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Key Points:

- Increase in magnitude, frequency and areal extent of heat stress on wheat cultivation in India; frequency has the most pronounced trend
- Quantitative links established between yield and heat stress magnitude, frequency and areal extent in observed and projected climate
- Probabilistic estimates of below-average wheat production rise by 8%–27% in the worst case, with largest impact in Punjab

Supporting Information:

Supporting Information may be found in the online version of this article.

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Probabilistic Assessment of Extreme Heat Stress on Indian Wheat Yields Under Climate Change

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Abstract The wheat belt along the Indo-Gangetic Plains (IGP) in India is an emergent hotspot of climate change-driven crop loss threatening local food security. Using statistical Generalized Linear Models, observed temperature and wheat production data, we show an increase in magnitude, frequency and areal extent of heat stress episodes in the IGP region during 1967–2018. Such episodes comprise of temperatures exceeding a senescence-inducing threshold. Further, using a copula-based multivariate framework, we probabilistically assess wheat production conditioned on heat stress indicators, both in the historical period and also in the Coupled Model Intercomparison Project (CMIP6) future projections. Probabilistic estimates of below-average wheat production under scenario-averaged heat stress conditions are expected to rise by 8%–27% under the SSP5-8.5 scenario, with Punjab showing the largest increase. Quantitative links between heat stress indicators and loss of crop yield highlight increased agricultural vulnerability in India under climate change.

Plain Language Summary The three states of Punjab, Haryana and Uttar Pradesh in the Indo-Gangetic Plains are the largest wheat producers in India, playing a crucial role in ensuring food security of this densely populated country. Wheat, a winter crop, is reported to be sensitive to heat stress because of rising temperatures and climate change. However, in previous studies, the sensitivity of wheat yield has been mainly explored with respect to the magnitude of temperature. Here, based on statistical analysis of observed temperature and actual wheat production data, we show that the magnitude, frequency and areal extent of agricultural heat stress events are increasing in India's wheat belt, with frequency showing the most pronounced trend. Further, we establish a quantitative link between crop loss and these three heat stress indicators in a multivariate, probabilistic framework. This probabilistic approach is used to obtain likelihoods of reduced wheat yield in future, using state-of-art climate model projections. Under climate change, chances of below-average wheat production rise by 8%–27% in the worst-case scenario. Thus, our results quantify rising agricultural vulnerability in India's wheat-belt under climate change and variability.

1. Introduction

India is among the leading producers and consumers of wheat. The wheat-growing belt in the country is located along the Indo-Gangetic Plains (IGP; 21°35′–32°28′N and 73°50′–89°49′E) comprising of the states of Punjab, Haryana and Uttar Pradesh. In recent years, wheat cultivation in India is increasingly prone to loss, driven by high temperatures due to climate change and variability (Lavania, 2021; Tribune News Service, 2021). This is a major concern given the observed and projected changes in statistics of the past and future extreme temperatures in India (Basha et al., 2017). Shortfalls in national wheat productivity is expected to have cascading implications for trade and food security (Halarnkar, 2014). The mechanisms through which rising temperatures affect wheat yields in the region are well-established (Farooq et al., 2011; Nageswararao et al., 2018; New et al., 2012). For instance, high temperatures during the mid-anthesis period can affect grain-fertility, and cause decline in grain number at maturity (Ferris, 1998; Zhao et al., 2007). Accelerated leaf senescence that causes loss in viable leaf area (Asseng et al., 2011; Lobell et al., 2012; Shah & Paulsen, 2003) and pre-term maturing of crops occasionally leading to plant cell death (Akter & Islam, 2017; Porter & Gawith, 1999; Zampieri et al., 2017) are other temperature-driven processes that affect grain output.

In the past, process-based (e.g., Asseng et al., 2011, 2017) and statistical models (e.g., Mondal et al., 2014) have been widely used for quantifying the impacts of temperature on wheat. Such findings are largely deterministic in nature, reported as the absolute change in yields associated with temperature change. Dynamic crop model simulations show significant reduction in average wheat production in the IGP under hypothetical warming scenarios driven by unconstrained economic growth (Zacharias et al., 2014). However, these estimates are reportedly lower than the actual expected changes (Lobell et al., 2012; Wheeler, 2012) due to imperfect representation of crop processes in the models (Asseng et al., 2013; Koehler et al., 2013). Statistical methods such as panel regression-based techniques (e.g., Lobell, et al., 2011) and correlation analyses (e.g., Mukherjee et al., 2019; Nageswararao et al., 2018) are popular alternatives relying on observed data to relate climate variables to crop yields. However, such models are sensitive to the relationship between climate and yield data, and the representation of fixed-effects that control for omitted variables (Lobell & Asseng, 2017).

Further, existing literature on the effects of rising temperatures on wheat production rely on univariate approaches that consider only the magnitude of temperature rise. Probabilistic approaches, that make use of joint probability distributions of crop yields and relevant predictors, offer the flexibility of considering specific influencing variables thereby addressing region or crop-specific stakeholder concerns (Madadgar et al., 2017). Such approaches have been used in global and regional studies for major food crops under droughts (Leng, 2021; Leng & Hall, 2019) and under concurrent drought and heatwave conditions (Feng et al., 2019, 2021).

Here, we first investigate observed changes in agriculture-relevant heat stress events for wheat cultivation in the IGP region (Figure 1a), not only in terms of magnitude of such events, but also in terms of frequency and spatial extent, using the statistical Generalized Linear Model (GLM) framework. A suitable average duration of such events is identified based on correlation analysis. We choose the IGP region because it follows fairly homogeneous local cropping practices (Lobell et al., 2012). Heat stress events for wheat cultivation are defined as episodes when maximum day-time temperatures in the grain-filling period (Feb-March) exceed the reported senescence-inducing threshold of 34°C (Lobell et al., 2012; Rao, Chowdary, et al., 2015).

Further, we use a multivariate probabilistic framework to derive probability distributions of wheat yield, conditioned on three heat stress indicators: (a) magnitude, as represented by the extreme degree days, EDD (Lobell et al., 2012), (b) frequency, as represented by the number (count) of heat stress days in the season, and (c) spatial extent, as represented by the fraction of total area under heat stress. Based on these conditional distributions, we also offer a prognosis of the risk of yields falling below the long-term average in the region, for associated changes in the heat stress indicators in the observed climate, and for the near and far future from a set of integrated scenarios based on future climate and societal change (O'Neill et al., 2016), developed as part of the Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016).

2. Materials and Methods

2.1. Data

The state-wise yield data (in kilogram per hectare (kg/ha)) for winter wheat from 1967-2018 for Punjab, Haryana and Uttar Pradesh (UP) are compiled from repositories maintained by, (a) International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) known as Village Dynamics in South Asia (VDSA), and (b) Datanet India. The yields are detrended prior to further analysis for removing the effect of technological improvements on crop performance associated with development in irrigation facilities, improved fertilization and pesticides applications, and high-yielding genotypes (Lobell & Burke, 2009; Mukherjee et al., 2019; Subash & Ram Mohan, 2012), while preserving their sensitivity to year-on-year climatic fluctuations (e.g., Lobell, 2009; Skees et al., 1997; Zachariah et al., 2020). Daily values of the maximum recorded temperature are extracted for this period, for the states and the IGP region from the gridded temperature product at 1° × 1° lat-lon resolution provided by the India Meteorological Department (IMD; Srivastava et al., 2009). Mean day-time temperatures show a significant rise in this region (Figures 1c and 1d). Temperatures in UP are higher by at least 2–3°C than those in Punjab and Haryana (Figure 1b).

Historical simulations (1850–2014) and projections (2015–2100) of daily maximum temperature are extracted for eight global climate models (GCM; Table S1 in Supporting Information S1) that contribute to

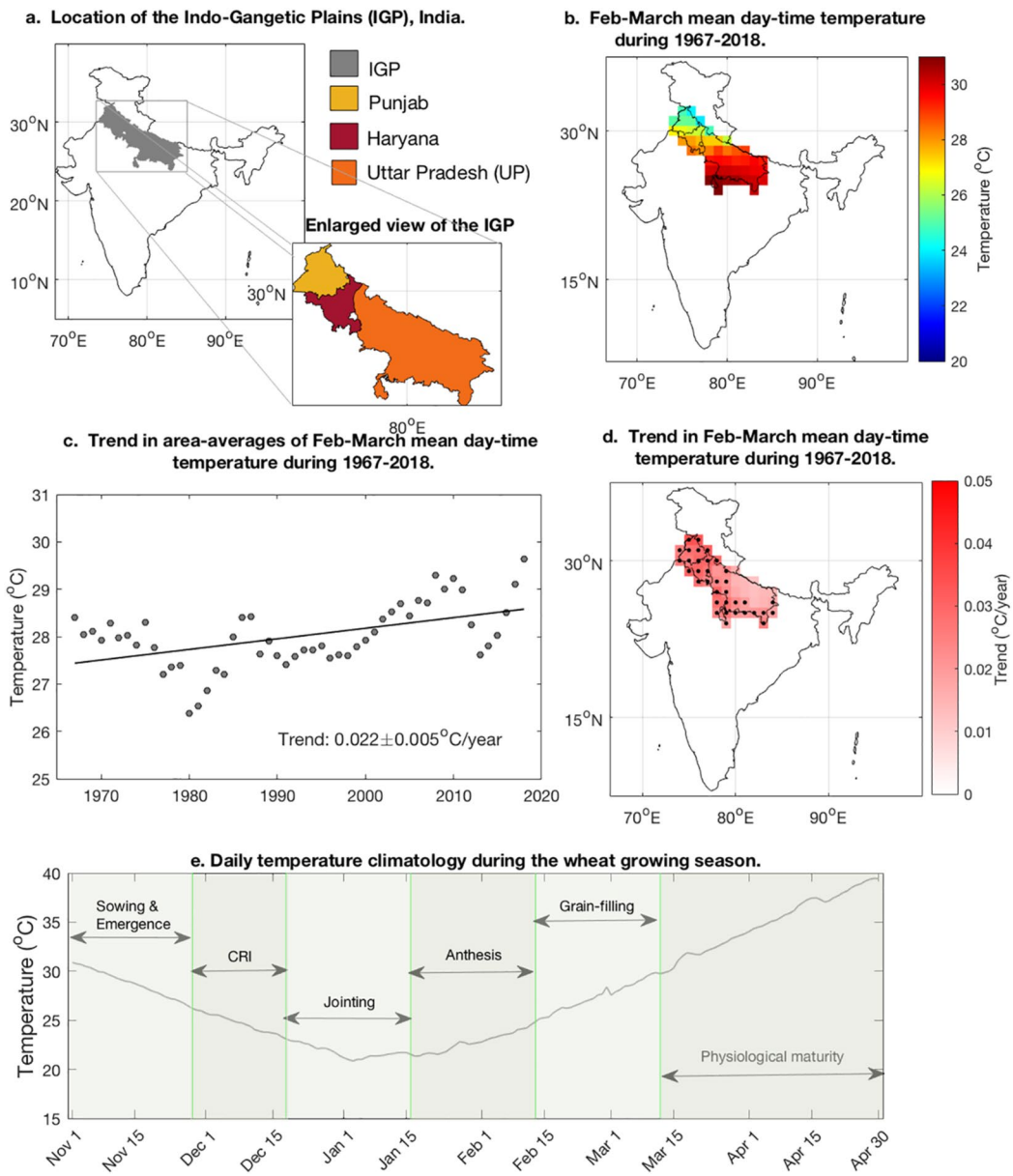

Figure 1. (a) Location of the study region. (b) Mean daytime temperature during February-March in the Indo-Gangetic Plains (IGP), for the 1967–2018 period. (c) Trends in mean day-time temperature during February-March season, area-averaged over the IGP, significant at 0.1 significance level (s.l). (d) Grid-wise trends in mean day-time temperature during February-March over the IGP; stippling shows the locations where the trends are significant at 0.1 s.l. (e) Daily temperature climatology averaged over the IGP and different stages of wheat growth (Rao, Subba Rao, et al., 2015).

Tier 1 scenarios of the Scenario Model Intercomparison Project (ScenarioMIP) activity under CMIP6. Tier 1 consists of a set of integrated scenarios of future climate and societal change, based on combinations of shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs). The four scenarios- SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 represent the low end, medium part, medium to high end and the high end of the range of future forcing pathways, respectively (O'Neill et al., 2016; Text S1 in Supporting Information S1). The CMIP6 temperature ensembles replicate the decreasing trend in diurnal temperature range during 1950–1980 (Wang & Clow, 2020), observed globally (e.g., Easterling, 1997; Vose et al., 2005) and in India (Rao, Chowdary, et al., 2015), and is realistically attributed to the faster rates of increase of minimum daily mean temperature, as compared to the maximum temperatures.

Figure S1a in Supporting Information S1 shows the climatology of daily average day-time temperatures in the IGP during the grain-filling stage, from observed data and historical runs from the GCMs. Overall, with the exception of MPI-ESM1-2-HR (Figure S1c in Supporting Information S1), the spatial distribution of day-time temperatures from the GCMs (Figure S1d–S1j in Supporting Information S1) are found to match well with IMD (Figure S1b in Supporting Information S1). These simulations are further bias-corrected against IMD observations, using the change factor method (Anandhi et al., 2011). This is a reliable approach for correcting temperature which has a more predictable seasonality and temporal pattern compared to rainfall (Lange, 2019; Navarro-Racines et al., 2015). This method is widely used in climate impact assessment on agriculture studies (e.g., Lesinger et al., 2020, Mudbhatkal & Mahesha, 2018; Steinbauer et al., 2018). Post-bias correction, even MIROC6 & ACCESS-ESM1-5 that showed the highest biases (Figure S1a in Supporting Information S1) are consistent with the other models (Figure S2 in Supporting Information S1). Therefore, these models are also included for estimating the multi-model average heat stress conditions for subsequent analyses (Kim et al., 2020).

2.2. Characterization of Heat Stress

The average maximum day-time temperatures during the entire wheat growing season (November–March) climb steadily from mid-January during anthesis, into the grain-filling and maturing stages where hot conditions prevail (Figure 1e). Prolonged exposure to temperatures above prescribed thresholds during the grain-filling period cause wheat crops to become heat stressed (Farooq et al., 2011), and is an established cause for yield loss in the IGP (Lobell et al., 2012; Ortiz et al., 2008; Song et al., 2020). To this end, three variables that sufficiently represent the spatial and temporal characteristics of the heat stress events are identified. Extreme degree days (EDD; Lobell et al., 2012; explained in detail in Text S2 in Supporting Information S1) represent the cumulative sum of the temperature exceedances over 34°C during the grain-filling period. The count of heat stress days is the number of days when average day-time temperatures in the region exceed 34°C during grain-filling (Rao, Chowdary, et al., 2015). The spatial extent is the fraction of grid cells that are exposed to such exceedances for at least 5 days during grain-filling.

A Generalized Linear Modeling (GLM) framework (Nelder & Wedderburn, 1972) is adopted for analysing historical trends in the three heat stress indicators. Though not in the context of agricultural vulnerability, GLMs have been previously used for studying changes in heat waves and hot spells in different world regions (Abaurrea et al., 2018; Furrer et al., 2010; Keellings & Waylen, 2015; Ouarda et al., 2019; Photiadou et al., 2014; Wang et al., 2015). The Gaussian distribution is chosen for cumulative variables such as EDD and spatial extent (e.g., Carleton, 2017; Sharma & Mujumdar, 2017), while the Poisson distribution is used for discrete variables such as frequency (or count) of heat stress events (e.g., Furrer et al., 2010; Mondal & Mujumdar, 2015). GLMs offer a flexible, parametric approach to trend detection where parameters of the fitted probability distributions are allowed to vary as a function of one or more covariates through an appropriate link. For example, for the Poisson regression model for frequency (Lovett & Flowerdew, 1989), the rate parameter can be written as $\lambda_i = exp\left(\beta_0 + \beta_1 * t_i\right)$ where t_i represents time at the ith step, while β_0 and β_1 represent the intercept and slope terms, respectively. If the confidence interval of β_1 excludes zero, there is significant evidence of trends.

2.3. Conditional Probabilities of Wheat Production

We use copulas (Nelsen, 2006) for estimating the joint probability distributions between wheat yields (Y) and each of the heat stress indicators (X), i.e., $F_{XY}\left(x,y\right) = C\left[F_X\left(x\right),F_Y\left(y\right)\right]$. Here, $F_X\left(x\right)$ and $F_Y\left(y\right)$ are the marginal distributions of X and Y, and C is the copula. This function has the distinct advantage of modeling the dependence between variables that do not follow same marginal parametric distributions, and therefore, has wide applications in multivariate probabilistic modeling (e.g., AghaKouchak et al., 2014; Hao et al., 2020; Sahana et al., 2020).

The conditional probability of yield falling below a certain amount ($Y < y$) under a specific heat stress condition ($X = x$) i.e., $f_{Y|X}\left(y\right)$ is derived from the relationship developed by (Madadgar & Moradkhani, 2013), as follows.

$$f_{Y|X}\left(y\right) = c\left[F_X\left(x\right), F_Y\left(y\right)\right].f_Y\left(y\right) \tag{1}$$

where $c\left(u,v\right)$ is the PDF of the copula function and $f_Y\left(y\right)$ is the marginal distribution of wheat yield (see Table S3 in Supporting Information S1). Here, $u = F_X\left(x\right) = 1 - \int_0^x f_X\left(x\right)$ represents the marginal survival CDF of X, $v = F_Y\left(y\right) = \int_0^y f_Y\left(y\right)$ represents the marginal CDF of Y. The survival approach allows multivariate analysis when there is an inverse relationship between X and Y. Table S3 in Supporting Information S1 also shows the expressions of *c(u,v)* for different copula functions whose parameters are derived from historical values of X and Y. From the conditional PDF, we can estimate the probability of yields falling below a certain amount, i.e., $F_{Y|X}(Y|X = x)$, as the area under the PDF curve given by $f_{Y|X}\left(y\right)$, for $Y < y$ (Madadgar et al., 2017; Mazdiyasni et al., 2017). It may be noted that the heat stress indicators might be correlated with each other; however, such correlations do not influence the conditional probability density $f_{Y|X}\left(y\right)$.

3. Results and Discussions

The detrended area - averaged wheat yields and average of Feb-March day-time temperatures for 1967–2018 shows negative association for the entire IGP region (Figure 2a), and for Punjab, Haryana, and UP (Figures 2b–2d). This suggests that wheat yields are sensitive to temperatures during grain-filling. However, average daily temperature alone may not be sufficient for discerning heat impacts on the yields, emphasizing the need for extreme heat indicators. Interestingly, the state-wise average yields are lowest in UP, although its total production and acreages are substantially higher (Figure S3 in Supporting Information S1). The low yields are attributed mainly to rising temperatures, erratic rainfall and inefficient crop management (Prasad et al., 2018; Tewari et al., 2017). The high total production in the region is on account of the high acreage under wheat cultivation (Balaganesh et al., 2019).

3.1. Observed Changes in Heat Stress Events

Figure 3 shows the trends in the three heat stress indicators - EDD, frequency and spatial extent of heat stress as obtained by the GLM approach. The EDD for the season is found to increase everywhere, with significant trends over Punjab and parts of UP (Figure 3a). Frequency shows the most pronounced rise, with significantly increasing trends reported at nearly all the locations in the IGP. For obtaining the areal extent under heat stress, an appropriate average minimum duration of the heat stress events is chosen as 5 days based on the correlation between annual yields and the fraction of area under heat stress, as shown in Figure 3c (Figures S4a–S4c in Supporting Information S1) for individual states). Spatial extent of heat stress also shows an overall rise in the IGP region (Figure 3d), and for each of the three states (Figure S4d in Supporting Information S1; significant at 0.1 significance level (s.l)). The positive trends in all of these variables imply that the heat stress events have become more persistent in recent years and may continue to become more frequent under future warming.

3.2. Conditional Distributions of Wheat Production

The Pearson correlation coefficient between wheat yield and heat stress indicators for all the study regions show negative association as expected (Table S4 in Supporting Information S1). We choose the best-fitting marginal probability distribution model for the variables based on the lowest values of Mean Squared Error (MSE), Akaike Information Criterion (AIC; Akaike, 1974; Bozdogan, 2000) and Kolmogrov-Smirnov (K-S) distance (Kolmogorov, 1933; Massey, 1951; Smirnov, 1948), as shown in Table S5a in Supporting Information S1. Similarly, the joint probability distributions of yield and heat stress are modeled using the best-fitting copula using the same three metrics (listed in Table S5b in Supporting Information S1). Conditional probability distributions of wheat yield for average historical heat stress conditions are derived from the joint probability distributions, by conditioning on the long-term average of the heat stress variable. The curves in black color in Figure 4 show the conditional probability density functions based on observations, for each of the three heat stress indicators.

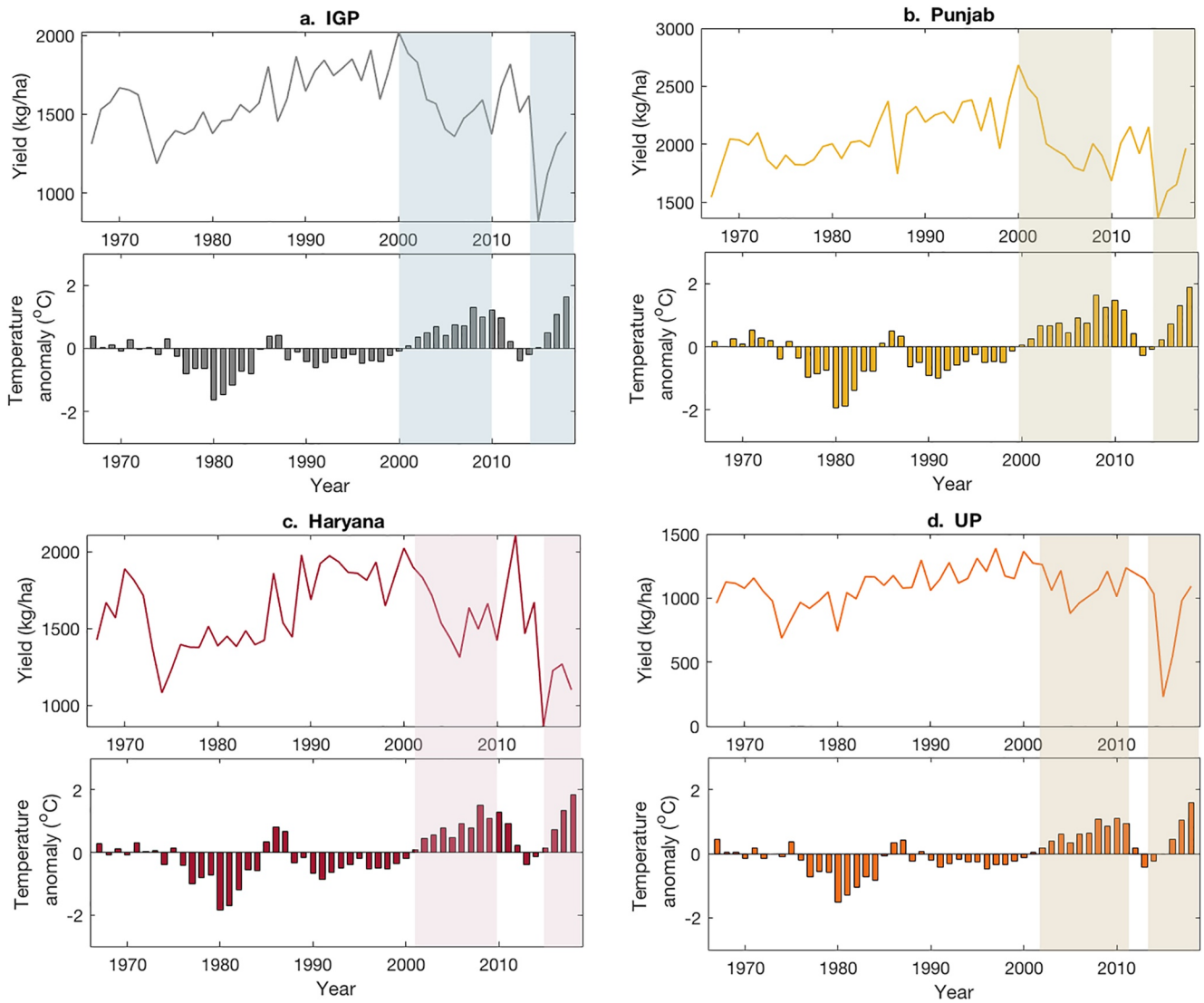

Figure 2. (a) Detrended wheat yields and seasonal anomaly in average of day-time temperatures during the grain-filling period (February–March), for the (a) Indo-Gangetic Plains region and or individual states of (b) Punjab, (c) Haryana and (d) Uttar Pradesh. The shaded areas highlight the time periods when the rise in temperature is accompanied by declining yield.

3.3. Future Prognosis of Agricultural Risk

The probability distributions of wheat yield, conditional on the heat stress indicators, are further used for evaluating future agricultural risk under climate change. For this, we first eliminate the confounding role of rainfall, since 85% of the region is irrigated (Daloz et al., 2021; Kumar et al., 2014), relying strongly on groundwater reserves (Vatta et al., 2018). In a standardized mixed-effects linear regression model (e.g., Davis et al., 2019; Zachariah et al., 2020), we find pronounced sensitivity of wheat yields to irrigation and temperature (significant at 10% s.l) as compared to JJAS rainfall (Text S2 and Table S2 in Supporting Information S1). Further, we also assume that the crops continue to be entirely irrigated, although the irrigation efficiency may alter depending on the adaptation/mitigation potential of the SSP scenarios. This is a valid assumption since precipitation is not expected to increase substantially over Asia (Tebaldi et al., 2021), making irrigation necessary to meet the crop-water demands.

We also assume the crop variants to remain unchanged. Since 1980s, significant progress has also been made for stabilizing the yields at the best yielding levels through development of genetically modified variants (Bailey-Serres et al., 2019). The final assumption is that the area under wheat cultivation in the IGP

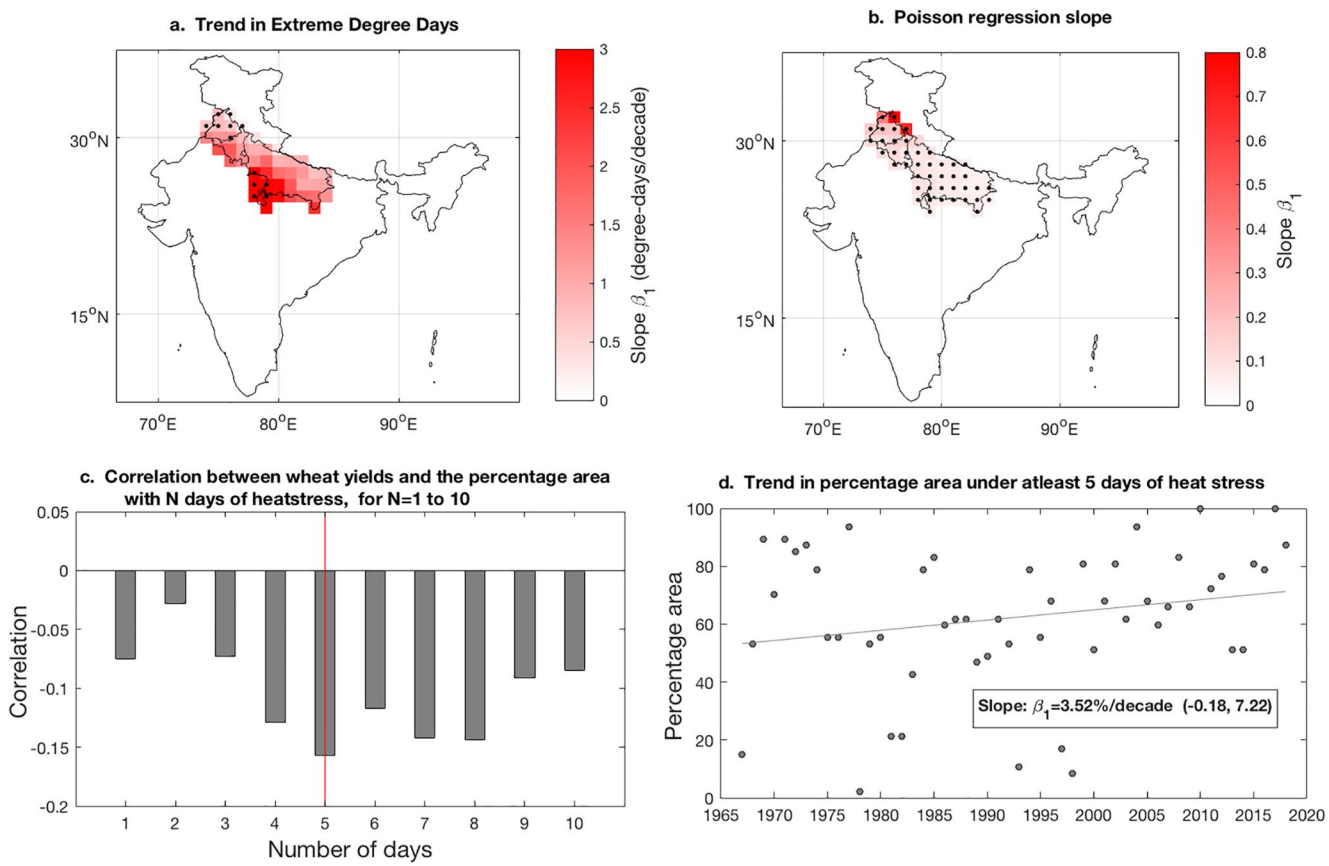

Figure 3. (a) Trend in magnitudes, Extreme degree days, and (b) frequency of heat stress events, plotted in terms of the slope parameter of the Generalized Linear Model (GLM). Stippling shows the locations where the trends are significant at 0.1s.l. (c) Correlation between wheat yields and the percentage area under N days of heat stress during February–March over the Indo-Gangetic Plains (IGP), for $N = 1$–10 days (d) Spatial extent of heat stress events over the IGP, plotted as the percentage area under at least 5 days of heat stress during February–March. Trend in terms of the slope parameter of the GLM is also shown.

remain unchanged under future scenarios. The reason for such an assumption is that over the last few years in South Asia, competition from urbanisation sectors has caused the focus to shift from cropped area expansion to technologies that promote yield intensification, in order to meet the growing food demand (Kakraliya et al., 2018; Popp et al., 2017). Therefore, the joint behavior of wheat yields and each of the heat stress indicators is likely to be valid even under future climate scenarios.

We estimate the average heat stress conditions for the IGP region and the three states for four future scenarios, for two periods- 2021–2050 (near-future), and 2071–2100 (far-future), from the GCM temperature projections., Figures S5a–S5d in Supporting Information S1 shows these estimates for the IGP region and the three states. The probability distributions of wheat yield in the SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios are derived, conditioned on the respective multi-model averages of the heat-stress conditions, and are shown in Figures 4a–4f (Figures S6–S8a-S8f in Supporting Information S1) for the individual states). The risk of wheat production falling below the long-term average is given by the area under the respective curves, and are presented in Tables S6 and S7 in Supporting Information S1, for the near- and far-future periods, respectively. Risk of reduced wheat production is found to consistently increase from SSP1-2.6 (best-case) to SSP5-8.5 (worst-case), and from the near-future to the far-future period for all the regions, due to overall rise in temperatures. The increase in risk of below-average yields under future scenarios, relative to the risk in the observed climate is defined as the change in risk.

We find that the changes in risk of below-average wheat yields are very small (less than 5%) in the near-future, for all the heat stress variables (Figures 4a–4c). In general, for all scenarios, such changes are found to be the least pronounced when conditioned on spatial extent (Figure 4i) as compared to the other two indicators of heat stress (Figures 4g and 4h). Under SSP5-8.5 scenario, the change in risks under EDD and count of

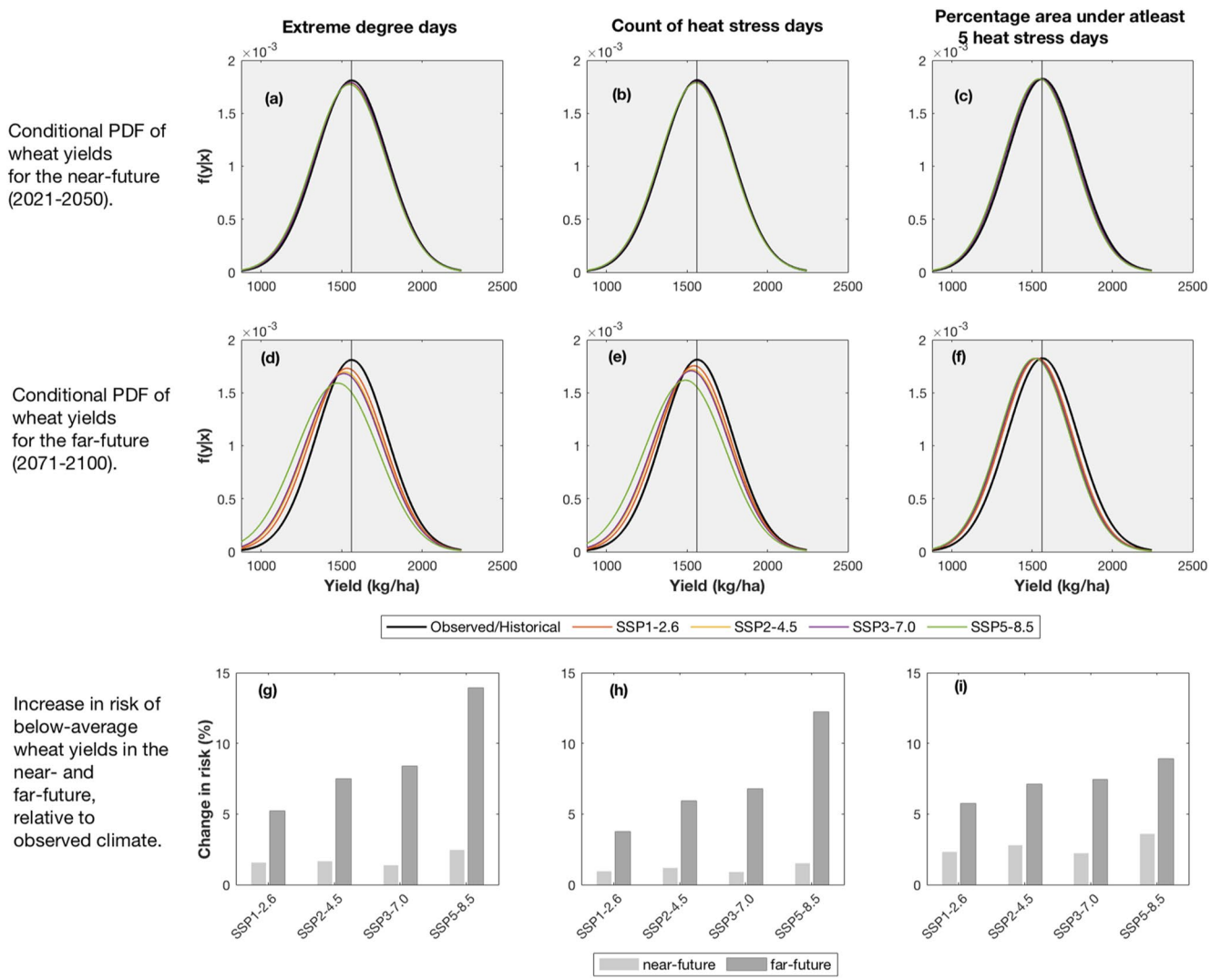

Figure 4. (a) Probability distributions of wheat yields in the Indo-Gangetic Plains region, conditional on the average Extreme degree days (EDD), for the historical climate (1967–2014, black) and the four future climate scenarios- SSP1-2.6 (orange), SSP2-4.5 (yellow), SSP3-7.0 (purple) and SSP5-8.5 (green) for the near-future period (2021–2050). (b) same as (a), conditional on the average count of heat stress days and (c) same as (a), conditional on the average fraction of area under heat stress. (d) same as (a), for the far future period (2071–2100). (e) same as (b), for the far future period. (f) same as (c), for the far future period. (g) Change in risk of wheat yields falling below average yields under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios relative to the observed climate for associated changes in average EDD. (h) same as (g), for associated changes in average count of heat stress days. (i) same as (g), for associated changes in average fraction of area under heat stress.

heat stress days, range from 12% to 27% (panel *(g)* in Figure 4, Figures S5–S7 in Supporting Information S1 and 12% to 19% (panel *(h)* in Figures 4, Figures S6–S8 in Supporting Information S1), respectively. This implies that unmitigated future warming will worsen agricultural heat stress in the IGP in terms of these two indicators, thereby leading to reduced yields. Further, agricultural risk due to heat stress conditions is found to be largest over Punjab (Figure S6 in Supporting Information S1), as compared to the other two states (Figures S6 and S7 in Supporting Information S1). Being a significant contributor to the total wheat production (Figure S3 in Supporting Information S1), increased risk of below-average yields in the region can adversely affect the national grain output.

Conditional on spatial extent of heat stress, the risk of yields falling below the long-term average remain very close to the observed risk (change <4%) for both near- and far-future scenarios for UP (Tables S6c and S7c in Supporting Information S1). This is to be expected, since the area under heat stress in UP has been greater than 70% even under observed climate (Figure S5d in Supporting Information S1), leaving no room

for further increase in future (Figure S8c in Supporting Information S1). The persistence of heat-stressed area in UP can partially explain low yields in the state, as has been suggested in other studies that attribute lower yields in the region to temperature (Balaganesh et al., 2019; Prasad et al., ; Tewari et al., 2017). This also implies that research focusing on bioengineered wheat variants that can withstand environmental changes will be crucial (Bailey-Serres et al., 2019), particularly for UP, which has about 1.5 times more area under wheat cultivation than Punjab and Haryana put together (Figure S3 in Supporting Information S1).

4. Concluding Remarks

Rising temperatures due to climate change is a major driver of wheat loss in the Indo-Gangetic Plains, with important implications for food security in this highly populated and vulnerable region. Several studies have focused on determining the change in wheat yields from observations and crop models, mainly based on rising magnitudes of temperature. In this study, we evaluate the risk of wheat production falling below its long-term average considering the magnitude, frequency as well as spatial extent of heat stress events and their interactions in the region, all of which show increasing trends in the recent past. We also provide changes in these risks under future climate change scenarios using CMIP6 projections.

Frequency of heat stress events show the most pronounced rising trend in the region. Probabilistic estimates of agricultural risk show larger changes in the future when conditioned on the magnitude and frequency of heat stress, as compared to its spatial extent. Below-average wheat production is expected to rise by 8%–27% under SSP5-8.5, with Punjab showing the largest increase.

Our approach has the distinct advantage of providing probability distributions of wheat yields for different heat stress conditions, which allows us to further quantify the change in these probabilities in a warming climate. Such information is important for targeted adaptation and mitigation strategies, particularly for the wheat belt region of the IGP. Although the assumptions made in our study are well-founded, an important caveat is that these assumptions have not been validated against process-based crop model simulations. Future works in this direction may also be strengthened by using crop yield projections for the future scenarios from projects such as the Agricultural Modeling Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2013) and the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP; Warszawski et al., 2014), as they become available.

Data Availability Statement

The CMIP6 runs are available for download from https://esgf-node.llnl.gov/search/cmip6/. The state-wise annual wheat yields used in this study are downloaded from Village Dynamics in South Asia (VDSA; available at http://vdsa.icrisat.ac.in/vdsa-database.aspx), and (ii) Datanet India (available at https://www.indiastat.com/data/agriculture).

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