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Swapping rice for alternative cereals can reduce climate-induced production losses and increase farmer incomes in India

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The rising homogeneity of global crop supply has increased vulnerability to climatic and economic disruptions. While substantial work has examined yield variations in relation to climate variability, little is known about the influence of harvested area on production stability. To investigate this, here we take the example of monsoon cereal production in India, which has steadily shifted towards climate-sensitive rice and away from alternative cereals (finger millet, maize, pearl millet, and sorghum). We find that variations in harvested area are significantly associated with current and past price fluctuations for all cereals except rice. This suggests that farmer decisions based on economic factors may exercise great influence in determining variations in harvested area. We also show that optimized allocations of harvested area can reduce climate-induced production loss by 11% or improve farmer net profit by 11% while maintaining calorie production and cropland area. Such improvements would be possible by reducing harvested areas dedicated to rice and increasing areas allocated to alternative cereals. Our findings show that strategies using harvested area to address cereal yield fluctuations and improve farm profits could complement ongoing efforts to improve alternative cereal yields and stabilize cereal production.

Global food supply will need to increase substantially in the coming decades to support rising populations and richer diets[1–3]. While agricultural systems must increase their output, improve nutrition, and minimize their environmental burden[4–6], achieving more sustainable food production is made more challenging by rising climate change and variability. Climate variability is exercising substantial influence on the stability of crop production[7–9]. Over the past half century, droughts and extreme heat have reduced global crop production by one-tenth[10]. At the same time, crop mixes have become less diverse[11], leaving production more prone to instability[12]. With episodes of extreme climate expected to become more frequent[13], a large body of research has recognized the urgent need to understand and address the critical challenge of enhancing the climate resilience of agriculture and has focused in particular on interrogating the relationship between climate variability and crop yields (e.g., refs. 14,15). However, by attributing production volatility solely to yields, other important factors may be ignored that also influence production stability. Indeed, emerging work has shown that changes in harvested area in association with climate variability can also exercise important influence on crop production outcomes[16]. For instance, recent work has shown that fluctuations in crop production in the US are in large part associated with variations in planted and harvested areas[17]. In Brazil, variations in harvested area in response to climate variability were found to play a more important role than yield variations in dictating the production

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of maize-soybean systems[18]. Another study in central India found a significant relationship between interannual variations in winter crop cover and variability in mean daytime temperature[19]. These variations in harvested area can be due to farmer perceptions based on climatic conditions at the beginning of the growing season (and therefore how much area to plant) (e.g., ref. 20) as well as due to non-ideal climate conditions after the crops have been sown (perhaps leaving farmers only able to harvest a portion of their planted area due to damaged crops). In addition to the effects of climate variability on harvested area, farmer planting decisions are based on economic and agricultural information from both the current year and the previous growing season[16]. Higher prices for a crop in the previous year may mean that a farmer sows a larger area with that crop (in order to increase profits) (e.g., ref. 21) or dedicates only the most fertile plots to that crop (thereby achieving the same amount of production with less land) (e.g., ref. 22). In addition, a large body of literature has both highlighted the responsiveness of acreage to price fluctuations and stressed the significance of considering competing crop prices in agricultural supply response[23–26]. Given this suite of factors potentially influencing production stability, this suggests that allocations of harvested area to less crops with lower climate-related yield variability may offer benefits for production stability overall.

Monsoon (kharif) cereal production in India provides the ideal case by which to explore these production stability dynamics (Fig. 1). On one hand, high-yielding rice has increasingly come to dominate monsoon cereal production in the country, currently accounting for 73% of monsoon cereal production, while maize (15%), pearl millet (8%), sorghum (2.5%), and finger millet (1.5%) (i.e., alternative cereals)

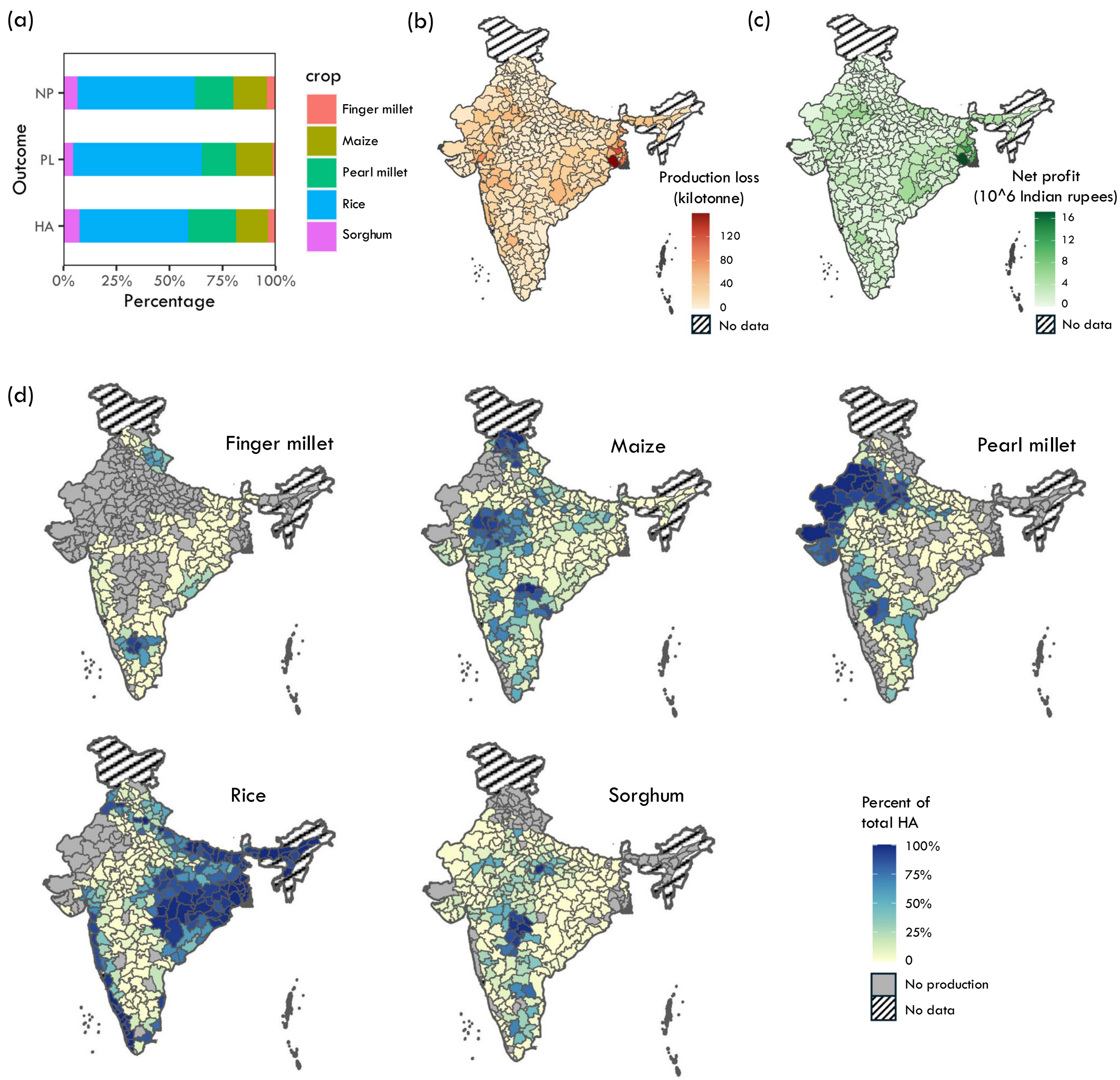

Fig. 1 | Recent status (average of year 2002-2011) of India kharif cereals. **a** Cereal-specific contributions to national total rainfed harvested area (HA), production loss (PL), and net profit (NP). Maps show the district-level annual (**b**) production loss and (**c**) net profit. **d** District-wise percentage of total rainfed harvested area for study cereals. These data and documents are licensed under a Creative Commons Attribution 4.0 International license. Readers are free to copy, distribute and transmit the data as long as you acknowledge the ICRISAT through DOI provided in this page: http://data.icrisat.org/dld/src/about-dld.html.

contribute much of the rest[27]. On the other hand, emerging work suggests that the yields of alternative cereals (millets, maize, and sorghum) may be less sensitive to climate variability compared to rice[28–32], depending on the nature of a particular climate extreme (e.g., maize sensitivity to high temperature[27,28]). This presents a potential tradeoff between the quantity of cereal production and its stability. With climate variability and extremes expected to increase in South Asia over the coming decades[33–35], it is therefore important to understand to what extent crop prices may influence variations in harvested area and whether reallocations of harvested area towards less climate-vulnerable and more profitable crops can ultimately both enhance monsoon cereal production stability and improve farmer profitability.

Here we quantify price elasticities in relation to harvested areas for five major cereals produced during the monsoon season—finger millet, maize, pearl millet, rice, and sorghum—, estimate current levels of cereal production instability, and determine to what extent shifts in cropping patterns can stabilize cereal production (Scenario 1) and maximize farmer net profit (Scenario 2). To do so, we combine district-level crop harvested area data with deflated price data for the years 1966 through 2011 and employ a linear fixed effects modeling approach to estimate the harvested area responses to interannual variability in price volatility. We complement this analysis with a suite of optimizations that re-allocate harvested areas between cereals in order to minimize production instability—measured as climate-associated production losses—and to maximize total net profit, while maintaining calorie production and cropland area. This new integrated understanding of the role and importance of cropping patterns in determining production stability can inform uniform strategies to minimize cereal production shocks and maximize farmers profit due to climate extremes.

Table 1 | Model coefficients for rain-fed harvested area and prices

Crop	Current price	Lagged price
Rice	−0.010	−0.001
Sorghum	**−0.050**	**−0.030**
Pearl Millet	**−0.047**	**0.020**
Maize	**−0.037**	**−0.012**
Finger Millet	**−0.026**	**−0.007**

Fixed-effect regression models were developed to evaluate the relationship between harvested areas and crop prices for each crop. All statistical analyses were conducted using two-sided tests, and no adjustments were applied for multiple comparisons. The fixed effect accounted for variations at the district level.

Statistically significant coefficients (p value < 0.01) are shown in bold.

Results

Price elasticities of harvested areas

Our results focus on rainfed production, which constitutes approximately two-thirds (62%) of Indian cereal area[27] and is more susceptible to climate variability. For rainfed harvested area, we find that variations in harvested areas of all cereals except rice are significantly associated with current prices (Table 1). Notably, sorghum exhibits the highest sensitivity to current price fluctuations – with a -0.05% decrease in rainfed harvested area for every 1% increase in price – followed by pearl millet, maize, and finger millet in order. We observed similar but smaller magnitude outcomes when comparing harvested areas and lagged crop prices. There was no significant correlation between harvested area and prices (both current the lagged price) of rice.

Optimization harvested areas allocations

The influence of prices on harvested area suggests that targeted reallocations of harvested area could serve to stabilize production and improve profit and that these changes may be achieved through strategic pricing. To this end, we first examined to what extent optimized allocations of the harvested area to each crop could minimize national climate-associated production losses overall—where production loss within each district was measured as the product of crop-specific climate sensitivity (measured as the percent reduction in median yield under extreme climate conditions), yield, and harvested area—or enhance net profit. Currently, rice accounts for more than half of total rainfed harvested area (55%, Fig. 1a), with decreasing fractions occupied by pearl millet (18%), maize (16%), sorghum (7%), and finger millet (4%); we estimate 3.4 megatonnes of climate-associated production losses (10% of current total rainfed production for the five cereals) under this allocation of harvested areas. We find that rice disproportionately accounts for these production losses (61% of total losses) while only contributing 51% of total net profit. Conversely, all of the alternative cereals either show lower levels of production losses relative to their share of harvested area and/or higher contributions to net profit relative to their share of harvested area. Geographically, high production losses and net profit are both concentrated in eastern India where the largest extents of rainfed cropland occur (Fig. 1b, c) and where rainfed rice cultivation is concentrated (Fig. 1d).

We observed a steady decrease in harvested areas for rice and maize when minimizing national production losses (Scenario 1) (Fig. 2a). Not surprisingly, production losses become smaller as the allowable change in crop-wise harvested area increases. At the stage

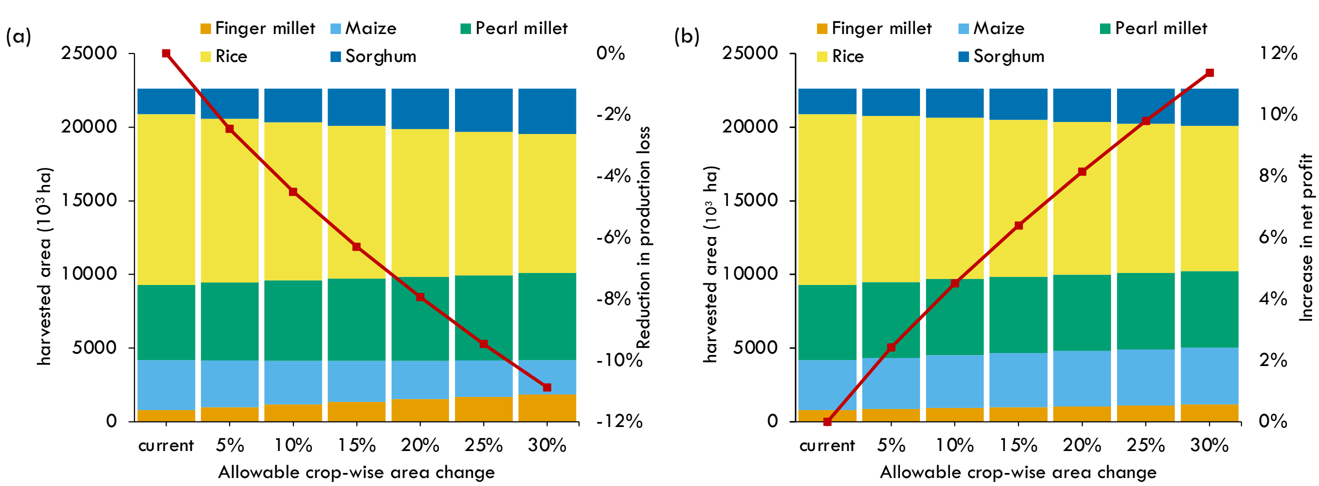

Fig. 2 | Optimized cropping mixes under spatial optimizations. The red line shows the (**a**) reduction in production loss and (**b**) increase in net profit.

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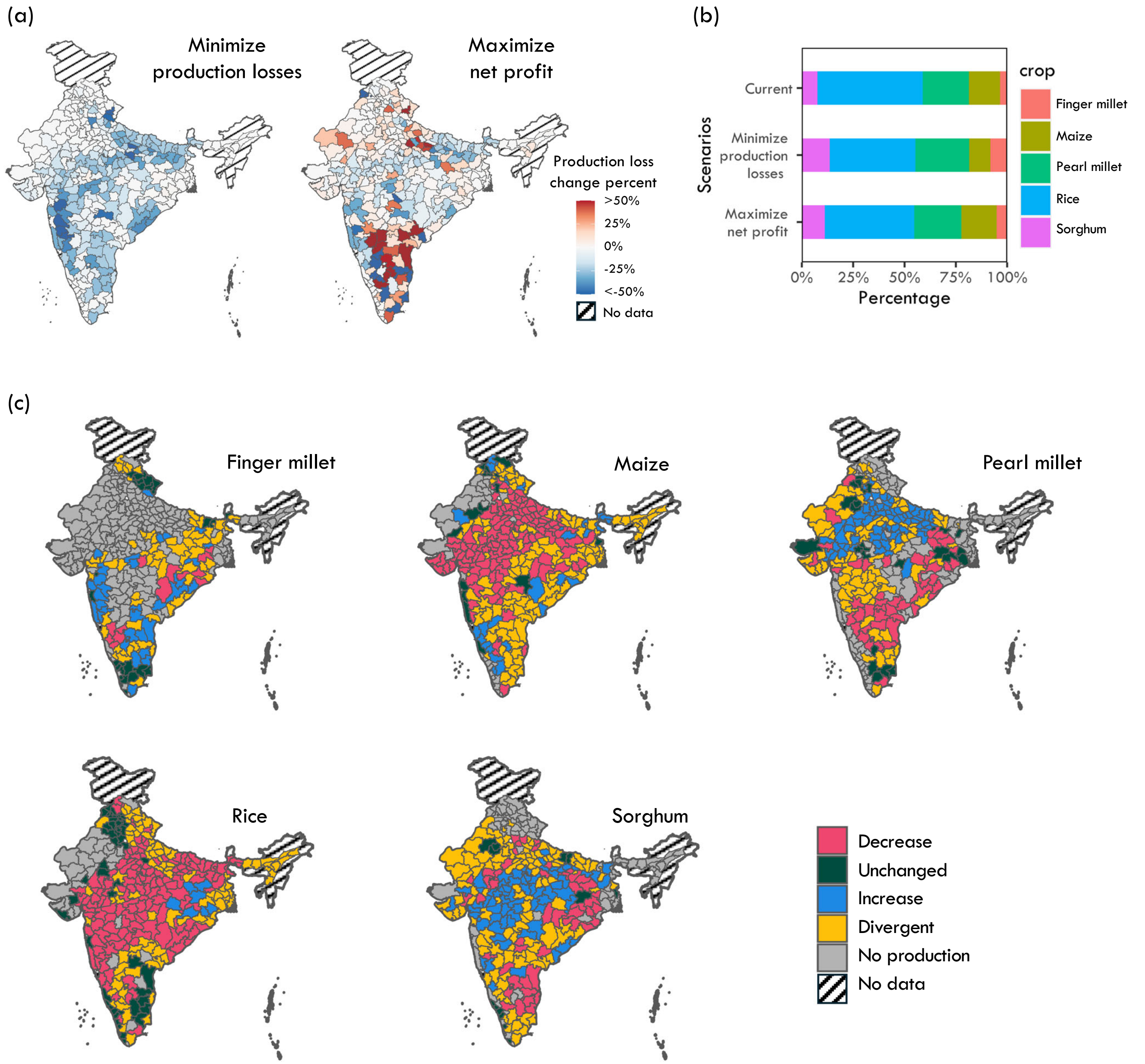

Fig. 3 | Outcomes of optimized scenarios. a Distribution of relative changes in production loss. **b** Crop-specific contributions to total harvested area in current condition, scenario to minimize production losses and scenario to maximize net profit. **c** Comparisons of directions between two optimized scenarios. These data and documents are licensed under a Creative Commons Attribution 4.0 International license. Readers are free to copy, distribute and transmit the data as long as you acknowledge the ICRISAT through DOI provided in this page: http://data.icrisat.org/dld/src/about-dld.html.

when the harvested area of each cereal was allowed to vary by 30 percentage point from current levels, we found a 11% reduction in national production losses. The optimization to maximize net profit (Scenario 2) showed a decrease in harvested area for rice (Fig. 2b), with national total net profit increasing by as much as 11%. Under both optimization scenarios, we observed a consistent increase in finger millet, pearl millet, and sorghum (Figs. 2, 3b). In comparing the spatial patterns of change between these two scenarios, we also found substantial consistency—pointing to potential priority areas for promoting crop shifts that can achieve co-benefits for production stability and net profit. Specifically, our optimizations consistently suggested decreasing harvested areas of rice and maize in central and northern India. Pearl millet shifts showed a transition from southern to northern areas, whereas sorghum cultivation would become more concentrated in the central region of the country. These findings demonstrate that promoting cropping patterns to enhance production stability or maximize net profit does not necessarily need to compromise overall calorie production and that targeted adjustments in the harvested areas allocated to alternative cereals may offer superior climate resilience and profitability. This also suggests that research efforts to improve the yields of alternative cereals may serve to deepen co-benefits between production stability and farmer profitability.

Discussion

Our findings demonstrate that prices exercise significant influence on variations in the harvested area for alternative cereals (i.e., maize, millets, sorghum) in India and that selectively increasing the harvested area allocated to alternative cereals can both enhance production stability and improve farmer profits. These results thus shed new light on the important role of harvested area decisions for determining the stability and profitability of cereal production. This also suggests that efforts to reduce price volatility can be an important avenue for reducing variations in harvested area and thereby stabilizing cereal production. With these findings, it is important to highlight that—in reality—harvested area decisions are responsive not only to the price volatility of the crop itself but also to the prices of substitute crops[25,26]. Therefore, our assumption that ignores cross-price effects may result in an underestimation of the price elasticity outcomes. Accounting for agricultural supply responses due to competing crop prices is therefore essential in developing any economic policies intended to encourage alternative cropping patterns. We also observe a clear contrast between rice and alternative cereals in the responsiveness of their harvested areas to variations in price, with rice being the only study crop with no significant influence from price volatility (Table 1). This difference is likely explained (at least in part) by the current structure of cereal prices in India, which appear to be artificially encouraging harvested area decisions towards less climate-resilient crops. These prices are influenced in large part by minimum support prices and procurement targets set by the country to support the Public Distribution System[6], the Midday Meal Scheme, and other supplementary nutrition programs as well as government grain stocks. Thus, well-crafted crop pricing schemes, government subsidies, or restructured unloading of strategic grain reserves targeted at climate-resilient crops and climate-smart practices could be effective tools for counteracting the effects of climate variability on cereal production stability. Such new pricing schemes in favor of alternative cereals may also have important implications for the sustainability of Indian cereal production[6], potentially incentivizing the cultivation of crops that are less nutritious[36], require more irrigation water[37], use more energy[38], and produce greater GHGs[39].

Demonstrating that harvested areas are influenced by prices offers an economic lever whereby planting decisions may be incentivized to achieve certain objectives. As such, we evaluated whether alternative allocations of harvested area—potentially achieved through economic incentives or altered levels of government procurement—could offer superior production stability or increased profit. For both scenarios that we examined, we consistently found that selectively reducing rice harvested areas (-8% to -10%) and increasing the harvested areas of finger millet (+ 2% to +5%), pearl millet (+ 0% to +4%), sorghum (+ 4% to +6%), could achieve reductions in production loss (-11%) (while maintaining net profit) or gains in net profit (+ 11%) (while maintaining production losses) (Fig. 3). We found that this could be achieved without compromising overall food calorie production or expanding croplands. Our optimizations also showed consistent recommendations for a large number of districts, indicating opportunities for co-benefits regardless of the objective. All of this suggests that incentivizing only modest changes in cereal production mixes could offer meaningful benefits for stabilizing production and improving profit in the face of increasing climate variability and extremes. While the opportunity for co-benefits is clear, reducing production instability is also well aligned with multiple policymaker objectives[40]. For one, fluctuations in production can disrupt agricultural markets and crop prices – with knock-on effects for farmer incomes and rural development – and can undermine investor confidence. From a food security perspective, production instability can also lead to fluctuations in food availability and prices, thereby compromising the affordability of food and the economic access of consumers. In addition, improving the stability of crop production can enhance the overall resilience of food systems from local to national scales and reduce the overall risk profile of the agricultural sector.

Such targeted and selective changes in cropping patterns could potentially be realized through carefully structured procurement targets, in which all crops considered here are assigned minimum support prices (MSP) but only rice currently has set levels of procurement across the country. A set of optimization models using average harvest prices instead of MSP (Figure S1), or selectively using MSP or harvest prices based on procurement levels (Figure S2) suggest that current price structures are promoting less climate-resilient cropping choices (i.e., switching from other cereals to rice for higher net profit) (Figure S1). However, before considering any potential changes to incentives or procurement targets, it is imperative that policymakers perform a full economic evaluation that accounts for expected changes in farmer decision-making which may occur under new policy and economic environments[41]. Encouragingly, efforts to incorporate alternative cereals into supplementary nutritional programs are being undertaken in certain states (e.g., Odisha Millets Mission; millets distribution through Karnataka PDS). These initiatives will provide critical insights into whether the suite of intended benefits is realized and can serve as a blueprint for adapting such efforts in other states of India. More broadly, it will be important to understand the extent to which selective switching to larger shares of alternative grains can complement other government efforts to align farmer profitability with climate adaptation, including promoting the cultivation of high-value crops (e.g., pulses, oilseeds) in rainfed areas, selectively expanding irrigation infrastructure, and incentivizing rabi (winter) season sowing to compensate for kharif (monsoon) production shortfalls.

In sum, current pricing structures—which currently exercise influence on the harvested areas of alternative cereals—are at odds with the heightened climate sensitivity of rice yields. Together, these factors determine the stability of cereal production in India. Our findings indicate that the promotion of alternative cereals – with less emphasis on rice—may offer benefits for reducing the climate sensitivity and increasing net profit of Indian cereal production without entailing large shifts in production mixes or compromising calorie supply. More generally, our findings indicate that climate assessments of crop production which only consider yield volatility do not provide a complete picture of the factors determining production stability. Further, this work demonstrates that strategies utilizing harvested area shifts to address cereal production stability could be an important solution to complement ongoing intensive and well-researched efforts to improve and stabilize crop yields. Taken together, our results demonstrate the importance of cropping patterns and harvested area allocations for achieving co-benefits in production and profit and for ultimately enhancing the resilience of cereal production to both environmental and economic disruptions.

Methods

Data

Our study focused on the five main cereals grown during the monsoon (kharif) season: finger millet, maize, pearl millet, rice, and sorghum. Information on yield (tonne ha^{-1}), harvested area (kilohectares), and harvest price (Indian rupees $tonne^{-1}$)—disaggregated by year, crop, and district— came from the International Crops Research Institute for the Semi-Arid Tropics Village Dynamics of South Asia (VDSA)[27]. These data were reported using consistent 311 district boundaries for the year 1966 through 2011 (Figure S3). 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[42]. State-level cost of production data came from Devineni et al. [43], who calculated average costs across three cropping years (2013-2014, 2014-2015, and 2015-2016). These cost estimates include all expenses incurred by the farmer, such as the interest on the value of owned lands and fixed capital assets; the rental value of owned land, and the credited value of fixed capital assets, along with the direct expenses like seeds, fertilizers, irrigation, labor, etc[44]. We assume the cost is the same for all districts in a state. In states where data were not available, we assumed a national average per crop following Devineni et al. National Minimum Support Price (MSP) data and state-level crop-specific procurement levels came from the

Ministry of Agriculture of the Government of India[44]. We performed three sets of optimization models, where: 1) net profit for each crop was calculated by subtracting the production costs from the inflation-adjusted three-year average harvest prices in each district (Figure S1); 2) net profit for each crop was calculated by subtracting the production costs from MSPs in each district (Fig. 3); or 3) net profit is calculated based on procurement levels – using MSPs for the states/crops for which procurement currently occurs, while using harvest prices for the other crops/states (Figure S2). The calorie content (kcal/100 g) of each crop was obtained from Longvah et al. [45].

Price elasticity

Crop-specific, district-level harvest prices for 1966 to 2011 were all inflation-adjusted relative to the latest year (2011) using the India crop-specific wholesale price index[46] for each crop. In the absence of crop-specific price index prior to 1982, we used the average cereals wholesale price index[46]. Harvest price and area data were detrended using the "Singular Spectrum Analysis" package in Python[47] and then log-transformed. We then developed fixed effect regression models compare harvested areas and crop price for each crop using the "PanelOLS" in "linearmodels" package in Python[48], and we included 'district' as the entity (fixed) effect in the model:

$$ar_{d,t} = \alpha_d + \beta p_{d,t} + \epsilon_{d,t} \tag{1}$$

where $ar_{d,t}$ denotes the rainfed area for district d in year t for a crop, β is the model coefficient, $p_{d,t}$ is the current or lagged harvest price for district d in year t. α_d captures the fixed effect from district, ϵ is the error term.

Estimation of crop climate sensitivity and climate-associated production losses

Gridded (5 arcminute) crop-specific climate sensitivity (CS) (i.e., measured as the percent reduction in median yield under extreme climate conditions) data for all crops came from Tuninetti & Davis[49]. *CS* quantifies how daily and interannual variations in temperature and precipitation impact crop yields. To isolate the influence of climate variability on a crop's yield in a given grid cell, the authors used a process-based crop water model[50] to estimate a crop's daily actual evapotranspiration (ET_a) across a crop's growing season for a given year, while keeping constant all management practices – a standard protocol in the gridded crop modelling community[51]. Taking the sum of the daily ET_a values provides annual ET_a, and annual ET_a values were estimated for the years 1960 through 2022. For a given crop and grid cell, the annual ET_a values were sorted in ascending order to identify the 10th percentile ET_a (taken to represent historically observed extreme adverse climate conditions) and the median ET_a (taken to represent historically observed normal climate conditions). Combined with information on current ET_a and current yield, the 10th percentile and median ET_a values were then related to yield changes via the Doorenbos-Kassam water production function[52]. Finally, Tuninetti and Davis[49] quantified crop-specific *CS* as the relative difference between median yield and 10th percentile yield at the grid cell level. Grid cells were spatially averaged to estimate each crop's climate sensitivity at the district level.

The method of partitioning yield between rainfed and irrigated area was adopted from Davis et al. [30]. VDSA grain yields are reported as the total production of a grain within a district divided by its harvested area. Davis et al. [30] employed a three-step process to partition the aggregate VDSA yields into rainfed and irrigated yields. This involved separating plot-level data into rainfed and irrigated observations, computing weighted average irrigated and rainfed yields for each district between 2007 to 2011, and determining a national average ratio of irrigated-to-rainfed yields for each crop, which was then applied to derive irrigated and rainfed yields (to be used in the estimation of climate-associated production losses and in the spatial optimization). Following Davis et al. [30], we assume that all rainfed production of rice, maize, finger millet, and pearl millet occurs during the kharif season. This assumption is largely supported by crop production data reported by season from the Directorate for Economics and Statistics[53], which shows that millet production during rabi is negligible and that only for selected states (e.g., rice in Andhra Pradesh, Odisha, Tamil Nadu, West Bengal; 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 the harvested area between kharif and rabi season. Given the relatively small percentages of harvested area change that occur under our optimizations, we do not expect this assumption would meaningfully alter our estimates.

Finally, climate-associated production losses were estimated for each crop and district as the product of *CS*, yield, and harvested area.

Optimizations

We calculated the average yield and harvested area per district over a 10-year period (2002-2011). Optimizations were performed on all districts rainfed area to determine the extent to which crop switching could minimize national production losses (Scenario1) or maximize net profit (Scenario2). Following Davis et al. [30] and Richter et al. [54], we set the basic constraints that: (1) national calorie production for all crops except for maize could not decrease; (2) national calorie production for maize could not decrease by more than half of current levels (i.e., the fraction of maize production currently consumed for food[55]; this was done to avoid knock-on effects of our optimizations on downstream supply chains (e.g., livestock feed); (3) the total harvested area within each district remained constant, (3) only crops that have been planted in the district within the last 10 years and have available climate sensitivity data could be considered as a substitute within each district, (4) the net profit of each district could not decrease, and (5) allowable percent point changes in any individual crop were limited to between 5% and 30% in each district. Scenario 2 had the additional constraint that national production losses could not increase. All optimizations were performed using the 'lpSolve' package in R[56].

Statistics

All statistical analyses were performed using Python or R. Harvest price and harvested area data were detrended using "Singular Spectrum Analysis" in python[47] and then log-transformed. Fixed effects regression models were developed using the "PanelOLS" class in "linearmodels" package[48] in Python, with districts included as the fixed entity effect. These models assessed the relationship between harvested area and current or lagged harvest prices for each crop. Statistical significances were validated for all models. Linear optimizations were conducted using the 'lpSolve' package[56] in R to achieve specific objectives, such as minimizing production losses or maximizing net profit. The optimization results provided the allocation of crop rainfed area for each district under the given objectives. Constraints on calorie production, net profit, and harvested area shifts were incorporated.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All raw data used in this study are publicly available online. Optimization input data is available at https://zenodo.org/records/14713402 (ref. 57). Crop-specific agricultural information is available on the International Crops Research Institute for the Semi-Arid Tropics Village Dynamics of South Asia (VDSA) official website (http://data.icrisat.org/dld/). The India Cost of Cultivation Survey data is accessible at https://desagri.gov.in/document-report-category/cost-of-cultivation-production-estimates-archive/. State-level cost of production data was sourced from Devineni et al. [43]. National Minimum Support Price (MSP) data and state-level crop-specific procurement levels were obtained from https://eands.dacnet.nic.in. The calorie content (kcal/100 g) of each crop was referenced from Longvah et al. [45]. The India crop-specific wholesale price index is available at https://eaindustry.nic.in/default.asp. Crop-specific climate sensitivity data was derived from Tuninetti & Davis[49].

Code availability

All calculations performed in this study can be performed without custom code. Code to optimize the crop-specific harvested area can be found via the Zenodo repository at https://zenodo.org/records/14713402 (ref. 57).

References

1. Godfray, H. C. J. et al. Food Security: The Challenge of Feeding 9 Billion People. *Science* **327**, 812–818 (2010).
2. Alexandratos, N. & Bruinsma J. *World agriculture towards 2030/2050* (FAO, 2012).
3. Springmann, M. et al. Options for keeping the food system within environmental limits. *Nature* **562**, 519–525 (2018).
4. Foley, J. A. et al. Solutions for a cultivated planet. *Nature* **478**, 337–342 (2011).
5. Pingali, P. L. Green revolution: Impacts, limits, and the path ahead. *Proc. Natl Acad. Sci. USA* **109**, 12302–12308 (2012).
6. Davis, K. F. et al. Assessing the sustainability of post-Green Revolution cereals in India. *Proc. Natl Acad. Sci. USA* **116**, 25034–25041 (2019).
7. Lobell, D. B., Schlenker, W. & Costa-Roberts, J. Climate trends and global crop production since 1980. *Science* **333**, 616–620 (2011).
8. Iizumi, T. & Ramankutty, N. Changes in yield variability of major crops for 1981–2010 explained by climate change. *Environ. Res. Lett.* **11**, 034003 (2016).
9. Ray, D. K. et al. Climate change has likely already affected global food production. *PLoS ONE* **14**, e0217148 (2019).
10. Lesk, C., Rowhani, P. & Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **529**, 84–87 (2016).
11. DeFries, R. et al. Metrics for land-scarce agriculture. *Science* **349**, 238–240 (2015).
12. Renard, D. & Tilman, D. National food production stabilized by crop diversity. *Nature* **571**, 257–260 (2019).
13. Bathiany, S., Dakos, V., Scheffer, M. & Lenton, T. M. Climate models predict increasing temperature variability in poor countries. *Sci. Adv.* **4**, eaar5809 (2018).
14. Ray, D. K., Gerber, J. S., MacDonald, G. K. & West, P. C. Climate variation explains a third of global crop yield variability. *Nat. Comm.* **6**, 5989 (2015).
15. Vogel, E. et al. The effects of climate extremes on global agricultural yields. *Environ. Res. Lett.* **14**, 054010 (2019).
16. Iizumi, T. & Ramankutty, N. How do weather and climate influence cropping area and intensity? *Glob. Food Sec.* **4**, 46–50 (2015).
17. Wei, D., Gephart, J. A., Iizumi, T., Ramankutty, N. & Davis, K. F. Key role of planted and harvested area fluctuations in US crop production shocks. *Nat. Sustain.* **6**, 1177–1185 (2023).
18. Cohn, A. S., VanWey, L. K., Spera, S. A. & Mustard, J. F. Cropping frequency and area response to climate variability can exceed yield response. *Nat. Clim. Change* **6**, 601–604 (2016).
19. Mondal, P. et al. Winter crop sensitivity to inter-annual climate variability in central India. *Clim. Change* **126**, 61–76 (2014).
20. Koide, N. et al. Prediction of rice production in the Philippines using seasonal climate forecasts. *J. Appl. Meteorol. Climatol.* **52**, 552–569 (2013).
21. Furuya, J. & Kobayashi, S. Impact of global warming on agricultural product markets: stochastic world food model analysis. *Sustain. Sci.* **4**, 71–79 (2009).
22. Miao, R., Khanna, M. & Huang, H. Responsiveness of crop yield and acreage to prices and climate. *Am. J. Agr. Econ.* **98**, 191–211 (2015).
23. Magrini, E., Balié, J. & Morales-Opazo, C. Price Signals and Supply Responses for Staple Food Crops in Sub-Saharan Africa. *Appl. Economic Perspect. Policy* **40**, 276–296 (2018).
24. Mythili, G. Acreage and Yield Response for Major Crops in the Pre- and Post-Reform Periods in India: A Dynamic Panel Data Approach. *Mumbai: Indira Gandhi Institute of Development Research* (2012).
25. Tenaye, A. New evidence using a dynamic panel data approach: Cereal supply response in smallholder agriculture in Ethiopia. *Economies* **8**, 61 (2020).
26. Arisena, G. M. K. & Oktavia, H. F. Agricultural Commodity Supply Response. *SOCA: J. Sos. Ekon. Pertan.* **14**, 362–380 (2020).
27. International Crops Research Institute for the Semi-Arid Tropics. *Village Dynamics in South Asia Meso Level Data for India: 1966–2011* (ICRISAT, 2015).
28. Birthal, P. S., Khan, M. T., Negi, D. S. & Agarwal, S. Impact of climate change on yields of major food crops in India: Implications for food security. *Agric. Econ. Res. Rev.* **27**, 145–155 (2014).
29. DeFries, R. et al. Synergies and trade-offs for sustainable agriculture: Nutritional yields and climate-resilience for cereal crops in Central India. *Glob. Food Sec.* **11**, 44–53 (2016).
30. Davis, K. F., Chhatre, A., Rao, N. D., Singh, D. & DeFries, R. S. Sensitivity of grain yields to historical climate variability in India. *Environ. Res. Lett.* **14**, 064013 (2019).
31. Kumar, S., Raju, B. M., Rao, C. A., Kareemulla, K. & Venkateswarlu, B. Sensitivity of yields of major rainfed crops to climate in India. *Indian Journal of Agricultural Economics* **66** (2011).
32. Butler, E. E. & Huybers, P. Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase. *Environ. Res. Lett.* **10**, 034009 (2015).
33. Menon, A., Levermann, A. & Schewe, J. Enhanced future variability during India's rainy season. *Geophys. Res. Lett.* **40**, 3242–3247 (2013).
34. Sharmila, S., Joseph, S., Sahai, A. K., Abhilash, S. & Chattopadhyay, R. Future projection of Indian summer monsoon variability under climate change scenario: An assessment from CMIP5 climate models. *Glob. Planet. Change* **124**, 62–78 (2015).
35. Mukherjee, S., Aadhar, S., Stone, D. & Mishra, V. Increase in extreme precipitation events under anthropogenic warming in India. *Weather Clim. Extr.* **20**, 45–53 (2018).
36. DeFries, R. et al. Impact of historical changes in coarse cereals consumption in India on micronutrient intake and anemia prevalence. *Food Nutr. Bull.* **39**, 377–392 (2018).
37. Davis, K. F. et al. Alternative cereals can improve water use and nutrient supply in India. *Sci. Adv.* **4**, eaao1108 (2018).
38. Rao, N. D., Poblete-Cazenave, M., Bhalerao, R., Davis, K. F. & Parkinson, S. Spatial analysis of energy use and GHG emissions from cereal production in India. *Sci. Tot. Environ.* **654**, 841–849 (2019).
39. Rao, N. et al. Healthy, affordable and climate-friendly diets in India. *Glob. Environ. Change* **49**, 154–165 (2018).
40. Davis, K. F., Downs, S. & Gephart, J. A. Towards food supply chain resilience to environmental shocks. *Nat. Food* **2**, 54–65 (2021).
41. Lucas, Jr R. E. *Econometric policy evaluation: A critique*. In Carnegie-Rochester conference series on public policy (Vol. 1, pp. 19-46). North-Holland (1976).
42. Ministry of Agriculture and Farmers Welfare. *Manual of Cost of Cultivation Surveys* (Ministry of Agriculture and Farmers Welfare, 2018).
43. Devineni, N., Perveen, S. & Lall, U. Solving groundwater depletion in India while achieving food security. *Nat. Commun.* **13**, 3374 (2022).
44. Dacnet, Web-based crop and land use statistics information system. https://eands.dacnet.nic.in (2019).
45. Longvah, T., Anantan, I., Bhaskarachary, K., Venkaiah, K. & Longvah, T. Indian food composition tables. Hyderabad: National Institute of Nutrition, Indian Council of Medical Research (2017).

46. *Office of the Economic Adviser of the Ministry of Commerce & Industry, Government of India* https://eaindustry.nic.in/default.asp Press release dated 12-May-2017.
47. Faouzi, J. & Janati, H. pyts: A python package for time series classification. *J. Mach. Learn. Res.* **21**, 1–6 (2020).
48. Sheppard K. linearmodels: Panel Data Models in Python. https://github.com/bashtage/linearmodels (2018).
49. Tuninetti, M., & Davis, K. Addressing global hotspots of climate-related crop production losses (2022).
50. Tuninetti, M., Tamea, S., D'Odorico, P., Laio, F. & Ridolfi, L. Global sensitivity of high-resolution estimates of crop water footprint. *Water Resour. Res.* **51**, 8257–8272 (2015).
51. Müller, C. et al. Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications. *Geosci. Model Dev.* **10**, 1403–1422 (2017).
52. Doorenbos, J. & Kassam, A. H. Yield response to water. *Irrig. Drain. Pap.* **33**, 257 (1979).
53. Directorate of Economics and Statistics. State of Indian Agriculture 2015–2016 (New Delhi: Ministry of Agriculture and Farmers Welfare) (2016).
54. Richter, B. D. et al. Alleviating water scarcity by optimizing crop mixes. *Nat. Water* **1**, 1035–1047 (2023).
55. Food and Agriculture Organization of the United Nations. FAOSTAT statistical database (2023).
56. Berkelaar, M., Eikland, K. & Notebaert, P. lpSolve: Interface to 'Lp_solve'v. 5.5 to solve linear/integer programs. *R package version* **5** (2015).
57. Wei, D. et al. *Zenodo* https://zenodo.org/records/14713402 (2025).

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Author contributions

D.W. and K.F.D. designed the research. D.W. performed the analysis. D.W. and K.F.D. drafted the paper. L.G.C., M.T., K.F.D., and D.W. contributed to data preparation. All authors reviewed and revised the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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