Environmental Research Letters

LETTER • **OPEN ACCESS**

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Environmental Research Letters

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OPEN ACCESS

RECEIVED
16 December 2018

REVISED
16 May 2019

ACCEPTED FOR PUBLICATION
20 May 2019

PUBLISHED
13 June 2019

LETTER

Sensitivity of grain yields to historical climate variability in India

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Keywords: climate variability, crop production, India, yield variation, rice, monsoon, coarse grains

Supplementary material for this article is available online

Abstract

Fluctuations in temperature and precipitation influence crop productivity across the planet. With episodes of extreme climate becoming increasingly frequent, buffering crop production against these stresses is a critical aspect of climate adaptation. In India, where grain production and diets are closely linked, national food supply is sensitive to the effect of climate variability on monsoon grain production. Here we quantitatively examine the historical (1966–2011) relationship between interannual variations in temperature and rainfall and rainfed yield variability for five monsoon crops—rice and four alternative grains (finger millet, maize, pearl millet, and sorghum). Compared to rice, we find that alternative grains are significantly less sensitive to climate variation and generally experience smaller declines in yield under climate extremes. However, maximizing harvested area allocations to coarse grains (i.e. holding maize production constant) reduced grain production by 12.0 Mtonnes (−17.2%) under drought conditions and 12.8 Mtonnes (−18.0%) during non-drought years (non-drought). Increasing the harvested area allocated to all alternative grains (i.e. including maize) can enhance production by +39.6% (drought) and by +37.0% (non-drought). These alternative grains therefore offer promise for reducing variations in Indian grain production in response to climate shocks, but avoiding grain production shortfalls from increased alternative grains will require yield improvements that do not compromise their superior climate resilience.

Introduction

The variability of crop production from year to year depends in large part on the sensitivity of crop yields to variations in climate [1, 2]—a relationship with profound implications for food supply and rural livelihoods. The impacts of these yield anomalies on production can be compounded by reductions in cropping frequency and harvested area in response to climate variability [3]. Drought and extreme heat reduced global grain production by one-tenth over the past half century [4]. There is also evidence that climate-related crop failures contribute to a host of indirect and dire consequences including increased human migration (e.g. Bangladesh [5], Mexico [6], Pakistan [7]) and conflict (e.g. Syria [8]). With episodes of extreme climate expected to become more frequent [9, 10], measures to buffer crop production against these stresses are a critical aspect of climate adaptation.

In India, climate variability has increased both spatially and temporally over the past 50 years. The country's monsoon region has seen significant decreases in rainfall totals [11, 12] concurrent with enhanced daily precipitation variability [13]. Extreme rainfall events have become more frequent [13, 14] and spatially more variable [15, 16], and there have also been increases in the severity and frequency of drought since the 1970s [17]. Projections also suggest an

Table 1. Production and harvested area of kharif (monsoon) grains. Values are disaggregated between rainfed and irrigated shares.

		Finger millet	Maize	Pearl millet	Rice	Sorghum
Production (ktonne)	Irrigated	156	7043	1373	57 973	174
	Rainfed	1928	12 383	8983	39 026	3164
	Rainfed (% of kharif total)	93%	64%	87%	40%	95%
Harvested area (10^3 ha)	Irrigated	90	1868	833	22 183	138
	Rainfed	1350	6073	8532	21 412	2985
	Rainfed (% of kharif total)	94%	76%	91%	49%	96%

increase in climate variability and extremes across South Asia in the coming decades [9, 10, 18, 19]. These trends towards more uneven distributions of precipitation throughout the monsoon season—compounded by rising temperatures—are expected to adversely impact the yields of major crops in India [20].

Driven by an increasing dominance of rice–wheat systems—where rice is primarily grown during the monsoon (kharif) season and wheat is grown during the winter (rabi) season, Indian grain production has more than tripled since the start of the Green Revolution, and the share of Indian grain production contributed by rice and wheat has steadily increased from 65% (1966) to 85% (2011) [21]. Currently rice accounts for 44% of annual grain production—the most of any crop—and 73% of grain production during the monsoon (kharif) season [21]. Maize (15%), pearl millet (8%), sorghum (2.5%), and finger millet (1.5%) (i.e. alternative grains) contribute the vast majority of the remaining portions of monsoon grain production and are regionally important for rural livelihoods and diets, with roughly half of monsoon (kharif) grain production being rainfed (table 1) [21]. The ongoing homogenization of India's grain production [22]—combined with increasing climate variability—raises important questions about the vulnerability of its food supply to extreme climate events, particularly during the monsoon season. It is therefore important to understand not only to what extent the current mix and distribution of crop production in the country is susceptible to variations in temperature and precipitation but also whether certain crops offer superior resilience in the face of more frequent climate extremes.

As a C3 crop whose cellular machinery does not physically separate CO_2 fixation from the biochemical cycle for generating sugars, rice typically uses water less efficiently than the C4 grains—finger millet, maize, pearl millet, and sorghum—grown during monsoon [23] but achieves higher yields. While we would expect that these differences in crop physiology would leave rice more susceptible to variations in climatic conditions, the sensitivity of kharif grain yields to climate variability remains poorly understood. Recent studies have clarified aspects of this relationship. One examined the climate sensitivity of grain yields in central India, finding that the yields of all grains were significantly sensitive to interannual rainfall variability but that only rice yields were significantly affected by temperature [24]. Another study assessed the yield sensitivity of selected rainfed crops (maize, pearl millet, and sorghum) to climate across India and showed that extreme temperatures and the number of rainy days reduced yields of all three crops across most districts [25]. Rainfall totals were also an important determinant for pearl millet yields across the country and for maize yields in certain districts. Other work showed that the yields of rice, maize, and sorghum were significantly sensitive to maximum temperature but that only rice yields were significantly sensitive to rainfall [26]. Much of the other previous studies relating climate variability and crop yields in India has focused on rice and wheat (e.g. [20, 27]), limiting the ability to compare the climate sensitivity of all grains. A comprehensive national analysis is therefore needed to account for the full basket of monsoon grains produced in India and the wide variations in climate and cultivation methods that span the country.

Here we quantify the influence of historical precipitation and temperature variability on the yields of the five major grains produced during the monsoon (kharif) season—finger millet, maize, pearl millet, rice, and sorghum—and determine whether India's alternative grains may offer benefits over rice for reducing the volatility of grain production to climate variability. To do so, we combine district-level crop production data with seasonal (June/July/August average) temperature and precipitation data for the years 1966 through 2011 and employ a linear mixed effects modeling approach to estimate the magnitude and significance of grain yield responses to interannual variability in precipitation and temperature. Given the dominance of rice in monsoon (kharif) grain production, we compare the climate sensitivity of each alternative grain to that of rice by only considering districts where the rice was produced in the same district as each alternative grain. We then utilize these models to estimate changes in crop yields under scenarios of climate stress—deficit precipitation and high temperature conditions. We then examine district by district the variation in grain production across a suite of historical climate conditions and compare production levels under the current allocation of cropland to monsoon grains with a scenario under which the allocation of cropland to alternative grains is prioritized in lieu of rice to minimize yield losses in the face of drought. This understanding of where and to what extent alternative grains may be less sensitive to interannual climate variability relative to rice can inform strategies to minimize grain production shocks due to climate extremes and to potentially enhance grain production overall.

Methods

We combined time series of district-level grain yields with information on soil and climate characteristics within a mixed effects modeling framework to examine the sensitivity of grain yields to interannual variability in monsoon climate. To allow for the comparison of the climate sensitivity of each alternative grain—finger millet, maize, pearl millet, and sorghum—to rice, we only considered those districts where each alternative grain and rice were produced in the same district. We then used the results of this modeling exercise to estimate expected changes in yields under historically extreme monsoon precipitation and temperature. Finally, we compared the changes in the magnitude of rainfed grain production across a suite of climate conditions between the current allocation of cropland to each grain and under a maximum allocation of cropland to alternative grains to minimize production sensitivity to drought conditions.

Data

Our study focused on the five main grains grown during the monsoon (kharif) season: finger millet, maize, pearl millet, rice, and sorghum. Information on yield (tonne ha^{-1}), harvested area (ha), and irrigated area (ha)—disaggregated by year, crop, and district—came from the International Crops Research Institute for the Semi-Arid Tropics Village Dynamics of South Asia (VDSA) [21]. These data were reported using consistent 1966 district boundaries for the year 1966 through 2011 (figure S1 is available online at stacks.iop.org/ERL/14/064013/mmedia). Plot-level estimates of production, plot area, irrigation pumping hours, irrigation canal fees, and cluster weights for the years 2007 through 2011 came from India's Cost of Cultivation Survey dataset—an annual survey of farmers with data representative at the state-level [28]. Data on soil texture (% clay, % sand, % silt; 1 km resolution) were taken from the SoilGrids database [29]. Precipitation datasets included in this study were CHIRPS (spatial resolution: 0.05°; temporal resolution: daily; time period used/available: 1981–2011) [30], TRMM (0.25°; daily; 1998–2011) [31], Indian Meteorological Department (0.25°; daily; 1966–2011) [32], and Willmot-Matsura (0.5°; monthly; 1966–2011) [33]. Temperature datasets used in this study were BEST (1°; monthly; 1973–2011) [34], CRU v3.24 (0.5°; daily (mean and maximum); 1966–2011) [35], and Willmot-Matsura (0.5°; monthly; 1966–2011) [33]. All gridded datasets were aggregated to the district level through a spatial average weighted by the proportion of grid cell area in the district in the case of grid cells that spanned across districts.

Partitioning grain yields between rainfed and irrigated

VDSA grain yields are reported as the total production of a grain within a district divided by its harvested area. Following Davis *et al* [23], we assume that all production of rice, maize, finger millet, and pearl millet occurs during the kharif season. This assumption is supported by crop production data reported by season from the Directorate for Economics and Statistics [36], which shows that millet production during rabi is negligible and that only for selected states (for example, rice in Andhra Pradesh, Odisha, Tamil Nadu, and West Bengal, and maize in Andhra Pradesh, Bihar, Madhya Pradesh, and Tamil Nadu) is rabi production substantial for rice or maize. For sorghum, the VDSA dataset separates production and harvested area between kharif and rabi season. We employed a three-step process to partition these aggregate VDSA yields into rainfed and irrigated yields. First, we separated plot-level observations from the Cost of Cultivation Survey [26] into rainfed and irrigated observations, where any observations that reported a value greater than zero for either irrigation pumping hours or canal fees were categorized as irrigated. Second, we used this plot-level data to calculate a weighted average irrigated yield ($vi_{j,s}$) for crop j in state s across the years 2007 through 2011 for states in which data were available, with the state-level irrigated yield for crop j in year t calculated as:

$$vi_{j,s,t} = \frac{\sum\left(\frac{ci_{x,j,s,t}hi_{x,j,s,t}}{pi_{x,j,s,t}}\right)}{\sum(ci_{x,j,s,t})}, \qquad (1)$$

where hi is the quantity of crop j harvested in plot x, pi is the area of plot x, and ci is the plot x cluster weight—a value provided within the Cost of Cultivation dataset to calculate representative yields at the state-level. State-level rainfed yield for each crop ($vr_{j,s}$) was calculated in the same way using information from rainfed observations. Because Cost of Cultivation data were not available for all states in which VDSA data reported crop production, we then calculated for each crop a national average ratio of irrigated-to-rainfed yields, z_j, as:

$$z_j = \frac{1}{n}\sum\left(\frac{vi_{j,s}}{vr_{j,s}}\right), \qquad (2)$$

where n is the number of states for which data were available from the Cost of Cultivation dataset for crop j. Third and finally, we calculate rainfed and irrigated yields for all of the crops, districts, and years reported in the VDSA production dataset. The rainfed yield for crop j in district d and year t was calculated as:

Table 2. Model coefficients for rainfed grain yield variability in India. *P* is total monsoon precipitation, *T* is the mean daily monsoon temperature, and S_1 and S_2 are the percents of clay and silt. Marginally significant coefficients with *p*-values between 0.05 and 0.01 are italicized, and highly significant coefficients with *p*-values less than 0.01 are bold. 'Rice-F', 'Rice-M', 'Rice-P', and 'Rice-S' correspond to the rice models developed considering only those districts and years in which rice and each of the alternative grains (finger millet, maize, pearl millet, and sorghum, respectively) were both produced. Larger coefficients imply higher yield sensitivity to covariates.

Variable	Finger millet	Rice-F	Maize	Rice-M	Pearl millet	Rice-P	Sorghum	Rice-S
P	4.80E-05	**3.11E-04**	9.37E-06	**3.27E-04**	**1.26E-04**	**3.22E-04**	3.15E-05	**3.59E-04**
P^2	−1.56E-09	**−5.64E-08**	3.58E-09	**−7.24E-08**	*−5.20E-08*	**−7.94E-08**	−1.51E-08	**−6.98E-08**
T	−0.013	0.016	*−0.160*	−0.041	−0.145	*−0.253*	**−0.556**	**−0.515**
T^2	5.47E-04	5.07E-04	*2.91E-03*	1.05E-03	*3.27E-03*	**4.68E-03**	**9.26E-03**	**9.12E-03**
S_1	**−0.029**	**−0.060**	*−0.016*	**−0.048**	−0.001	**−0.065**	**0.017**	**−0.064**
S_2	**−0.033**	**−0.081**	**−0.040**	**−0.030**	0.007	**−0.037**	0.008	**−0.039**
marg. R^2	0.09	0.22	0.04	0.12	0.06	0.19	0.05	0.21
cond. R^2	0.53	0.74	0.54	0.78	0.56	0.77	0.44	0.76

$$yr_{j,d,t} = \frac{y_{j,d,t}\, a_{j,d,t}}{a_{j,d,t} - ai_{i,j,d,t} + (z_j ai_{i,j,d,t})}, \quad (3)$$

where $y_{j,d,t}$ is the original yield reported by VDSA for crop *j* in district *d* and year *t*, $a_{j,d,t}$ is the harvested area reported by VDSA for crop *j* in district *d* and year *t*, and $ai_{j,d,t}$ is the irrigated area reported by VDSA for crop *j* in district *d* and year *t*. Irrigated yields ($yi_{j,d,t}$) were calculated as the product of $yr_{j,d,t}$ and z_j.

Assessing climate sensitivity using mixed effects models

We developed national mixed effects models separately for each crop and for rainfed and irrigated yields. Each model included squared terms for precipitation and temperature to account for nonlinear effects and included random effects for district and year as the relationship between yield and the fixed effects may vary across time and space. Our approach followed that of DeFries *et al* [24] who used the lmer() package in R [37]. Rainfed yields for crop *j* were modeled as:

$$f(yr_j) = \alpha r_j P_{d,t} + \beta r_j (P_{d,t})^2 + \gamma r_j T_{d,t} + \delta r_j (T_{d,t})^2 + \varepsilon r_j S_{1,d} + \zeta r_j S_{2,d} + (1|d) + (1|t), \quad (4)$$

where αr, βr, γr, δr, εr, and ζr are model coefficients, *P* is total precipitation over the monsoon months of June, July, and August, *T* is the mean daily temperature over those same three months, S_1 and S_2 are the percentages of clay and silt, and the terms $(1|d)$ and $(1|t)$ represent random effects for district and year, respectively. The use of a random effect for time—as opposed to de-trending a time series of crop yields—is preferable in this case because some districts had incomplete time series of crop yields and because this avoids assumptions about the shape of historical yield trends. Percent sand was not included due to issues of collinearity. No data were available on crop-specific fertilizer application through time. This model therefore generated a single set of national coefficients for each rainfed crop. This was repeated for irrigated yields.

Collinearity between predictor variables was determined using variance inflation factors (VIFs), with all variables having VIF values less than 5. Model performance was assessed using Akaike Information Criterion (AIC) and marginal (i.e. variance explained by fixed effects) and conditional (i.e. variance explained by fixed and random effects) R^2 values. The combination of the IMD precipitation dataset and the CRU mean daily temperature dataset was preferred for several reasons: (1) the IMD dataset is India-specific, (2) both datasets offered longer time series than the other datasets, which is desirable when assessing climate sensitivity of crop yields, and (3) this IMD/CRU-mean combination agreed with the outcomes of the majority of the other climate dataset combinations which we examined (figures S2, S3). As such, the IMD/CRU-mean results are reported in the main text.

Effects of climate variability and extremes on crop yields

To control for the differing geographies between production areas for each grain and because of the current dominance of rice in determining the magnitude and variability of monsoon grain production, we ran these models for each alternative grain and rice, only considering those district-years in which rice and the alternative grain were both produced. Because each alternative grain is primarily cultivated in a different region, this required the development of four different rainfed rice models—each depending on the alternative crop to which rice was being compared—and one for each alternative grain (8 rainfed models in total) (table 2). We also developed 8 irrigated models (4 for rice and 1 for each of the alternative grains) (table S1). Following Fishman *et al* [20] and DeFries *et al* [24], we also included other potential climate variables (i.e. number of monsoon dry days, Simple Daily Intensity Index (*P*/number of rainy monsoon days)) in place of *P* and *T* and found that model explanatory power declined based on AIC. We also ran alternative models considering only temperature, precipitation, their squared terms and random effects for district and year and again found a reduction in model explanatory power based on AIC. All of the models described above were used to calculate national-level rainfed and irrigated coefficients (and their significance at the 0.05 level) for each of the predictor variables. By comparing the effect sizes of the crop-specific coefficients calculated for P and T, we were then able to examine the relative climate sensitivity of each alternative Indian grain in comparison to rice.

We then used P and T model coefficients that were found to be significant to estimate incremental changes in yield that would be expected under an extreme low rainfall year. To do this, we identified for each district the lowest monsoon precipitation (and its corresponding temperature) occurring between the years 1966 and 2011—the time span of the VDSA yield dataset. We then used significant model coefficients for P, T, and their squared terms to estimate resultant incremental changes in crop yields for each crop j, district d, and year t under an extreme dry year. Non-significant coefficients were interpreted as being invariant to their respective monsoon variable. As an example, the incremental change in rainfed yield, $\Delta y_{r,j,d,t}$, under an extreme dry year was calculated as:

$$\begin{aligned}\Delta yr_{j,d,t} = &\left[\alpha r_j P_{d,\,min} + \beta r_j \left(\min_{x\in t}(P_{d,t})\right)^2\right.\\ &\left.+\gamma r_j T_{d,\,min} + \delta r_j (T_{d,\,min\,P})^2\right]\\ &-[\alpha r_j P_{d,t} + \beta r_j (P_{d,t})^2\\ &+\gamma r_j T_{d,t} + \delta r_j (T_{d,t})^2],\end{aligned} \tag{5}$$

where $\min(P_{d,min})$ is the lowest monsoon precipitation amount observed in district d throughout the study period and $T_{d,minP}$ is the average daily monsoon temperature observed during the minimum precipitation year in district d. If a model coefficient was not significant, it was assigned a value of zero. If αr was not significant, βr was also assigned a value of zero. If γr was not significant, δr was also assigned a value of zero. We also repeated this analysis using the highest monsoon temperature in the time series for each district and its corresponding precipitation.

Crop production in drought and non-drought years

Finally, to examine the sensitivity of grain production across a suite of climate conditions, we used our model coefficients from the geographically unconstrained models (table S2) to calculate variations in rainfed grain production solely attributable to climate variability. To control for all factors other than temperature and precipitation, we held the random effect for year constant (using the year 2011 value) and held total harvested area constant for each district (year 2007–2011 average harvested area). Current modeled rainfed production for a given year t in district d was then calculated as:

$$\begin{aligned}pr_t = &\sum[(a_{j,d,t} - ai_{j,d,t})\\ &\times (f(yr_{j,d,t}) - (1|t)_{j,t} + (1|t)_{j,2011})],\end{aligned} \tag{6}$$

where $f(yr_{j,d,t})$ is the rainfed yield predicted by our model and $(1|t)_{j,t}$ is the rainfed coefficient for the random effect for time. Model coefficients are set equal to zero under the same conditions as for equation (5). The time series of calculated rainfed production for a district was then separated into 'drought' and 'non-drought' production following the definition of drought used by the Indian Meteorological Department, where drought years were defined as those years when monsoon precipitation for a district was less than 75% of the long-term average precipitation for that district. This process was then repeated under a maximum allocation of rice harvested area to alternative grains (i.e. finger millet, maize, pearl millet, and sorghum) in order to examine how these grains may contribute to reducing the climate sensitivity of food production. For each district where at least one of the alternative grains was cultivated, we replaced the harvested area of rice with the crop with the lowest coefficient for P from the geographically unconstrained rainfed models (table S2); non-significant P coefficients were considered to have a value of zero. In cases where multiple alternative grains were planted in a district and their P coefficients were equally low (i.e. finger millet, maize, and sorghum), rice was replaced with the crop with the largest reported harvested area for that district. The calculations of this section were also repeated excluding maize as a potential replacement for rice. This exclusion of maize was performed because it is not a traditional crop in Indian food systems, and it is unclear whether the increased production of maize would lead to increased grain availability for diets or would be used for other purposes (e.g. animal feed) which may or may not indirectly benefit nutrition in diets.

Results

Because the majority of Indian grain production is rainfed (especially for alternative grains) and because rainfed agriculture is typically more vulnerable to climate variability, we focus our results on rainfed yield sensitivity (table 1). We first examined the rainfed yield distributions of each alternative grain and rice, only considering those districts and years in which rice and the alternative grain were both produced (figure 1). For finger millet, pearl millet, and sorghum, we observed mean yields substantially lower than for corresponding rice areas. Compared to the range of values observed for these crops, rice yields showed a substantially wider distribution. The yield distributions for maize and rice were nearly identical both in terms of median and range. Looking at the variation in crop yields through time, the distribution of rice yields for a given year had a larger range across districts than for all of the alternative crops (figures 2; S4). In general, the yields of alternative grains were lower than for rice, but it is also worth noting that—for certain districts and crops—the rainfed yields of alternative grains exceeded those of rice, especially for pearl millet and sorghum in central India and maize in many parts of the country (figure S5).

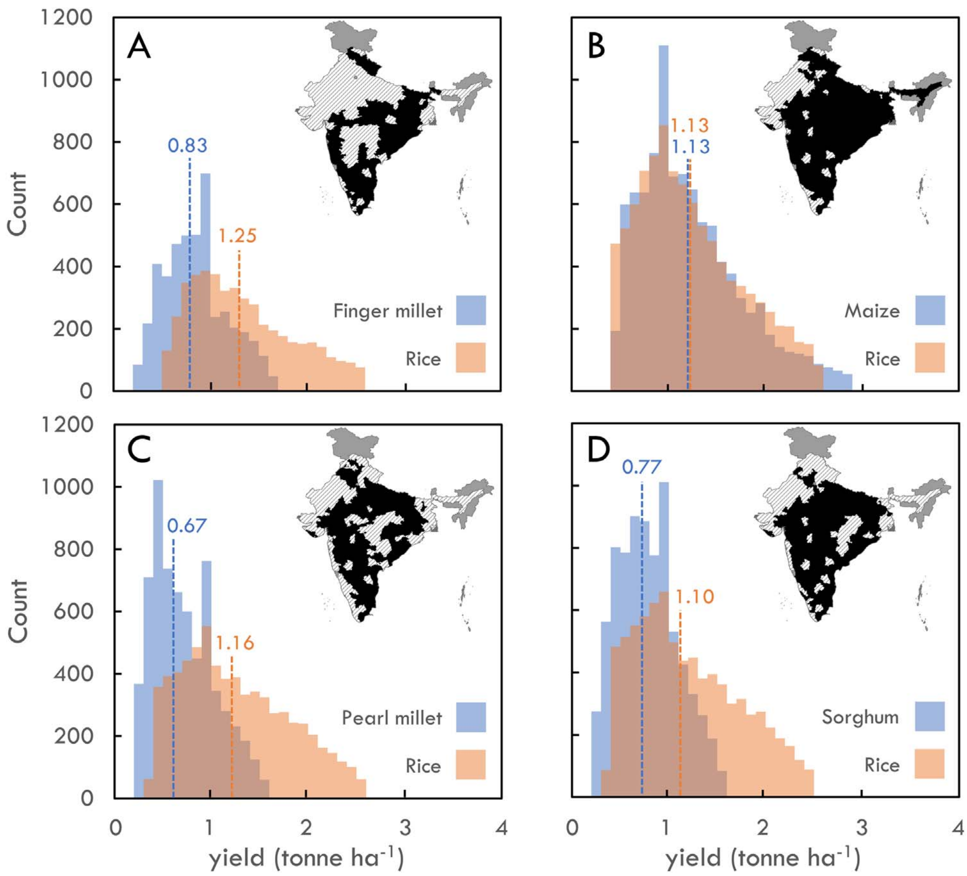

Figure 1. Rainfed yield distributions for Indian grains. Yield distributions were compared for districts and years where rice and each of the alternative grains (finger millet (A), maize (B), pearl millet (C), and sorghum (D)) co-occurred. As a result, the shape of the yield distribution for rice varies between panels. Dashed vertical lines show the median values of each distribution. Inset maps show the districts (in black) where production was co-located for rice and each of the alternative grains. Values below the 5th percentile or above the 95th percentile were not included.

We examined the sensitivity of rainfed grain yields to climate variability. Among the alternative grains, only pearl millet showed significant sensitivity to interannual fluctuations in rainfall over the study period, though the effect size of this coefficient was less than half of that for the corresponding rice model ('Rice-P') (table 2). Conversely, all rice models showed significant sensitivity to precipitation variability. Regarding temperature variability, maize, sorghum, and rice grown in areas where pearl millet and sorghum were also grown ('Rice-P' and 'Rice-S') showed significant sensitivity. These findings related to climate sensitivity are largely consistent with previous work at the national scale [25, 26]. For all crops except pearl millet, soil texture played a significant role. Results for significance and effect sizes were consistent with the majority of combinations of different climate datasets considered in this study (figure S2). The overall model results were also consistent when we did not control for districts where rice and the alternative grain were both produced (tables S2, S3).

We then assessed incremental yields (i.e. the portion of the yield described by precipitation and temperature coefficients) and their changes under historically extreme climate conditions. Under an extreme dry year (i.e. the district-wise minimum monsoon precipitation and its corresponding temperature), we estimated that the average reduction across districts in rainfed rice yield would be between 0.05 tonne ha^{-1} and 0.09 tonne ha^{-1} (or 5.9%–9.0%) (figures 3(A), (B)). By comparison, rainfed pearl millet—the only alternative grain significantly sensitive to precipitation variability—would experience an average reduction of 0.02 tonne ha^{-1} (or 4.2%). Relative to rainfed rice yields, this suggests that the yields of all rainfed alternative grains are less sensitive to reductions during an extreme dry year relative to rice. Under an extreme hot year (i.e. the district-wise maximum monsoon temperature and its corresponding rainfall), rainfed pearl millet performed worse than rice on average (figures 3(C), (D)). Maize and finger millet yields were less sensitive to an extreme hot year than rice, and sorghum performed similar to rice—with a median change in incremental yield close to zero. The above patterns were also generally true for irrigated yield distributions (figure S6), yield sensitivity (table S1), and reductions to yield under extreme dry (figures S7(A), (B)) and hot years (figures S7(C), (D)).

Finally, we quantified the changes in production solely attributable to precipitation and temperature

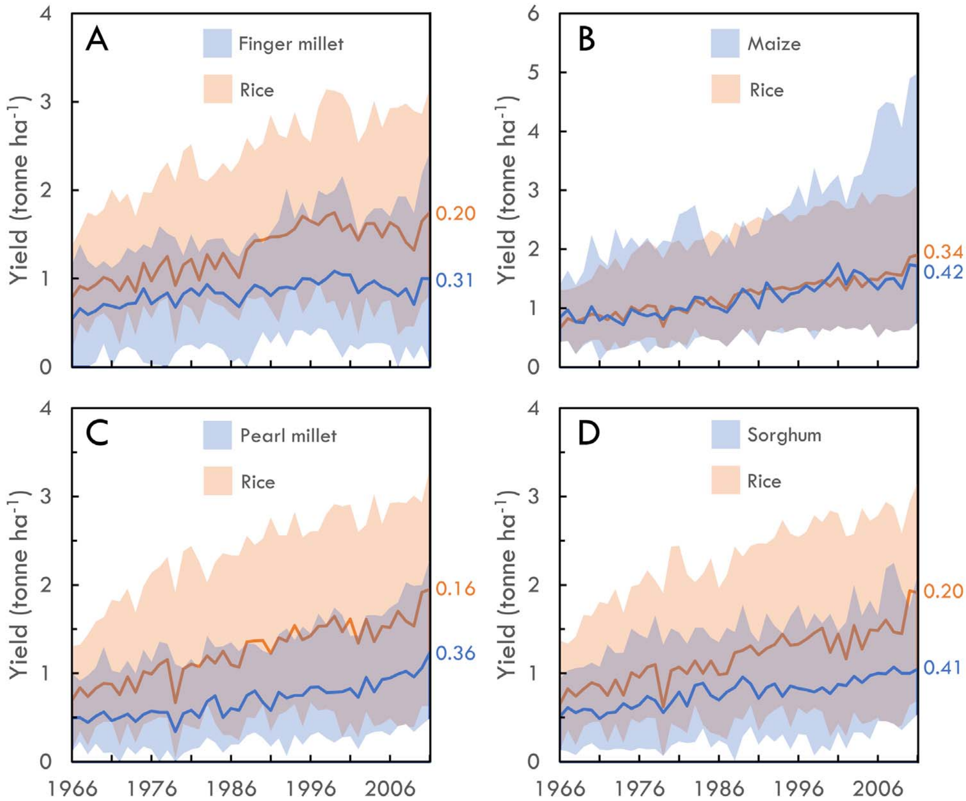

Figure 2. Time series of yield distributions for rainfed yields. For each year, yield distributions were compared for districts where rice and each of the alternative grains (finger millet (A), maize (B), pearl millet (C), and sorghum (D)) co-occurred. As a result, the shape of the band for rice varies between panels. Colored lines represent the 50th percentile value for each, and the top and bottom of the bands correspond to the 95th and 5th percentile values, respectively. Gray areas show the overlap between bands. Numbers to the right of each panel represent the production-weighted district-level coefficient of variation for the yields of rice and each of the alternative grains.

across a suite of historical climate conditions and under a maximum allocation of croplands to coarse grains (i.e. finger millet, pearl millet, and sorghum). For 87% of rice-producing districts, increasing the share of harvested area allocated to coarse grains would contribute to improving the stability of grain supply in the face of drought but would lead to production shortfalls (figures 4(A), (B)). Only districts in Madhya Pradesh would not experience a tradeoff between production and variability due to relatively high sorghum yields (figure S5). The average net losses in production would be −12.0 Mtonne (drought years) and −12.8 Mtonne (non-drought years) (table S4). When considering all alternative grains (i.e. including maize) as potential replacements for rice, we found substantial increases in grain production and reduced variability (figures S8(A), (B), table S5). While including maize would eliminate the tradeoff between production and resilience, the social, cultural, economic, and food security implications of and obstacles to doing so would, however, likely be numerous as maize is not a widely consumed traditional grain in India and is increasingly used for feed. Overall, these results indicate that—for certain crops and states—selectively increasing the production of alternative grains already offers the opportunity to enhance production levels and to contribute to the stability of grain supply against climate variability. We note that this does not take into account other important aspects of stability such as implications for farmer incomes and nutrition which would be essential to consider under such a change. Further efforts to increase the yields of coarse grains—without making them more sensitive to climate variability—would be necessary to eliminate existing tradeoffs between production and climate resilience.

Discussion and conclusion

The potential effects of climate variability on crop productivity are essential to consider in developing sustainable and resilient food systems. Our analysis provides a comprehensive national assessment of the sensitivity of rainfed and irrigated grain yields to historical climate variability in India. We find that—compared to all alternative grains—rice yields are significantly more sensitive to interannual fluctuations in monsoon rainfall on both irrigated and rainfed croplands (tables 2; S1–S3). We also show that increased allocation of croplands to alternative grains can contribute to stabilizing grain production across a spectrum of climatic conditions. These results

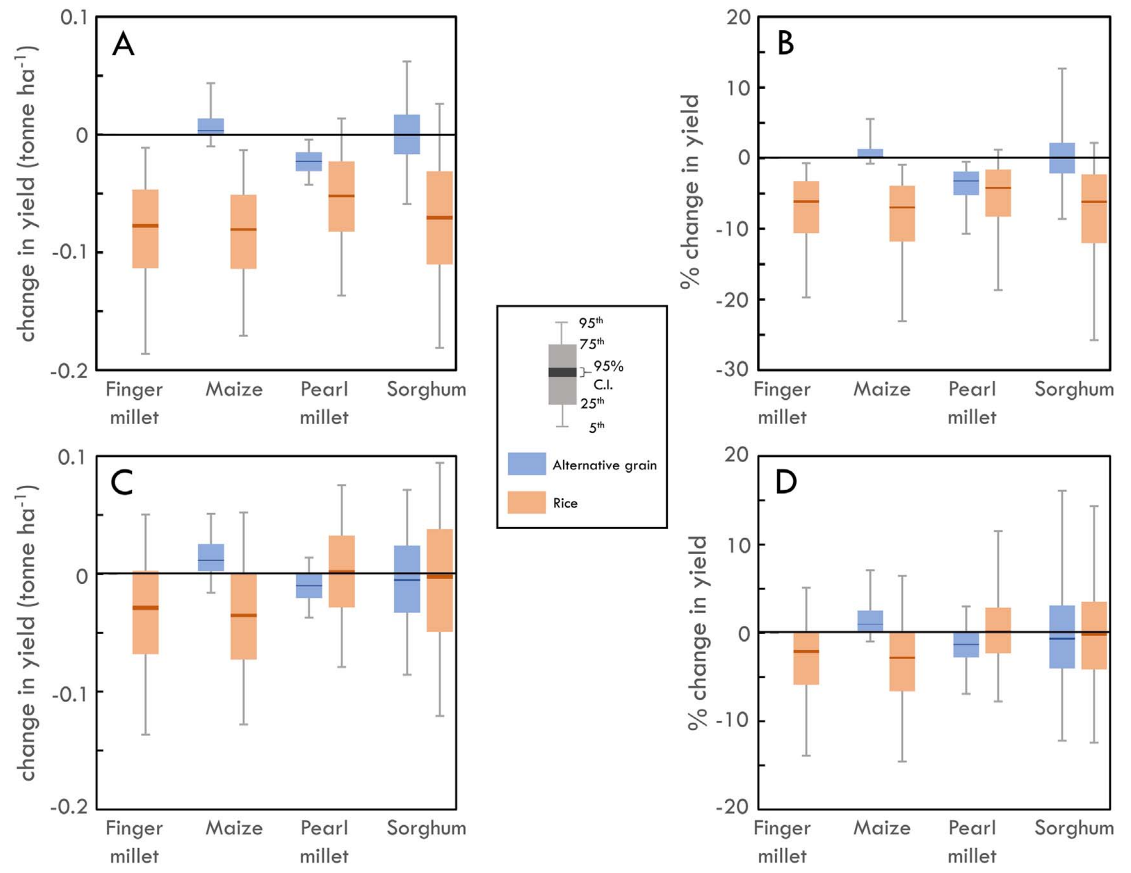

Figure 3. Absolute and relative changes in yield under extreme climate conditions from 1966 to 2011 for rainfed alternative grains and co-occurring rice. Panels show (A) absolute and (B) relative changes in rainfed yields during an extreme dry year and (C) absolute and (D) relative changes in rainfed yields under an extreme hot year. Values were calculated for each district and each year where co-produced yields were reported using the model coefficients for precipitation, temperature, and their squared terms. If a model coefficient was not significant, it was assigned a value of zero. If the model coefficient for precipitation was not significant, its squared term was also assigned a value of zero. The same was done for the model coefficients for temperature.

highlight the potential benefits of increasing alternative grain production in order to buffer against increasingly frequent climate extremes, especially considering that half of kharif grain production is rainfed (table 1). These findings also suggest that irrigation may only play a limited role in buffering rice yields in particular against increased rainfall variation. Indeed, during an extreme dry year, we find significant reductions in rice yields under all rice models considered here (figure 3). We also find that almost all rainfed grains—with the exception of finger millet—display some yield sensitivity to variability in monsoon temperatures. Our study therefore indicates that all grains will likely experience some impacts from an increasingly variable climate but that the relative importance of precipitation and temperature variability varies between crops. Taken together with evidence of increasing temperatures, a changing monsoon, and more frequent climate extremes [9, 10, 18, 19], this collectively indicates that rice yields may be particularly hard-hit. Our results show that selectively increasing coarse grains in the crop production mix may offer promise for enhancing the climate resilience of food supply in India. This approach may be combined with other strategies to enhance the resilience of grain supply against climate shocks including strategic reserves, improved access to and utilization of irrigation resource, and the development of high-yielding drought-tolerant varieties of India's dominant crops. However, the relatively high yields of rice mean that in many districts a tradeoff between production levels and yield sensitivity will persist with coarse grains unless their yields improve (figures 4, S5). As such, any efforts to this end must take into account that a focus on developing the few traits desired for high-yielding crop varieties can often come with a loss in climate resilience (e.g. European wheat [38]).

Recent work also highlights that the potential improvements to the climate resilience of Indian grain supply through increased alternative grain production could also be complemented by other environmental and nutritional benefits. In particular, promoting the production of alternative grains offers the potential to reduce agricultural water demand [23], greenhouse gas emissions [39], and energy use [40] while also alleviating certain micronutrient deficiency diseases (e.g. anemia [41]). There also remains a large potential to reduce tradeoffs between efficient land use (i.e. yields) and high nutrient content for alternative grains

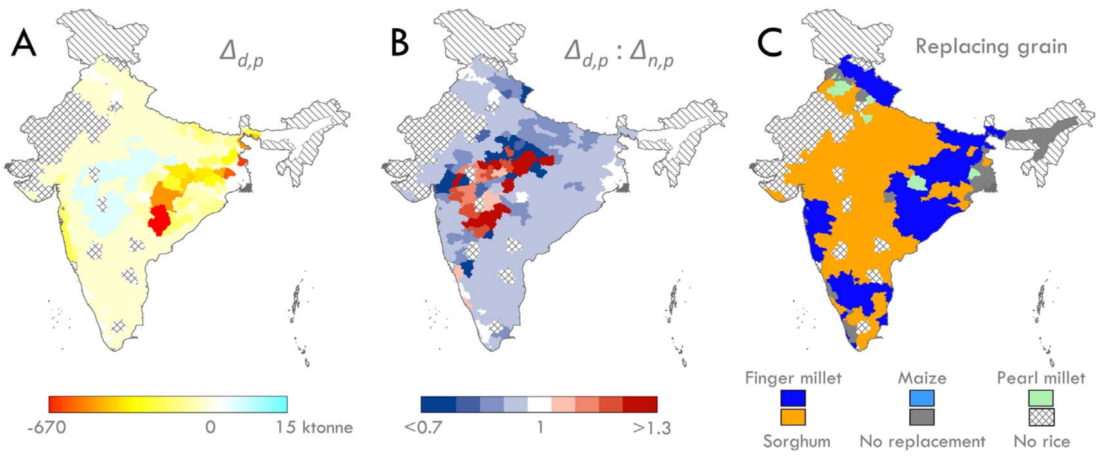

Figure 4. Changes in monsoon rainfed grain production during drought and non-drought years under maximum allocation of harvested areas to coarse grains. Unconstrained model coefficients (table S1) were used to calculate crop yields for each year. Modeled estimates of 'BAU' production (i.e. production under the current (year 2007–2011) allocation of harvested areas) and 'MaxAlt' production (i.e. production under the maximum allocation of rice harvested areas to coarse grains) were calculated for each district and each year using equation (6). For each district, 'BAU' and 'MaxAlt' production were then separated into 'drought' and 'non-drought' years following the definition of the Indian Meteorological Department and averaged. (A) We then took the difference between average 'MaxAlt' production and average 'BAU' production for 'drought' years ($\Delta_{d,p}$). We also took the difference between average 'MaxAlt' production and average 'BAU' production for 'non-drought' years ($\Delta_{n,p}$; not shown). (B) For a given district, if $\Delta_{d,p}$: $\Delta_{n,p}$ is greater than unity and $\Delta_{d,p}$ is positive, this means that increasing coarse grains can contribute to stabilizing production in the face of drought and increase overall production. (C) The criteria for selecting the crop for replacing rice harvested area are described in the Methods. Areas with diagonal lines were districts with no data.

through increased research efforts, as rice and wheat have received the bulk of the scientific focus since the start of the Green Revolution [42].

Our study adds to the empirical information needed for comprehensively assessing the potential co-benefits and tradeoffs associated with increased alternative grain production. The extent to which crop production is vulnerable to climate extremes is an increasingly important consideration in developing adaptable and resilient food systems. Future work examining other agriculturally relevant climate variables (e.g. dry spells, monsoon onset) can enhance our understanding of the relationship between climate variability and crop productivity in India. The work presented here demonstrates that increasing alternative grains in India's grain production basket can potentially reduce variations in supply in response to growing climate variability but that such interventions should be made selectively (both geographically and for the appropriate crops) in order to avoid any production shortfalls.

Acknowledgments

KFD was supported by The Nature Conservancy's NatureNet Science Fellows program and Columbia University's Data Science Institute Fellows program. NDR was supported by the European Research Council Starting Grant number 637462. We thank Manjusha Kancharla for her useful input regarding the regression analyses.

Author contributions

KFD, AC, DS, and RD gathered the data. KFD and DS cleaned the data. KFD, AC, NDR, and RD analyzed the data. All authors contributed to the writing of the manuscript.

Competing interests

The authors declare no competing interests.

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