulnerable. Our scientific inputs and tools for mapping vulnerability have been developed and deployed in the programme through a transdisciplinary partnership with the implementing agency. Our scientific contribution is in the conceptualization of dry spell vulnerability as a combination of crop water deficit, which is a function of farm biophysical attributes, and the farmers' adaptive capacity, which is driven by social attributes. We extend this concept to practice in the form of a tool that is embedded in the state process to target interventions and bring more transparency to the process. The development of our tool has been through an iterative effort of field validation, reporting, and model improvements. The paper presents the results of one such cycle of field application. Our work demonstrates how vulnerability to climate hazards may be mapped at micro-scales to assist policy-makers and practitioners in targeting interventions. Our methods can be easily adapted to plan for climate resilience in other ecologically fragile regions which experience high variability in rainfall and other weather parameters. Our tool and the process in which it is embedded is a significant step in current intervention planning for climate-resilient agriculture, yet there continue to be several areas of improvement. Our key learning is that enhancing climate resilience in agricultural production requires infusion of new science within state processes through long-term partnerships with different agencies and communities.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. (1998). FAO irrigation and drainage paper. *Irrigation and Drainage 300*(56), 300. https://doi.org/10.1016/j.eja.2010.12.001.

Bhopale, M. (2019). *Implementing Climate Resilience in Agriculture*, M.Tech. Thesis, Indian Institute of Technology Bombay, India. Available at: https://www.cse.iitb.ac.in/~pocra/MTP2reportmanasi.pdf.

Brooks, N., (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for climate change research working paper*, (38).

Dagdeviren, H., Elangovan, A. & Parimalavalli, R. (2021). Climate change, monsoon failures and inequality of impacts in South India. *Journal of Environmental Management 299*(August), 113555. https://doi.org/10.1016/j.jenvman.2021.113555.

de Sherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B. & Zhang, S. (2019). Climate vulnerability mapping: a systematic review and future prospects. *Wiley Interdisciplinary Reviews: Climate Change 10*(5), 1–23. https://doi.org/10.1002/wcc.600.

DTE (2019). *Drought but why: What Happened to the Promise of Drought-Free Maharashtra?* Down to Earth. Available at: https://www.downtoearth.org.in/news/agriculture/drought-but-why-what-happened-to-the-promise-of-a-drought-free-maharashtra–63417 (accessed 9 March 2019).

Duncan, J. M., Tompkins, E. L., Dash, J. & Tripathy, B. (2017). Resilience to hazards: rice farmers in the Mahanadi Delta, India. *Ecology and Society 22*(4). https://doi.org/10.5751/ES-09559-220403.

Enfors, E. (2013). Social – ecological traps and transformations in dryland agro-ecosystems : using water system innovations to change the trajectory of development. *Global Environmental Change 23*(1), 51–60. https://doi.org/10.1016/j.gloenvcha.2012.10.007.

Gao, X., Lu, C., Luan, Q., Zhang, S., Liu, J. & Han, D. (2016). Mapping farmland-soil moisture at a regional scale using a distributed hydrological model: case study in the North China plain. *Journal of Irrigation and Drainage Engineering 142*(9). https://doi.org/10.1061/(ASCE)IR.1943-4774.0001036

Garg, K. K., Singh, R., Anantha, K. H., Singh, A. K., Akuraju, V. R., Barron, J., Dev, I., Tewari, R. K., Wani, S. P., Dhyani, S. K. & Dixit, S. (2020). Building climate resilience in degraded agricultural landscapes through water management: a case study of Bundelkhand region, Central India. *Journal of Hydrology 591*(April), 125592. https://doi.org/10.1016/j.jhydrol.2020.125592.

Hessari, B. & Oweis, T. (2021). Conjunctive use of green and blue water resources in agriculture: methodology and application for supplemental irrigation*. *Irrigation and Drainage 70*(5), 1193–1208. https://doi.org/10.1002/ird.2611.

Imbulana, N. & Manoharan, S. (2020). Hydrological and water balance studies to evaluate options for climate resilience in smallholder irrigation systems in Sri Lanka. *Water Policy 22*(6), 1024–1046. https://doi.org/10.2166/wp.2020.111.

Jurriens, M., Mollinga, P. P. & Wester, P. (1996). Scarcity by design. Protective irrigation in India and Pakistan. *Liquid gold paper 1*(July 2016), 1–60.

Kadiyala, M. D. M., Gummadi, S., Irshad, M. A., Palanisamy, R., Gumma, M. K. & Whitbread, A. (2021). Assessment of climate change and vulnerability in Indian state of Telangana for better agricultural planning. *Theoretical and Applied Climatology 143*(1–2), 309–325. https://doi.org/10.1007/s00704-020-03425-8.

Keshavarz, M. (2016). Agricultural water vulnerability in rural Iran. *Water Policy 18*(3), 586–598.

Kienberger, S., Borderon, M., Bollin, C. & Jell, B. (2016). Climate change vulnerability assessment in Mauritania: reflections on data quality, spatial scales, aggregation and visualizations. *GI_Forum 4*(1), 167–175. https://doi.org/10.1553/giscience2016_01_s167.

Kuchimanchi, B. R., Nazareth, D., Bendapudi, R., Awasthi, S. & D'Souza, M. (2019). Assessing differential vulnerability of communities in the agrarian context in two districts of Maharashtra, India. *Climate and Development 11*(10), 918–929. https://doi.org/10.1080/17565529.2019.1593815.

Kuchimanchi, B. R., van Paassen, A. & Oosting, S. J. (2021). Understanding the vulnerability, farming strategies and development pathways of smallholder farming systems in Telangana, India. *Climate Risk Management 31*(April 2020), 100275. https://doi.org/10.1016/j.crm.2021.100275.

Kumar, M. D. & Saleth, R. M. (2018). Inequality in the Indian water sector: challenges and policy options. *Indian Journal of Human Development 12*(2), 265–281. https://doi.org/10.1177/0973703018793727.

Kumar, M. D., Reddy, V. R., Narayanamoorthy, A., Bassi, N. & James, A. J. (2018). Rainfed areas: poor definition and flawed solutions. *International Journal of Water Resources Development 34*(2), 278–291. https://doi.org/10.1080/07900627.2017.1278680.

Lindoso, D. P., Rocha, J. D., Debortoli, N., Parente, I. I., Eiró, F., Bursztyn, M. & Rodrigues-Filho, S. (2014). Integrated assessment of smallholder farming's vulnerability to drought in the Brazilian Semi-arid: a case study in Ceará. *Climatic Change 127*(1), 93–105. https://doi.org/10.1007/s10584-014-1116-1.

Manivasagam, V. S. & Nagarajan, R. (2017). Assessing the supplementary irrigation for improving crop productivity in water stress region using spatial hydrological model. *Geocarto International 32*(1), 1–17. https://doi.org/10.1080/10106049.2015.1120355.

Meza, I., Eyshi Rezaei, E., Siebert, S., Ghazaryan, G., Nouri, H., Dubovyk, O., Gerdener, H., Herbert, C., Kusche, J., Popat, E., Rhyner, J., Jordaan, A., Walz, Y. & Hagenlocher, M. (2021). Drought risk for agricultural systems in South Africa: drivers, spatial patterns, and implications for drought risk management. *Science of the Total Environment 799*. https://doi.org/10.1016/j.scitotenv.2021.149505.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R. & Williams, J. R. (2011). Soil & water assessment tool theoretical documentation version 2009. *Texas Water Resources Institute*, 1–647. https://doi.org/10.1016/j.scitotenv.2015.11.063.

Nyantakyi-frimpong, H. (2020). Unmasking difference : intersectionality and smallholder farmers ' vulnerability to climate extremes in Northern Ghana. *Gender, Place & Culture 27*(11), 1536–1554. https://doi.org/10.1080/0966369X.2019.1693344.

Panigrahi, B., Panda, S. N. & Agrawal, A. (2005). Water balance simulation and economic analysis for optimal size of on-farm reservoir. *Water Resources Management 19*(3), 233–250. https://doi.org/10.1007/s11269-005-2701-x.

Prasad, P. & Sohoni, M. (2020). Agricultural intensification and risk in water-constrained hard-rock regions: a social-ecological systems study of horticulture cultivation in Western India. *Ecology and Society 25*(4), 1–20. https://doi.org/10.5751/ES-11825-250402.

Prasad, P., Damani, O. P. & Sohoni, M. (2022). How can resource-level thresholds guide sustainable intensification of agriculture at farm level? A system dynamics study of farm-pond based intensification. *Agricultural Water Management 264*. https://doi.org/10.1016/j.agwat.2021.107385.

Preston, B. L., Yuen, E. J. & Westaway, R. M. (2011). Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. *Sustainability Science 6*, 177–202. https://doi.org/10.1007/s11625-011-0129-1.

Ramprasad, V. (2018). Debt and vulnerability : indebtedness, institutions and smallholder agriculture in South India. *The Journal of Peasant Studies 0*(0), 1–22. https://doi.org/10.1080/03066150.2018.1460597.

Rockström, J. & Falkenmark, M. (2000). Semiarid crop production from a hydrological perspective: gap between potential and actual yields. *Critical Reviews in Plant Sciences 19*(4), 319–346. https://doi.org/10.1080/07352680091139259.

Rockström, J., Karlberg, L., Wani, S. P., Barron, J., Hatibu, N., Oweis, T., Bruggeman, A., Farahani, J. & Qiang, Z. (2010). Managing water in rainfed agriculture-The need for a paradigm shift. *Agricultural Water Management 97*(4), 543–550. https://doi.org/10.1016/j.agwat.2009.09.009.

Sikka, A. K., Islam, A. & Rao, K. V. (2018). Climate-smart land and water management for sustainable agriculture. *Irrigation and Drainage 67*(1), 72–81. https://doi.org/10.1002/ird.2162.

Singh, S. (2020). Bridging the gap between biophysical and social vulnerability in rural India: a community livelihood vulnerability approach. *Area Development and Policy 5*(4), 390–411. https://doi.org/10.1080/23792949.2020.1734473.

Singh, D., Tsiang, M., Rajaratnam, B. & Diffenbaugh, N. S. (2014). Observed changes in extreme wet and dry spells during the South Asian summer monsoon season. *Nature Climate Change 4*, 456.

Swami, D. & Parthasarathy, D. (2020). A multidimensional perspective to farmers ' decision making determines the adaptation of the farming community. *Journal of Environmental Management 264*(March), 110487. https://doi.org/10.1016/j.jenvman.2020.110487.

Swami, D., Dave, P. & Parthasarathy, D. (2018). Agricultural susceptibility to monsoon variability: a district level analysis of Maharashtra, India. *Science of the Total Environment 619–620*, 559–577. https://doi.org/10.1016/j.scitotenv.2017.10.328.

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