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LETTER

On the role of rainfall deficits and cropping choices in loss of agricultural yield in Marathwada, India

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Abstract
Crop loss and ensuing social crises can be detrimental for the agriculture-driven economy of India. Though some studies identify country-wide increasing temperatures as the dominant factor for crop loss, the agro-climatic diversity within the country necessitates an understanding of the influence of climate variability on yields at regional scales. We report a complex interplay among rainfall, temperature and cropping choices, with a focus on the drought-prone Marathwada region in Maharashtra. Our analysis based on observations, as well as statistical and process-based modelling experiments, and temperature projections of 1.5 °C and 2 °C warmer worlds show that for the two major cropping seasons, rainfall deficit is the primary cause of crop failure, as compared to rising temperatures. The gradual shift from drought-resilient food crops, such as sorghum and pearl-millet to water-intensive cash crops such as sugarcane in recent years, is seemingly responsible for aggravating this crisis. Our findings warrant strategies promoting drought-resilient food crops, that will be useful, not only for mitigating the immediate agrarian crisis, but also for curbing impending threats to food security in the region under future climate change.

1. Introduction
Crop failure and subsequent agrarian crises (Mohanty and Shroff 2004, Rao & Suri, 2006, Gruère and Sengupta 2011, Gutierrez, 2015) is a major concern for the agriculture-driven economy of India (DoES & MoAW, 2016). The geographical location, and the spatial heterogeneity in landforms and climate (figure S1), aids cultivation over two major cropping seasons: the rain-fed Kharif season (June-September) during the southwest monsoons, and the irrigated Rabi season (October-February). The vulnerability of crop production to monsoon variability (Prasanna 2014, Verma et al 2018) warrants understanding of the major meteorological drivers of crop loss, while framing relevant mitigation strategies.

Climate effects on crops are different at global (e.g. Lobell et al 2011, Iizumi and Ramankutty 2016, Lesk et al 2016), national (e.g. Olesen et al 2011, Gourdji et al 2015, Zampieri et al 2017) and sub-national scales (e.g. Almeayehu and Bewket 2016, Zhang et al 2016, Zampieri et al 2017). This is also true for the Indian sub-continent (Ghosh et al 2009, Pal & Al-tabba, 2011) where rainfall and warming trends are spatially non-uniform (Kothawale and Rupa Kumar 2005, Dash et al 2009, Lau and Kim 2010, Sonali and Nagesh Kumar 2013). Many studies have evaluated and reported variability in rainfall (Ray et al 2015, Fishman 2016) and/or temperature (Mondal et al 2015, DeFries et al 2016, Davis et al 2019, Bhatt et al 2019) to be the dominant driver of crop yields, among other climate-agriculture-environment interactions such as irrigation and fertilization, depending on the geographical location/spatial scale, crop type, and cropping season.

Carleton (2017) analyzed the link between crop yields and climate change over India and attributed about 6.8% rise in farmer suicides from 1987 to 2013 to rising growing season temperatures. Although the results were consistent with other studies that established the effect of global warming on declining crop yields (Lobell and Field 2007, Auffhammer
To quantify the relative contributions of rainfall, and to investigate the cause for observed shifts in crop yields, to offer a prognosis of agriculturally relevant temperature trends, during the major cropping seasons and years 2014 and 2015 that may have had a confounding effect on sharp fall in crop yields, in a set of model experiments (supplementary section S2).

\[ \text{Yield}_{d,t} = \beta_1 \text{Rain}_{d,t} + \beta_2 \text{Rain}_{d,t}^2 + \beta_3 \text{GDD}_{d,t} + \beta_4 \text{GDD}_{d,t}^2 + \beta_5 \text{NumRD}_{d,t} + \beta_6 \text{AccRain}_{d,t} + \beta_7 \text{Irrig}_{d,t} + 1|\text{District}_{j,d} + 1|\text{Year}_{t} \]  

where, \( \beta_1, \ldots, \beta_7 \) are the standardized partial regression coefficients for crop \( j \), for the fixed-effects. \( 1|\text{District}_{j,d} \) and \( 1|\text{Year}_{t} \) are random effects for district \( d \) and year \( t \), respectively.

2.2. Process-based model

For disaggregating the response of selected crop yields to the respective growing season precipitation and temperature, we use two analytical methods (e.g. Lobell and Asseng 2017) as discussed below. Figure S2 presents the detailed workflow of the analysis.

2.1. Statistical model

We use a mixed-effects regression approach for modeling the response of the selected crops to climate variability (Mondal et al 2014, DeFries et al 2016, Fishman 2016, Davis et al 2019), at district-scales (figure 1(a)). The observed meteorological effects on crop yields are the fixed-effects, while the unobserved spatial and temporal variations in soil quality and crop management practices form the random-effects. The crop yield (Yield) is modeled as a function of rainfall and temperature, via a suite of explanatory variables. The total rainfall received (Rain) and the number of rainy days (NumRD), both cumulated over the growing season, rainfall accumulations from the previous seasons (AccRain) and available irrigation amounts (Irrig; proxied by change in groundwater levels) are used to capture rainfall variability, while available growing degree days during the growing season (GDD) form the effect of temperature on yields. Intercepts for districts (District) and years (Year) account for the random-effects.

All variables are standardized prior to modeling, for facilitating comparison of sensitivities of yields to the various drivers, both for individual crops and across different crops (Schielzeth 2010). The details of the regression model are detailed in supplementary section S1 (available at stacks.iop.org/ERL/15/094029/mmedia). We arrive at the best performing model (equation 1), based on the sensitivity of the selected crops and overall performance of the models to the omission/inclusion of (i) higher order terms of rainfall and temperature, (ii) irrigation and rainfall accumulations from previous season, and (iii) the drivers in years 2014 and 2015 that may have had a confounding effect on sharp fall in crop yields, in a set of model experiments (supplementary section S2).

\[ \text{Yield}_{d,t} = \beta_1 \text{Rain}_{d,t} + \beta_2 \text{Rain}_{d,t}^2 + \beta_3 \text{GDD}_{d,t} + \beta_4 \text{GDD}_{d,t}^2 + \beta_5 \text{NumRD}_{d,t} + \beta_6 \text{AccRain}_{d,t} + \beta_7 \text{Irrig}_{d,t} + 1|\text{District}_{j,d} + 1|\text{Year}_{t} \]  

where, \( \beta_1, \ldots, \beta_7 \) are the standardized partial regression coefficients for crop \( j \), for the fixed-effects. \( 1|\text{District}_{j,d} \) and \( 1|\text{Year}_{t} \) are random effects for district \( d \) and year \( t \), respectively.
Figure 1. (a) Marathwada sub-division in Maharashtra, India. The districts that form the region are marked by numbers 1–8. (b) Seasonal average rainfall and temperature from 1951 to 2015 in Marathwada, for the Kharif season. (c) same as (b), for the Rabi season. The JJAS rainfalls and ONDJF temperatures are both significant at 5% significance level, based on the Mann-Kendall non-parametric trend test. (d) Cropped area under major crops cultivated in the region for the Kharif season. (e) same as (d), for the Rabi season. (f) Area-averaged standardized crop yield time series (1980–81 to 2015–16) for selected crops based on increasing/decreasing acreages with time, for the Kharif season. (g) same as (f), for the Rabi season.

our analysis to a single process-based model, for qualitative comparison with results from regression models. Despite difficulties in calibration, either arising from lack of reliable field data (Lobell and Burke 2010), or due to uncertainties in the different meteorological (Tao et al 2009) and phenological parameters (Izumi et al 2009), process-based models form important tools for assessing climate change impacts on agriculture (e.g. Challinor et al 2009, White et al 2011, Rötter et al 2012, Angulo et al 2013).

A summary of the model forcing data, both meteorological and crop specific, cultivar choices and associated assumptions in crop management is provided in Table S8. We use DSSAT simulations for two design scenarios for the period 1997–2015. The two scenarios, P_VAR and T_VAR, assume rainfall and temperature, respectively, to be the observed daily values while all other meteorological inputs are kept constant at their respective 1997–2015 daily means. Without loss of generality, the estimated yields for each crop are scaled to lie in the interval [0, 1] (normalized) to make the scenarios comparable. Further, we also report the coefficient of variation (ratio of standard deviation to mean) (Abdi 2010), based on the time series of annual yields in the P_VAR and T_VAR experiments. A lower (higher) coefficient indicates a larger (smaller) spread of the series about its mean, and translates to lower (higher) sensitivity of crop yield to the variability in rainfall or temperature.
Figure 2. DSSAT experiment results: Simulated response of crop yields to the growing season rainfall when temperature is held at a long-term mean (blue), and to the growing season GDD when rainfall is held at a long-term mean (red) for: (a) sugarcane, (b) cotton, (c) soybean, (d) wheat and (e) chickpea.

3. Data

The annual yield and area under cultivation for the various crops grown in Marathwada is compiled for 1997–2015, from the district-wise data, from the Area and Production Statistics portal, under the Ministry of Agriculture and Farmers Welfare, Government of India (aps.dac.gov.in). For sugarcane, cotton, sorghum, pearl millet, soybean, wheat, chickpea and sunflower, annual yields for 1980–1997 are obtained from the annual reports of the Commissionerate of Agriculture (1991, 1995, 1996). The cropping calendars (Table S6) are obtained from the Directorate of Economics and Statistics, Government of India (eands.dacnet.nic.in/At_A_Glance-2011/appendix-IV.xls). Optimum temperature ranges (Hatfield et al 2011) for the different growth stages of the crops are inferred from various studies and are presented in Table S10.

Observed daily gridded rainfall for 1901–2016 at 0.25° × 0.25° lat-lon. resolution (Pai et al 2013) and daily maximum and minimum temperatures for 1951–2016 at 1° × 1° resolution (Srivastava et al 2009) are obtained from the India Meteorological Department (IMD; available at http://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html). Total rainfall and growing degree days (GDD) over the growing season for the Marathwada region (17.5°N—20.75°N, 74.75°E—78.25°E, shown in figure 1(a)) are computed for 1997–2015 from the daily records. Gridded monthly root-zone soil moisture (cu.m/cu.m) for 1980–2015 is obtained from the Modern Era Retrospective-Analysis for Research and Applications (MERRA-Land, available at http://disc.sci.gsfc.nasa.gov/daac-bin/FTPSubset.pl?LOOKUPID_List=MSTMNXMLD) at a resolution of 0.5° x 0.66° (Reichle et al 2011,
Figure 3. Optimum temperature ranges for (a) sugarcane, (b) cotton, (c) soybean, (d) wheat and (e) chickpea, for different stages of crop growth (pink—sowing, green—growing, yellow—harvesting). Boxplots show the spread of daily temperatures for historical (1980–2015) observations (black), and future (2065–2100) projections under the 1.5 ◦C (blue) and 2 ◦C (red) warming scenarios. The temperature distribution in each of the crop growing stages in the 1.5 ◦C and 2 ◦C warmer worlds are significantly different from the observed distributions at 5% significance level (Table S11).
groundwater depletion (WWF 2004), thereby underlining its importance for further analysis (Khapre 2015, Joshi 2016). Further, industry-estimated sugarcane acreage from satellite observations is larger than the Government-reported figures (PTI, 2012), indicating that the acreages used in this study might be an understimation.

A careful examination of these crops, with regard to their relative importance in the economy (details in table S9 and figure S5), reveals that the crops showing increasing acreages in recent years namely, sugarcane, cotton, soybean and wheat, are cash crops. Therefore, the changing cropping patterns can be partially ascribed to expected higher returns arising from greater demand for these crops. The complex roles of the various agrarian welfare programs aimed at national food security and financial sustenance is yet another important dimension that influence these trends (Aditya et al. 2017, Dreze and Khera, 2013, Ranaware et al. 2015). Based on these findings, we focus on the sub-selection of Kharif and Rabi crops that show the highest change in acreages with time—sugarcane, cotton, soybean, sorghum, pearl millet, wheat, chickpea and sunflower.

4.2. Sensitivity of crop yields to hydrometeorological variability

Figures 1(f) and (g) shows yields of the selected crops, for 1980–2015, detrended to remove the effects of improvement in agricultural practices (Lobell and Burke 2009) while preserving the year-to-year climatic fluctuations (Rao et al. 2014) and normalized for comparability. In general, the yields show a strong sensitivity to monsoon rainfall. For Marathwada, which receives most of its annual rainfall from the southwest monsoons, the JJAS rainfall governs the Rabi crops also, via soil moisture, groundwater storage and irrigation (Kumar et al. 2004, Pavelic et al. 2012). The correlations between soil moisture during each month of the Rabi season and monthly rainfall for the previous June to September months (figure S6) show that soil moisture approximately has a memory of 3 months. The residual soil moisture is expected to influence Rabi crop growth during the initial months (OND) in the field, and subsequently the yields (figure S7). Regional groundwater levels in the post-Rabi season are also found to be strongly correlated with JJAS rainfall (figure S8), owing to the sensitivity of yields of heavily irrigated crops such as wheat to JJAS rainfalls.

4.3. Disaggregation of rainfall and temperature effects on yields using mixed-effects regression models

Table 1(a) shows the standardized partial regression coefficients for the five independent variables. Most Kharif crops show similar sensitivities to temperature (GDD), with regression coefficients ranging from 0.298 to 0.365 (significant at 5%). The rainfall sensitivities (Rain), on the other hand, are more for the cash crops—sugarcane and soybean, with coefficients greater than 0.4 (significant at 5%), as compared to the food crops. Sugarcane is also sensitive to the other markers of rainfall, namely, number of rainy days, soil moisture and irrigation. Cotton and soybean are also responsive to irrigation amounts. Interestingly, the food crops—sorghum and pearl millet, that have been declining in acreages in recent years, show lower sensitivities to rainfall with coefficient values less than 0.22. These coefficients are generally lesser than the respective temperature coefficients, which simply means that the crops show a higher sensitivity to temperature, as compared to rainfall. Further, though the food crops are sensitive to the number of rainy days during the season (significant at 5%), there is no evident response to irrigation, indicating that these crops require lesser water, thereby emphasizing their drought-resiliency. The pronounced sensitivity of the cash crops to rainfall variability, and the lack thereof, in the case of food crops, is suggestive of unwise cropping choices to be a major driver of crop loss in the region.

Among Rabi crops, wheat is found to be significantly sensitive to irrigation (Irrig; significant at 1%), while all the Rabi crops are sensitive (significant at 5%) to the rainfall accumulations from the preceding JJAS season (AccRain), via residual soil moisture. These findings are justified because, among the crops considered in this study, wheat uses the highest amount of irrigation water (450 mm, under flood irrigation). Chickpea, on the other hand, is a drought-resilient crop and requires only 130–240 mm. (The irrigation water requirements for these crops are taken from Fishman et al. (2015)). Sunflower on the other hand, is a short-duration crop that has a growing period of only four months (Oct-Jan) and survives on showers during the retreating monsoons and residual soil moisture, with small amounts of irrigation during the later months, if the rainfall distribution has been insufficient during the preceding season.

Furthermore, we arrive at similar results on repeating the analysis with the rainfall and temperature data used in Carleton (2017) (table S5; details in supplementary section S2). This emphasizes the importance of considering regional scales, rather than country-wide scales, for robustly concluding the effects of climate variability on crop loss and subsequent crises.

4.4. Disaggregation of rainfall and temperature effects on yields using DSSAT experiments

Figures 2(a)–(e) shows the disaggregated response of DSSAT simulated yields to growing season rainfall (P_VAR) and temperature (T_VAR), for the crops showing increasing acreages. The simulations confirm that increasing rainfall has a positive effect on
yield while rising temperatures reduce productivity consistently across all crops, except sugarcane (figure 2(a)) and soybean (figure 2(c)). Interestingly, most of these crops also show a stronger response to rainfall, than temperature. However, this is not true for the crops with declining acreages. Sorghum and pearl millet of the Kharif season show a weaker response to rainfall, as compared to temperature (figure S9), owing to their drought-resilient nature (Garg et al., 1981, Sanchez et al., 2002). Further, the coefficient of variation ($C_v$) of yields for all the crops (table 1(b)), report low variation with changing temperatures ($C_v < 10\%$). Interestingly, sugarcane and soybean, which are currently the dominant Kharif crops, report large $C_v$ in the P_V AR experiment. Sorghum and pearl millet reveal small values of $C_v$ even for P_V AR, indicating that they are resilient to changes in both temperature and rainfall.

The findings from the statistical models and the process-based models emphasize that the recent shift in cropping patterns, from drought-resilient food crops such as sorghum and pearl millet, to water-intensive cash crops such as sugarcane and soybean is an imprudent choice that can adversely affect production in the region. Based on this analysis, therefore, crop loss in Marathwada and the subsequent issue of farmer crises, can be ascribed to the rainfall deficits and the spread of rainfall-sensitive crops and their reducing productivity; at present, the role of growing season temperature seems insignificant.

4.5. Optimal crop growth in 1.5 °C and 2 °C warmer worlds

The observed range of daily average temperatures for the three main growth stages (sowing, growing and, harvesting), for the selected crops, alongside the corresponding optimum temperature ranges are presented in figure 3 (similar plots for other crops in figure S11). In general, the observations lie within the prescribed ranges beyond which the crops can be negatively impacted. For the harvesting stages of sugarcane (figure 3(a)) and soybean (figure 3(c)), such temperatures marginally exceed optimal ranges, but are well below the lethal threshold of 38 °C for these crops (Luo, 2011, Directorate of Sugarcane Development, 2015). Might such seasonal temperatures reach crop-damaging ranges under projected climate change? To address this question, we use regional temperature projections in 1.5 °C and 2 °C warmer worlds (figure 3). In general, future temperatures are found to lie within or close to the prescribed thresholds. Temperature during the harvesting period for cotton that was sub-optimal in the observed climate (figure 3(b)), are found to get closer to the optimal range in the future projections. However, sugarcane yields are expected to reduce as temperatures above the optimal range can cause a reduction in sucrose enrichment (FAO, 2018). The projected range of harvesting-period temperatures of wheat are also seen to exceed optimal thresholds, in agreement with studies for other regions (Lobel et al., 2012, Rao et al., 2014), though Maharashtra is not considered to be a significant producer of wheat. Interestingly, for drought-resilient crops—sorghum and pearl millet, the observed and projected temperatures are found to lie within or below the optimal ranges (figures S11(a) and S11(b)). Therefore, except for sugarcane and wheat, the role of temperatures in affecting agricultural yields in Marathwada is expected to remain insignificant in a future, warmer world.

Table 1. (a) Mixed-effects model results: Standardized regression coefficients generated by the mixed-effects regression model, for all the selected crops. (b) DSSAT experiment results: Coefficient of variation, $C_v$ (%) of crop yields for the P_V AR and T_V AR experiments.

| Season | Type | Crop Variable | Rain ($\beta_1$) | GDD ($\beta_2$) | NumRD ($\beta_3$) | Irrig ($\beta_4$) | AccRain ($\beta_5$) | R-squared |
|--------|-----|---------------|-----------------|----------------|-----------------|------------------|-----------------|-----------|
| Kharif | Cash Crops | Sugarcane | 0.421 *** | −0.314 *** | 0.274 *** | 0.151 ** | −0.078 | 0.726 |
|       |       | Cotton      | 0.065          | −0.026         | 0.073           | 0.177            | 0.007           | 0.786     |
|       |       | Soybean     | 0.430 ***      | −0.365 ***     | 0.037           | 0.195 **         | 0.158 **        | 0.718     |
|       | Food Crops | Cotton     | 0.218 **       | −0.365 ***     | 0.163 **        | 0.165            | 0.058           | 0.279     |
|       |       | Soybean     | 0.024          | −0.298 **      | 0.203 **        | 0.041            | −0.030          | 0.798     |
| Rabi   | Cash Crops | Sorghum     | −0.192         | 0.288          | 0.035           | 0.225 **         | 0.253 **        | 0.620     |
|       |       | Pearl millet| 0.190          | 0.252          | −0.060          | 0.061            | 0.345 **        | 0.355     |
|       | Food Crops | Sorghum    | −0.019         | 0.288          | 0.030           | 0.026            | 0.298           | 0.779     |
|       |       | Pearl millet| 0.023          | −0.171         | −0.218          | −0.101           | 0.041           | 0.798     |

(b) DSSAT model results

| Season | Type | Crop Experiment | Rain ($\beta_1$) | GDD ($\beta_2$) | NumRD ($\beta_3$) | Irrig ($\beta_4$) | AccRain ($\beta_5$) | R-squared |
|--------|-----|-----------------|-----------------|----------------|-----------------|------------------|-----------------|-----------|
| Kharif | Cash Crops | P_V AR | 13.9            | 6.1            | 57.3            | 0.5              | 0.5              | 17.5     |
|       |       | T_V AR       | 2.7             | 6.0            | 4.6             | 4.2              | 6.6              | 2.7      |
| Rabi   | Cash Crops | Wheat     | 17.5            | 29.5           | 28.8            | 2.7              | 4.9              | 7.1      |
5. Conclusions

As demonstrated, disaggregating the agricultural response to growing season precipitation and temperature serves as an important step to ascertaining the drivers of crop loss and subsequent farmer crisis. For the agro-climatically diverse country of India where regional trends in climate affect the Kharif/Rabi crops, an unequivocal attribution of crop loss and subsequent farmer suicides to country-wide rising temperatures disregarding cropping seasons (Carleton 2017) may be questionable (Murari et al 2018, Das 2018, Plewis 2018). Focussing on the crisis-prone Marathwada region in India, we use mixed-effects regression models based on observed records, and customised crop model simulations to build a framework for disaggregating agricultural response to rainfall and temperature. Further, we also show that yield loss results from an interplay of various factors, among which precipitation deficit and unwise shift in cropping patterns from drought-resilient food crops to water-intensive cash crops, are the most significant. Growing season temperatures are in general found to lie within the optimal bounds for crop growth, both for the observed records, and under projected warming.

An important caveat in this analysis is that multiple crop models have not been investigated. Although the relative sensitivities of crops to the major meteorological drivers such as rainfall and temperature are not expected to reverse among different crop models (Sultan and Gaetani 2016), such comparisons can improve the confidence of these estimates. The Global Gridded Crop Model Inter-comparison (GGCMI) initiative, under Agricultural Model Intercomparison and Improvement Project (AgMIP) offers a suite of crop-model experiments for the entire globe, for four major crops- wheat, soybean, maize and rice (https://www.agmip.org/ag-grid/ggcmi/). In regions where these crops contribute significantly to livelihoods, it would be meaningful to analyse AgMIP ensembles, to understand climate on yields (Rosenzweig et al 2014, Asseng et al 2015, Li et al 2015). Further, the crop yield estimates used in this study may suffer from inconsistencies due to sampling errors, particularly for the food crops that have been declining in acreages. The confounding roles of the various government assistance programs under National Food Security Mission, and market intervention measures such as minimum support prices, in the nexus between cropping choices and agrarian crisis (Kumar et al 2012, John et al 2019) in the region have not been investigated in this study. In addition to precipitation and temperature, the role of other meteorological or local physiographic factors, carbon-dioxide (CO$_2$) fertilization (Donohue et al 2013) and/or field-scale practices may also be investigated. Despite these limitations, our analysis can inform advisories on various coping strategies such as, alternative crop choices and income, water management practices, crop insurances and policies relevant to food security (Swain 2014, Pradhan and Mukherjee 2018). It is simple, and can be extended for different parts of India and other world regions.

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Data Availability Statement

Any data that support the findings of this study are included within the article.

Author contributions

Conceptualization—SG and AM; Methodology—MZ, MD and AM; Analysis—MZ; Crop Model Simulation—MD and MZ; Preparation of Figures—MZ and MD; Interpretation of Results—MZ, AM, MD and SG; Writing—MZ & AM; Supervision—AM, SG, KAR; Funding Acquisition—AM and KAR.

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