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Increasing agricultural risk to hydro-climatic extremes in India

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Abstract

Indian agriculture is globally well-documented to reflect the impacts of changing climate significantly. However, climate adaptation efforts are often hindered due to the inadequate assessment of coupled human-environment interactions. In this study, we propose a novel unified country-level framework to quantify the decadal agricultural risks derived from multiple hydro-meteorological exposures and adaptive consequences. We identify, for the first time, that rice and wheat risks have increased in the recent decade, with wheat at a twofold higher magnitude than rice. Increasing crops risk is found to be predominantly driven by the decreasing number of cultivators; in particular, the wheat risk is also attributed to increasing minimum temperatures during the crop growing season. We provide convincing evidence indicating that the hydro-climatic hazards related to precipitation extremes and droughts are specifically alarming the crops risk as compared to temperature extremes. These observation-based results highlight the sensitivity of India's agriculture and the risk associated with multiple agro-ecological and climatic components. We recommend these findings to facilitate the informed planning of adaptive measures and ensure sustainable food security of the nation.

1. Introduction

India has a population of approximately 1.3 billion, which is equivalent to 17.8% of the total world population [1]. India's Economic Survey 2017–18 [2] of the Government of India (GoI) depicts agriculture as one of the most crucial economic sectors in India and a key source of employment. Evidently, Wheeler and Von Braun [3] indicated that around 20% of the Indian population is facing food insecurity issues. Under such conditions, crop production needs to be increased twofold to meet the food demand and alleviate poverty [4]. However, with the increase in occurrences of extreme events such as precipitation extremes [5], droughts [6] and high maximum temperatures [7] across India due to climate change [8], agricultural growth is already being hindered. In addition, this impact on agriculture will likely continue with the increasing trend in extreme events [9, 10].

A considerable number of studies have been conducted globally, including in India, to understand the effects of climate variability on crop yields. For example, Lobell and Field [11] noted a negative response of global yields of wheat, maize and barley to the observed rising temperature trends. Similarly, Pathak *et al* [12] noted that an increase in minimum temperatures over the Indo-Gangetic plains in India caused downward trends in both rice and wheat yields. Rupa Kumar *et al* [13] further observed that yields of India's major crops such as rice, maize and wheat, were significantly associated with the stability of Indian Summer Monsoon Rainfall (ISMR). With regard to the ISMR, studies have reported a decrease in its magnitude in the recent past and have attributed this decrease to different phenomena [14, 15]. These results may indicate that the crop yields will further decrease and subsequently hamper the food security in India. Additionally, most of the previous studies addressing future food security were based on projected scenarios in which climate model outputs were used to simulate various crop models, over a large spatial domain. Although these simulations play a crucial role in providing the information related to climate-crop interactions, it is accompanied with uncertainties which are mainly due to the different initial and boundary conditions and convective schemes considered in the climate models [16]. An additional level of uncertainty is linked to the usage of different crop models [17], no matter how sophisticated they are.

Surprisingly, very few studies over India have been focused on understanding the land-atmospheric nexus of agriculture, climate, hydrology and socio-economics. For example, a study by Soora *et al* [18] used the InfoCrop-Rice model to identify the vulnerable regions for irrigated and rainfed rice cultivation, and further quantified the impacts and adaptations associated with future climatic scenarios in India. Nonetheless, this study primarily attempted to associate the response of crop yield to climate variables for estimating vulnerabilities and less emphasized on regional socio-economics. However, a holistic vulnerability framework should encompass coupled human-environment system [19], because 'vulnerability' as a metric should quantify the extent to which climate may affect or harm an agricultural system [20] and socio-economics of the region. Additionally, O'Brien *et al* [21] performed agricultural vulnerability analysis of observed yields by considering socio-economic factors and mapped the import sensitivity and globalization trend with precipitation-driven climate sensitivity. Meanwhile, a recent study by Das [22] reported that precipitation along with temperature-driven climate sensitivity does have a significant influence on the corresponding agricultural response. Thus, in combination with the vulnerability information provided by O'Brien *et al* [21], assessing the agricultural risk is essential and such assessments can be obtained by including probabilistic climatic hazard information. More recently, Sendhil *et al* [23] performed a detailed vulnerability assessment of wheat crop across the Indian states by considering agricultural, hydrological and socio-economic indicators. The states were ranked based on their sensitivity, exposure, adaptive capacity and vulnerability index. However, the analysis was performed at a very coarse spatial resolution and hence, less captured the diversity of multiple agro-ecological systems in India. These aforementioned studies notably followed the definition of 'vulnerability' provided in the third Assessment Report (AR3) by the Intergovernmental Panel on Climate Change (IPCC) [24], which described it as 'a function of the character, magnitude and rate of climate variation to which a system is exposed, its sensitivity and its adaptive capacity'. However, the fifth Assessment Report (AR5) by the IPCC significantly modified the definition of 'vulnerability' and introduced the term 'risk' as a function of 'exposure', 'hazard' and 'vulnerability' [25], which demands to be implemented to understand the agricultural risks throughout India.

In light of these imperatives, the main objective of the present study is to develop a fine-resolution district-level agricultural vulnerability map for India that considers a suite of agricultural, hydro-meteorological and socio-economic indicators procured from reliable data portals over the last two census decades (2001 and 2011). In this context, plausibly for the first time in the reported literature, we have performed a comprehensive agricultural risk and vulnerability analyses based on the framework provided in AR5 by IPCC, for entire India at a district-scale. Two major Indian staple crops, rice and wheat were considered in this study. The significance of assessing the agricultural risk for these crops can be ascertained from the fact that their collective production accounted for 78% of the total food grains produced in the year 2015–16 [26], thus resulting for a notable impact on the Indian economy with approximately 14% of the gross domestic product (GDP) shared by agriculture [27]. We selected these two decades and a suite of relevant indicators based on data parity in all the indicators at the same spatial scales as well as overall continuity and consistency. In addition, for the first time, we assessed the agricultural risk in a novel unified framework by considering agricultural vulnerability and the three most frequently occurring hydro-climatic hazards on the Indian subcontinent, viz., precipitation extremes, temperature extremes and drought. Here, the definition of 'risk' as reported in AR5 was followed, which is more holistic as compared to the definition of 'vulnerability' in AR3 [25]. Final risk maps derived from this study are the advanced cartographic products that can be utilized to prioritize the regions falling in high agricultural vulnerability and/or risk categories. These results may facilitate the development of suitable adaptations or the introduction of more intensive and innovative options under different hydro-climatic extreme conditions across India. Besides, the proposed framework may enable the development of a code of practice that can be applied in other countries to develop agricultural risk maps.

2. Materials and methods

We estimated agricultural vulnerability based on the district-level indicators that were classified into two segments: adaptation and vulnerability; the former is an inversely related positive segment to the agricultural vulnerability, whereas the latter is a directly related negative segment. A total of 40 (42) relevant indicators were selected to reflect an impact on the agricultural system of rice (wheat) across India. Segments utilized the data that were procured from publicly available data portals of the Census of India (agricultural population and water availability, credit

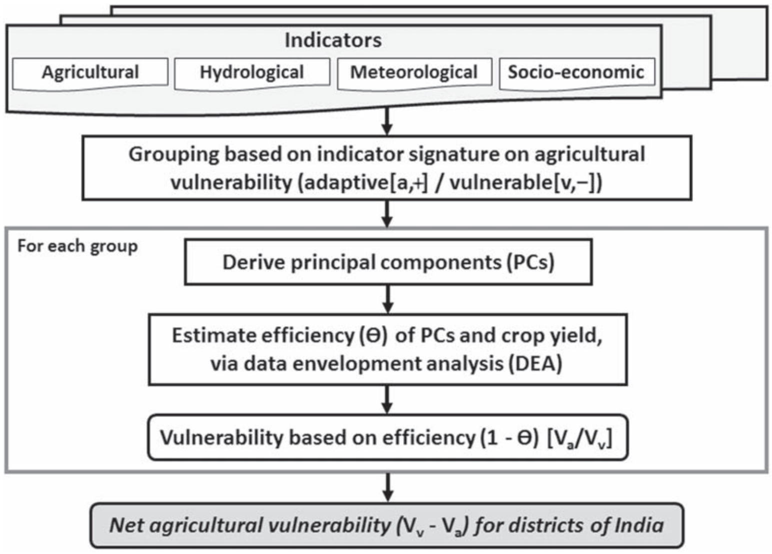

Figure 1. Proposed methodological framework for mapping the agricultural vulnerability.

societies and power supply for agricultural use, *Socio-economic*), India Meteorological Department (IMD) (wet spell, cold spell, warm spell and crop growth stage-wise temperature unfavorable durations, *Meteorological*), Central Ground Water Board of India (groundwater level, *Hydrological*), European Space Agency Climate Change Initiative (soil moisture, *Hydrological*), Crop Production Statistics Information System of the GoI (crop cultivable area and yield, *Agricultural*) and MODerate resolution Imaging Spectroradiometer (MODIS-vegetation index, *Agricultural*). Furthermore, the census data is prepared once in a decade, with census data of year 2001 representing the time period 1996–2005 and year 2011 representing the time period 2006–2015. Moreover, the data on crop yields are consistently available from 1998 to 2014. Hence, to maintain parity in the time-scale among all other time-variant meteorological and hydrological indicators, a common possible maximum data duration was considered from 1998–2013. This duration was divided into two equal intervals (1998–2005 and 2006–2013), the average of each representing the census year of 2001 and 2011 respectively. To derive meteorological indicators, we followed the definitions provided by IMD, for the temporal windows of sowing to harvesting months from June to October (for Kharif rice) and November to March (for Rabi wheat). Supplementary tables 1 and 2 is available online at stacks.iop.org/ERL/15/034010/mmedia list all the indicators that were considered in this study, with their detailed descriptions and supporting references.

On procuring all the indicators, we performed Principal Component Analysis (PCA) for each segment to decorrelate the data matrix and make it dimensionless to ensure a reliable comparison. We selected Principal Components (PCs) explaining 80% of the variability in indicators of both the segments for 2001 and 2011 census decades. These PCs were then considered as input in a robust nonparametric data envelopment analysis (DEA) [28] framework to obtain the rankings of each decision-making unit (DMU), which, in this case, were the districts of India. The rationale of considering DEA over other competing approaches such as cluster analysis, averaging and standard deviation has been discussed in supplementary Text 1. Here, observed crop yield was considered as output in the DEA framework. The rankings were derived in terms of efficiency (Θ), which were measured by the distance of input-output vectors to discrete piecewise frontier as estimated by a set of Pareto-efficient DMUs, through linear programming. A DMU will be considered technically efficient (a high value of Θ) if it uses the same amount of inputs (or less) to produce a given amount of output, compared to the other DMUs. Thus, an inefficient DMU (1-Θ) is the one that is incapable of using available inputs to produce a given output, which implies its vulnerability [29, 30]. Among different DEA models available, we used the Banker–Charnes–Cooper (BCC) [31] model because of its wide applicability. Here, net vulnerability of a DMU was the difference between measures derived from each segment. The proposed methodology has been illustrated in figure 1, which was used to derive the agricultural vulnerability of rice and wheat crops for both the census decades.

In order to understand the relative vulnerability behavior of each DMU, we standardized the net vulnerability V_i for each DMU '*i*' based on equation (1) [32] to obtain the agricultural vulnerability $V_{i_{Relative}}$ of that DMU. Here $V_{\min}$ and $V_{\max}$ are the minimum and maximum net vulnerability measures, respectively, among all the DMUs.

$$V_{i_{Relative}} = \frac{V_i - V_{\min}}{V_{\max} - V_{\min}} \quad (1)$$

Reliability of the proposed methodology was tested by comparing the agricultural vulnerability derived from two well-accepted methods: (i) variation-based approach (CF08) [33] that considers greater (less) than +2 (−2) standard deviations as high (low) vulnerability and (ii) a variant of DEA, i.e. Charnes, Cooper, and Rhodes (CCR) [34] model (supplementary figure 1). We found a significant consensus in the results obtained from all the three methods; although CCR and CF08 were comparatively less efficient to capture the spatial contrast. Moreover, DEA being an extreme point technique that is sensitive to data and measurement errors [35], the indicators in this study were optimally selected which have a direct influence on the India's agricultural system for rice and wheat productions, along with maintaining the data parity.

We derived hazards due to multiple hydro-climatic extreme events such as precipitation extremes, drought and temperature extremes from daily precipitation (0.25° resolution) and maximum temperature (1° resolution) data of the IMD for period 1961–2011. The period of meteorological datasets was divided into three durations: 1961–1990, 1991–2000 and 2001–2011. For deriving precipitation and temperature extremes, we performed a frequency-based hazard estimation by treating 1961–1990 as the base duration for obtaining threshold (95th percentile). This threshold was further applied for the other two durations to determine the intensity of each hazard. The exceedance probability of 99.5th percentile value of the base duration was considered as a potentially damaging (extreme) event for the two considered decades. To estimate drought, we applied the Standardized Precipitation Evapotranspiration Index (SPEI) [36, 37]. Based on data availability, the Hargreaves method [38] was used to derive potential evapotranspiration. Here, we implemented a non-parametric Gaussian kernel distribution [39] to obtain 3 month SPEI for the two decades. The reason for selection of Gaussian kernel is that it always reproduces characteristics of the sample accurately. Moreover, multimodality of the data may be captured more efficiently than any other traditional parametric distributions, such as log-logistic and gamma. The 3 month SPEI values less than or equal to −1.5 were then considered as potentially damaging (extreme) events. The exceedance probabilities of these hydro-climatic hazards were thus extracted by further fitting kernel distribution. Gridwise probability values of each hydro-climatic hazard component were aggregated at a district-scale. Finally, the agricultural risk for each crop was derived as a product of each of the hydro-climatic hazard component and the agricultural vulnerability.

3. Results and discussion

3.1. Regional link to agricultural vulnerability

We observed a decrease in the magnitude of agricultural vulnerability of rice, whereas an alarming increase was observed in wheat vulnerability with respect to the previous decade (supplementary figure 2). The changes in rice vulnerability were mostly negative in the eastern part of the country, except in the northeastern hilly states. A PCA at 80% variability showed that the country-level rice vulnerability changes were mainly affected by the indicators of cultivable area and number of agricultural labors from the adaptation segment, whereas wet and warm spell lengths were the major influencers from vulnerability segment (supplementary figure 3(a)). For the wheat crop, positive changes in agricultural vulnerability were significantly higher in northwestern and central parts of the country, possibly due to the effect of an increase in minimum temperature on its yield [40]. Notably, these regions are major wheat contributors and were responsible for approximately 50% of the total wheat production in the country for the year 2010–11 [41]. This result supports those of past global analyses and highlights the substantial and adverse impact of climate change on the wheat crop as compared to the other crops [42–44]. The country-level changes in wheat vulnerability were primarily influenced by growing season soil moisture, cultivable area and groundwater levels in the sowing and cultivation stages (supplementary figure 3(b)).

We understand that these changes in the agricultural vulnerability of crops are highly region-specific, given the diverse climatic and socio-economic characteristics of the Indian landmass. Based on the agro-climatic zones delineated by the Planning Commission of India (supplementary figure 4), we observed a varying impact of agro-hydro-meteorological and socio-economically dependent indicators on the changes in agricultural vulnerability. For instance, a decrease in the number of cultivators across the clusters of districts in trans-Gangetic plains (Box *a* of figure 2) and central plateau and hills (Box *d* of figure 2) was found to be one of the major factors responsible for contrasting rice vulnerability changes. Notably, other favorable factors such as an increase in the number of agricultural credit societies and irrigated area, and the changes in meteorological conditions played important roles in decreasing the rice vulnerability in central plateau and hills region; whereas trans-Gangetic plains did not resembled any prominent favorable conditions even though the region exhibited highest positive slope for rice yield trend, among the considered hotspots/panels. Here, trend values for each cluster were analyzed based on the Mann–Kendall's approach, which is a nonparametric test to detect the monotonic trend in time-series of the dataset [45, 46]. The slope trend of the time-series was further estimated by a nonparametric

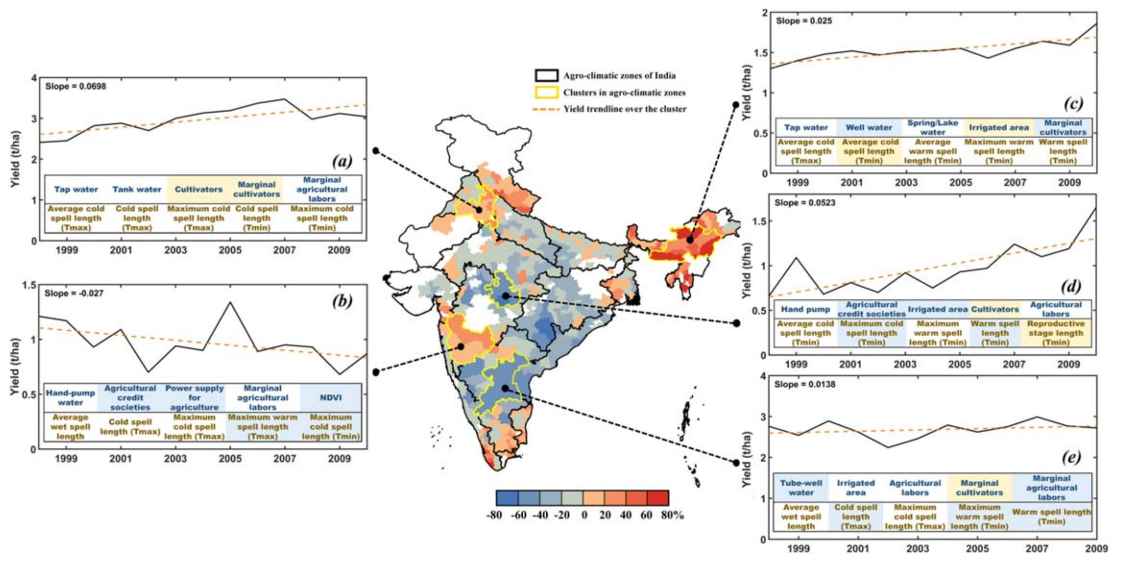

Figure 2. Decadal percentage changes in rice vulnerability (as represented in the color bar). Panels around the map represent Mann–Kendall trends and Sen's slope of crop yields for each cluster. Hotspots for clusters of districts located within the agro-climatic zones of trans-Gangetic plains (a), western plateau and hills (b), eastern Himalaya (c), central plateau and hills (d) and southern plateau and hills (e) were considered for rice. Five most influential indicators of adaptation (blue-text) and vulnerability (brown-text) segment, as derived through PCA, are provided for each cluster. Blue (orange) shading for indicators depict significant decreasing (increasing) impacts on decadal changes in the rice vulnerability.

Sen's slope estimator developed by Sen [47]. We obtained similar results for trans-Gangetic plains and southern plateau and hills (Box *e* of figure 2), possibly due to the decrease in number of marginal cultivators. Again, southern plateau and hills region exhibited favorable socio-economic conditions such as increasing number of tube-wells and marginal agricultural labors, with favorable meteorological conditions for the rice cultivation. In eastern Himalaya region (Box *c* of figure 2), we observed an interplay between indicators of adaptation and vulnerability segments, which resulted in increased rice vulnerability. Notably, although we observed favorable conditions over western plateau and hills (Box *b* of figure 2), the region was not found capable of addressing the declining trend in the rice yields. We suspect that an opportunity-oriented and spontaneous shift to the cultivation of cash crops by farmers might be a factor responsible for this change [48], which resulted in an insufficient water availability for the cultivation of Kharif rice.

The same western plateau and hills region displayed negative wheat vulnerability changes (Box *g* of figure 3). Notably, the region is dominated by rice production rather than wheat, and an increase in cold spell lengths during the crop growing season might have proven favorable for the wheat production, which requires comparatively colder temperatures for its photosynthesis. Other than this region, although satisfactory socio-economic conditions existed for wheat production, such as an increase in the number of hours of power supply for agricultural use and sources of water availability along with the rising trend in wheat yields, we observed an increase in agricultural vulnerability (figure 3). This change was majorly dominated by the increasing warm and cold spell lengths and decreasing number of cultivators.

Overall, our results highlight that the increasing agricultural vulnerabilities across the country are influenced by the intensifying meteorological indicators, which have counteracted the effects of adaptive measures.

3.2. Drivers of agricultural risk

Considering the spatial variability of agricultural vulnerabilities across India, assessing the frequency and intensity of extreme hydro-climatic events is crucial for providing comprehensive information about agricultural risk. Our results clearly revealed a significant increase in the probability of occurrences of all the considered hydro-climatic hazards. The adversely affected Indian states were Chhattisgarh, Gujarat, Karnataka, Maharashtra, Odisha, Telangana, Uttar Pradesh and the Northeastern hilly states. (Supplementary figure 5).

To gain a better understanding of the agricultural risk, we structured the agricultural vulnerability of both crops with individual hazard components in a bivariate map (figure 4). Results showed an evident increase in the darker shaded areas for both the crops in 2011 census decade, which were dominated by hydro-climatic hazards related to precipitation extremes and drought. For the rice risk, we found that certain major crop growing regions (eastern coast) were more prone to hydro-climatic hazards in census decade 2011 than in 2001, despite the decreased agricultural vulnerability.

The regions exhibiting high agricultural risks in 2011 census decade with equal contributions from

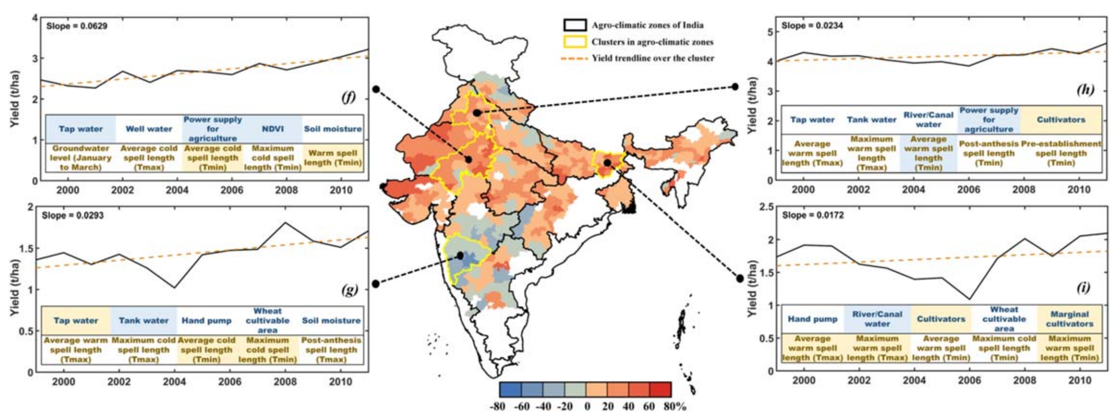

Figure 3. Similar to figure 2 but for wheat. Panels around the map represent trends of crop yield and the most influential indicators of clusters of districts located within agro-climatic zones of central plateau and hills (f), western plateau and hills (g), trans-Gangetic plains (h) and middle Gangetic plains (i).

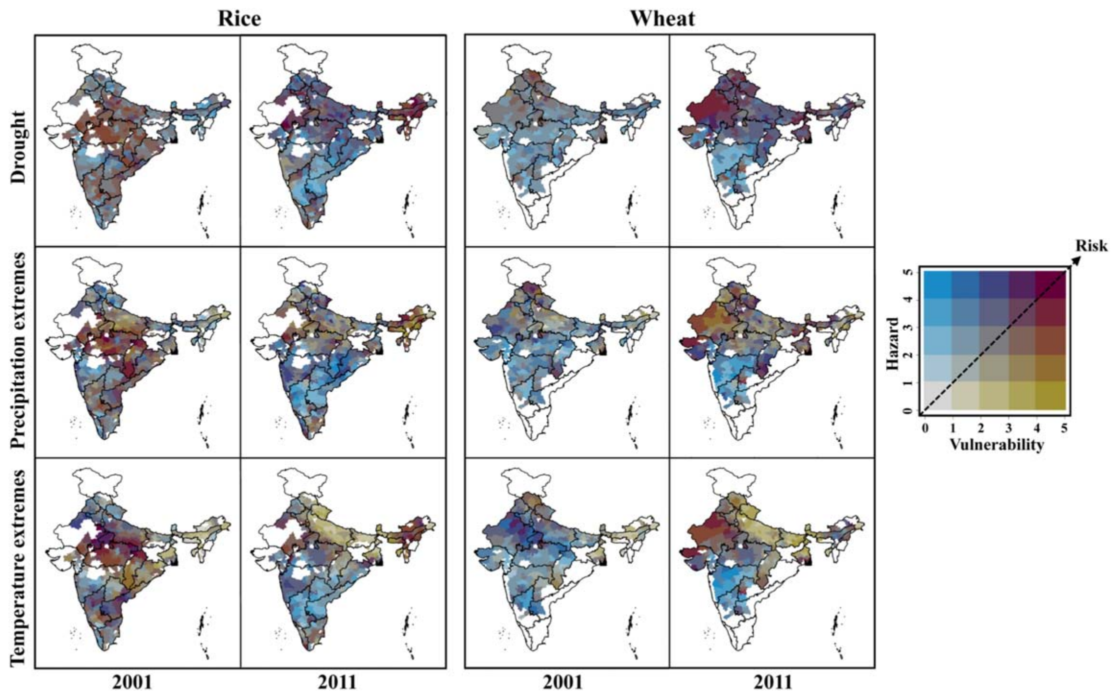

Figure 4. Bivariate agricultural risk map to drought (top panel), precipitation extremes (middle panel) and temperature extremes (bottom panel) for both the rice and wheat crops in census decades 2001 and 2011. Bivariate mapping can provide an effective understanding of the individual/marginal and combined/joint intensity of both the components. The representation of agricultural risk levels is provided in the right corner of panel in the form of a choropleth, wherein the agricultural vulnerability and hydro-climatic hazard components are depicted with variable yellow and blue intensities, respectively. The combination of yellow and blue colors provides information pertaining to the agricultural risk at different levels.

hydro-climatic hazards and rice vulnerability were the northern and northeastern states for drought and precipitation extremes; and northeastern states for temperature extremes. Whereas, an equal contribution of agricultural risk related to wheat crop was dominant over the northern and northwestern states for drought and precipitation extremes; and northwestern and central states for temperature extremes. The patterns in rice and wheat risks suggest that the food insecurity of the region may be affected by both agricultural vulnerability and hydro-climatic hazards or by any one of the related components, thus providing guidance for decision-makers regarding priority-based action plans. For instance, the regions with dominant hydro-climatic hazard exposure should prioritize improving the forecasting systems which can reduce the impacts caused by particular extreme events; whereas, regions with dominant agricultural vulnerability should prioritize improving the regional socio-economic conditions.

Upon attributing the agricultural vulnerability and all the considered hydro-climatic hazard components to the overall agricultural risk, we clearly noted an increase and shift in the peak probability density towards a higher magnitude (figure 5). This finding

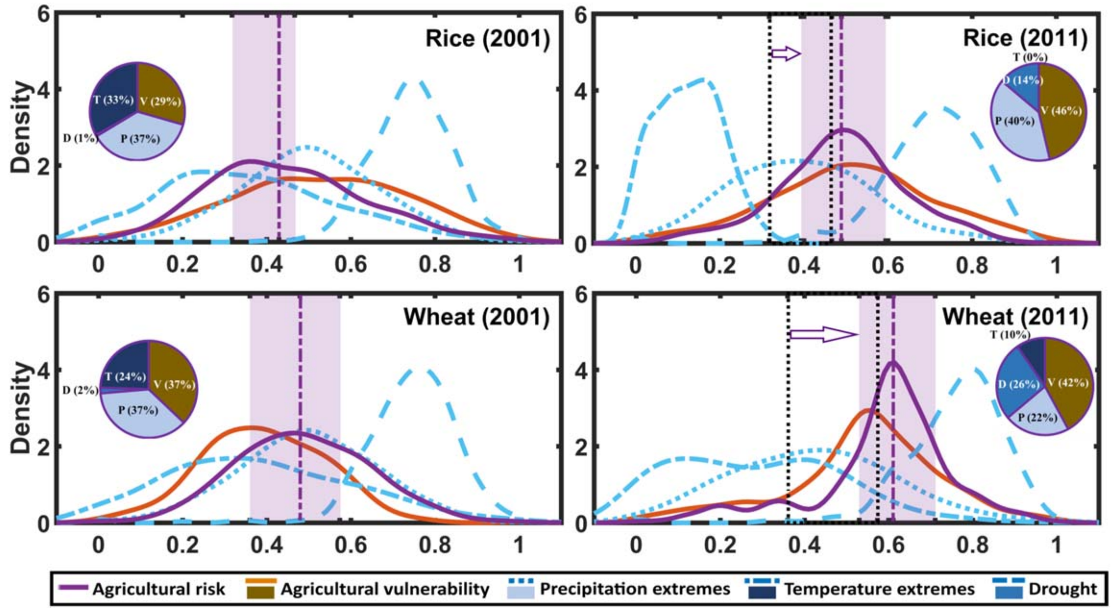

Figure 5. Nation-wide spatial variability in the overall agricultural risk, agricultural vulnerability and hydro-climatic hazards in terms of nonparametric Gaussian kernel probability distribution function (PDF). Purple-shaded region represents the density band greater than 2 for overall agricultural risk; black dashed-box in 2011 plot explicitly shows the density band of earlier decade (2001), with a shift from 2001 to 2011 census decade being depicted by horizontal arrow. Vertical purple dashed–dotted line represents the median of overall agricultural risk PDF. Inset pie-charts shows the percentage area of agricultural vulnerability (V), precipitation extremes (P), temperature extremes (T) and drought (D) PDFs in the purple-shaded density band.

further confirmed that the intensity of overall agricultural risk for rice and wheat crops has increased across the country. Here, the overall agricultural risk was defined as the product of agricultural vulnerability and all the considered hydro-climatic hazard components. We also identified that the influence on overall agricultural risk for both the crops has been mainly shifted from precipitation extremes (hazard-driven) in 2001 census decade to the agricultural vulnerability-driven in 2011 census decade. Additionally, the impact of hydro-climatic hazard related to drought on the agricultural risk has significantly increased in the later decade.

These findings suggest that although the occurrences of hydro-climatic hazard events have increased over India, the present status of agricultural socio-economy is not adequate and is demanding additional attention to attain sustainability. In this regard, further actions can be implemented as a part of bottom-up approaches that can reduce the adverse impacts of future climate change.

4. Conclusions

The prominence of agricultural sector in global economy was explicitly emphasized in the latest IPCC AR5 report, which addressed the UN Framework Convention on Climate Change (UNFCCC) food security issues [49]. For India, which is the seventh largest agricultural exporter worldwide [50], the contribution of agriculture to its GDP is considerable. However, statistics published by the Agricultural and Processed Food Products Export Development Authority [51] of the GoI showed that the exports of major crops such as rice and wheat decreased in 2016–17. The reasons for this reduction, apart from the imbalance in food demand-supply chain caused by the rapidly increasing population [52], could be the effect of climate change on crop yields or insufficient capacity of the farmers to cope with these changes. In such a case, the present agricultural vulnerability and risk maps can provide an invaluable information pertaining to the hotspots where the government can propose and implement evidence-based coordinated actions on climate and agricultural policies. For instance, on identification of the hotspots, a crop model-based risk and vulnerability analyzes can be performed at a regional-scale with finer resolution. This may reduce the computational cost as well as complexity of simulating the crop model over a large spatial domain. Moreover, the optimal selection of adaptive measures over a larger region is a challenging task, particularly for multi-crop systems. Thus, the identified hotspots will help the Agricultural Directorate offices, Public sector undertakings and the National-level Cooperative organizations in proposing cost-effective feasible measures to enhance the agricultural productivity over the region. This outcome at the national-scale will also configure a reliable framework that may help the end-users, primarily those who benefit from the advisory services (e.g. farmers, extension officers, monitoring and evaluation staff members of agri-business, non-governmental organizations and government agricultural workers, etc) to select suitable adaptation strategies. Moreover, the National Initiative on Climate Resilient Agriculture by the GoI has proposed certain opportunity-based optimal adaptation measures such as building resilience in soil, adapted cultivars and cropping systems, rainwater harvesting and recycling, crop contingency plans, weather-based agricultural advisories and institutional interventions [53, 54] which may play an essential role to enable farmers cope with the climate variability. The existing initiatives by the GoI such as developing Krishi Vigyan Kendras may also be benefited by enhancing the information content from the derived agricultural vulnerability and risk maps.

Our results showed that India's wheat risk to agricultural vulnerability and considered major hydro-climatic hazards has increased twofold in comparison to rice, in the recent decade. This increase has predominantly occurred due to the increase in agricultural vulnerability in the later census decade (2011); thus, demanding an additional attention to improve the agriculture related socio-economic condition over the region. We also found that along with the precipitation extremes, the drought impact on agricultural risk has significantly increased in the later census decade; whereas, the effect of temperature extremes has decreased. This suspects that the combined adverse effect of temperature and precipitation (i.e. drought) is playing a more detrimental role in agricultural productivity [55], than the individual impact of temperature extremes. The regional analysis on agricultural vulnerability showed that although few clusters of districts had favorable (unfavorable) conditions for the indicators, it eventually resulted in increased (decreased) agricultural vulnerability. For example, agricultural vulnerabilities of rice and wheat crops in the trans-Gangetic plains showed an increase, even though both the yields exhibited significant upward trend. This contrasting relation is mainly due to the decreased influence of some relevant adaptive indicators considered in our study. Other potential reasons may include costs of adaptive practices, costs of imports/exports, occupational migration and local-level activities such as excessive irrigation.

Considering the high dependency of Indian population on its agricultural system, as a measure for minimizing the agricultural risk, recent studies suggested the need for an optimal irrigable water allocation scheme [56] and an improved meteorological early warning system [57], among other proposed solutions. In addition to improving our understanding on the environmental mechanisms, different sociological schemes such as introducing urban farms and community gardens [58], increasing rural investments in infrastructure and technology [59], adhering to land-use zoning and implementing strategic organization of yield-enhancing loans and rural subsidies [60] may be considered as emerging sustainability measures to provide occupational security to the observed decreasing agriculture-based population.

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Summary

Agricultural risk across India is increasing, with wheat at a twofold higher magnitude than rice.

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Author contributions

SK, TS and VH designed the problem. TS, VH and SK performed the analysis. TS prepared the figures with input from SK, SG and VH, TS and VH wrote the manuscript with inputs from SK and SG.

Competing interests

The authors declare that they have no competing interests related to the study performed and presented in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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