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Crop switching for water sustainability in India's food bowl yields co-benefits for food security and farmers' profits

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Groundwater depletion due to agricultural intensification is a major threat to water and food security in the Indo-Gangetic Plain (IGP), a critical food bowl, home to 400 million people and currently producing 135 million metric tonnes of cereals. Among the solutions proposed to address this unsustainable water consumption, crop switching has received growing attention, yet its potential to produce co-benefits or trade-offs for other dimensions of sustainability (for example, food supply and farmers' profits) remains largely unquantified. In this study, we developed and applied a crop switching optimization model for cereals in the IGP to maximize calorie production and farmers' profits and minimize water consumption. We found that switching from rice to millets (pearl millet) and sorghum in the Kharif (monsoon) season and from wheat to sorghum in the Rabi (winter) season could potentially reduce water consumption by 32%, improve calorie production by 39% and increase farmers' profits by 140%. We also found that switching crops offers a larger reduction in groundwater depletion and energy savings than improving irrigation efficiency (that is, from flood to drip irrigation). Our findings demonstrate the potential for crop switching to address the multidimensional sustainability challenges of the IGP, with possible application to other regions facing similar issues.

To attain food security for the growing global population, which is expected to reach 10 billion by 2050, agricultural production will need to increase by approximately 70% (ref. 1). Meeting this demand is expected to substantially increase global water and energy demand in the coming decades, placing additional stress on natural resources. At the same time, millions more people are expected to be at risk of hunger[2]. If current trends continue, the future increases in food production will increase water and energy consumption, creating further degradation of resources and increasing environmental stresses[3]. Yet current agricultural practices around the globe do not attain either maximum production or minimum water consumption, creating conflicts between food and water security. As such, solutions are needed to simultaneously improve food security while reducing water demand.

Nearly 1 in 5 people live in India, which produces 300 Mt of cereals (in 2018) (ref. 4), 11% of the global production. Moreover, 59% of India's entire workforce is in agriculture, contributing to 23% of its gross domestic product[5]. India is also the second highest exporter of cereals worldwide[6]. Hence, India's cereal production plays an important role

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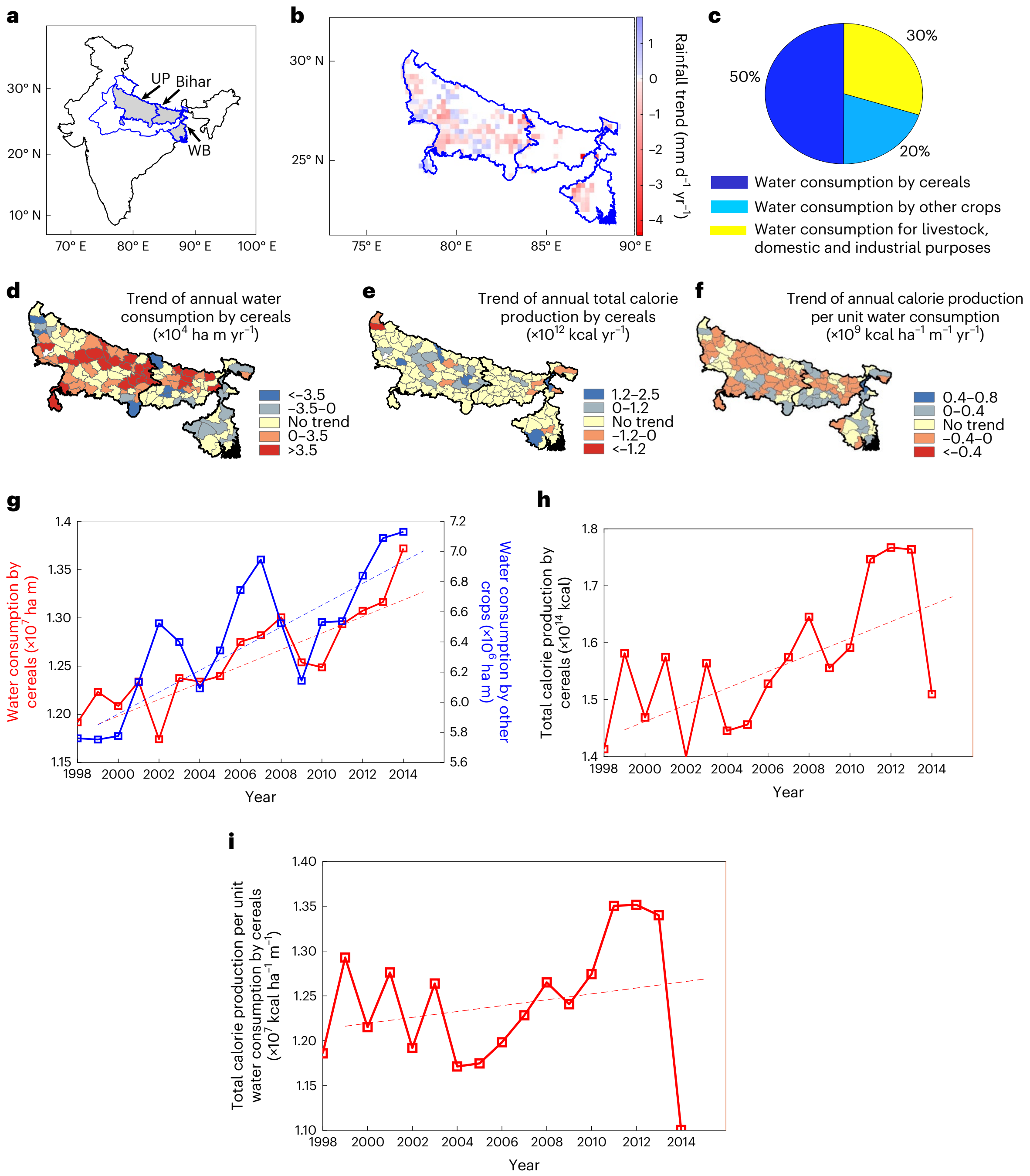

Fig. 1 | Rainfall pattern, water consumption and calorie production scenario in the study area (1998–2015). **a**, Gangetic basin in India showing three states in the IGP: Uttar Pradesh (UP), Bihar and West Bengal (WB). **b**, Spatial mapping of the trend of annual rainfall estimated on the basis of daily IMD gridded rainfall data (0.25° resolution). **c**, Fractions of water consumption by cereals, other crops, and the domestic, industrial and livestock sectors (averaged over the study period). **d**–**f**, District-wise mapping of the trends of the annual water consumption by cereals (**d**), the annual total calorie production by cereals (**e**) and the annual calorie production per unit of water consumption (**f**). **g**, Trend of annual water consumption by cereals and other crops. *P* values = 5.7757×10^{-6} and 4.6869×10^{-5}, respectively. **h**, Trend of annual total calorie production by cereals. *P* value = 0.005. **i**, Trend of annual calorie production per unit water consumption by cereals. *P* value = 0.35698. In all spatial maps of trends, zero values (no trend) represent no significant trends at a 0.05 significance level. In all spatial maps of annual trends, the null hypothesis was tested by the Mann–Kendall test, sample size = 17 for 17 yr. All district-wise mappings were created using ArcMap (ArcGIS10.5, https://www.esri.com/en-us/arcgis/products/arcgis-desktop/resources).

in both domestic and global food security. Of the country's total food production, 30% comes from the three major states of Uttar Pradesh, Bihar and West Bengal[7] (covering the upper, middle and lower Ganga basin, Fig. 1a) in the agricultural belt of the country, the Indo-Gangetic Plain (IGP), known as the Food Bowl of India. Water-intensive rice and wheat are the major staple cereals produced on a large scale in the IGP and meet 63% of the calorie demand of the country[8]. Because of this intensively cultivated rice–wheat system, the agricultural water demand for cereals is high and met largely by irrigation, 40% of which comes from groundwater sources[1]. In addition, government subsidies for electricity to withdraw groundwater in a few states in India result in the injudicious use of water and energy because of its common-pool nature[9,10].

As a result, rapidly declining groundwater levels in northern India have been observed at a rate of 1–2 cm yr^{-1} (ref. 11), attributable to declining monsoon rainfall and increased irrigation[12]. Punjab and Haryana, neighbouring states of the Ganga basin, are known to be the global hotspots of groundwater depletion, while the Ganga basin is always conceived as a water surplus region. However, recent years have seen a significant depletion of groundwater in the Ganga Basin, questioning the sustainability of present agricultural practices[11–14]. From 2002 to 2016, the Gangetic basin lost 227 ± 25 km^3 of groundwater[12]. These steeply declining groundwater levels lead to increased energy consumption to pump groundwater from greater depths[15], increasing the cost of cultivation and food prices, and thereby impacting food security[14]. Despite these widespread impacts, solutions to resolve this unsustainable groundwater consumption remain limited due to the complexity of addressing food and water security, energy savings, farmers' profits and environmental sustainability in tandem.

As such, solutions to these problems require consideration of potentially conflicting cross-domain objectives[16] across multiple spatial scales. These approaches involve analysis of trends and scenarios under present agricultural, water and energy management practices[17] and have been applied at local[16], continental[18] and global[19] scales. While global studies have shown the promise of optimized crop switching to improve water and food security[20], policy-relevant analyses must take place at local-to-regional scales to incorporate context-specific factors. This is true for the IGP, where such approaches targeting water, food and environmental sustainability are limited. In recent India-specific studies, single-objective optimizations have been performed, showing[21] that replacing rice and wheat with less water-intensive crops such as millet and sorghum can result in increased food supply, water and energy savings, and improved environmental sustainability. However, these assessments have not included considerations (for example, farmers' profits) that are critical for ensuring the real-world feasibility of crop switching interventions. Further, given the conflicting nature of many social, economic and environmental sustainability objectives, a multi-objective framework is essential to minimize trade-offs and find cropping configurations that improve multiple outcomes of interest. In this study, we focused on cereal crops (rice, wheat, maize, millet, sorghum and barley), which cover 52% of the total crop area[22] and consume 50% of the total water consumption in our study region in the IGP (Fig. 1c) while producing the major fraction of calories for the Indian population. Here, millet refers to pearl millets or bajra as it is primarily cultivated (if compared with other millet species, for example, finger millet or ragi) in our study region, the IGP[23]. We first quantified recent changes in water use, energy use and food production due to agricultural intensification of these crops in the IGP. Minimizing water use and maximizing calorie production are needed for water and food sustainability. In contrast, maximizing profit is the objective of farmers. These objectives may also conflict with each other. Hence, we have developed a multi-objective optimization model that reallocates cropped areas between cereals to maximize calorie production and farmers' profits while minimizing water consumption (and subsequent energy use) at the district level. The total cereal cropped area was held constant in each district. We also performed these optimizations considering a situation of yield gap closure (that is, increasing yields to the 90th percentile of district-level observed yield values of individual crops within an agroecological zone; Extended Data Fig. 1). Finally, we evaluated the outcomes of crop switching (with and without yield gap closure) in combination with a transition from flood to drip irrigation—a widely promoted water-saving practice—to quantify the potential co-benefits of complementary agricultural interventions. An earlier case study[24] on crop diversification challenges in the state of Punjab explored the challenges of, and resistance to, crop diversification, shifting the rice–wheat system to alternative cereals. Our study advances beyond this important work by demonstrating the need for an optimization framework that addresses multifaceted problems with respect to farmers' net revenue, groundwater savings and nutrition, which will motivate policy implementation.

Specifically, we addressed the following questions: (1) what are the trends in cereal production and water consumption in the IGP, (2) what cereal crop substitution would maximize calorie production and farmers' profits and minimize water consumption, and (3) which combination of irrigation practice (flood and drip irrigation) and crop switching maximizes groundwater net recharge?

Trends in groundwater use, levels and net recharge

In this study, we focused on three states, Uttar Pradesh, Bihar and West Bengal, which cover most of the IGP. Observed annual rainfall data from the India Meteorological Department (IMD)[25] show decreasing trends over Uttar Pradesh and West Bengal, with no prominent trend in Bihar (Fig. 1b). The annual trends follow the trends observed for monsoon rainfall (Supplementary Fig. 1). We simulated water consumption (see Methods for details) over these three states using the WaterGAP model[26], areas for different crops and crop-specific water needs[9]. We found that 50% of the total water consumption is used for the irrigation of cereal crops (Fig. 1c). Irrigated water consumption for cereal crops has increased significantly in Uttar Pradesh and parts of Bihar, where a decline in rainfall has been observed (Fig. 1b,d). Reduced rainfall signifies a greater need for irrigation. At the same time, this also indicates decreasing water availability, with increasing water demand due to irrigation resulting in water scarcity. Overall, there is an increasing trend in water consumption for cereal crops in the IGP (Fig. 1g). The observed calorie production from cereals (see Methods for details) at the district level does not show statistically significant increases across the IGP (Fig. 1e), despite increases in irrigation and other scientific and technological interventions in agriculture, even though there has been an increasing trend in the overall total calorie production from cereals (Fig. 1h). The trends shown in Fig. 1h,i capture well the interannual fluctuation in cereal production in response to droughts. For example, the drought in 2014 due to El Niño is reflected in the sudden dip in calorie production. The total calorie production per unit of water consumption shows improvements for only a very few districts (Fig. 1f) and no statistically significant trend on average over the IGP (Fig. 1i), signifying the unsustainability of current agricultural practices to meet the future growth in food demand. The increased water consumption for the irrigation of cereals is one of the contributing factors to the depletion of observed groundwater levels (from well data, obtained from the Central Ground Water Board, Government of India, Fig. 2a). The spatial patterns for increased water consumption for cereals (Fig. 1d) and declining trends in groundwater levels (Fig. 2) show marked similarities. A significant area of Uttar Pradesh and quite a few areas of Bihar and West Bengal have experienced declining well water levels since 1998. Interestingly, the decline in groundwater does not seem related to the changes in recharge from annual rainfall when the spatial patterns of both are compared (Figs. 1b and 2b).

We found no statistically significant change in the annual groundwater recharge over the groundwater depletion hotspot Uttar Pradesh. The monsoon recharge has not changed significantly over the IGP (Supplementary Fig. 2d), while the recharge during the non-monsoon season has improved (Supplementary Fig. 2e). Groundwater abstractions have increased for both monsoon and non-monsoon seasons (Supplementary Fig. 2b,c). We found that the total groundwater abstraction has increased at the rate of 3.9 km^3 yr^{-1} (P value = 8.25×10^{-11}) over Uttar Pradesh, Bihar and West Bengal with agricultural intensification. Therefore, the overall increasing water application for cereals has translated into increased abstraction and decreased net recharge (difference between recharge and abstraction, Fig. 2e).

We used the region-specific semi-empirical equations of the Ground Water Estimation Committee-97 (GEC-97), developed by the Central Water Commission (CWC), Government of India, to compute

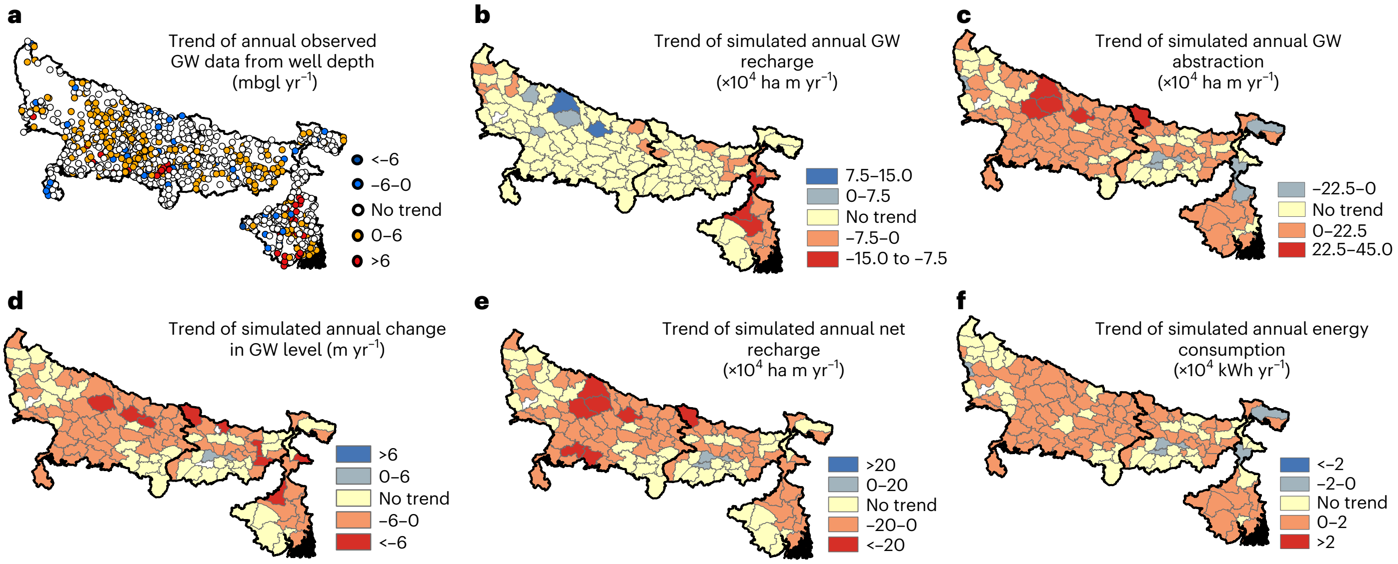

Fig. 2 | Groundwater and energy consumption (1998–2015). **a**, Trend of annual observed groundwater (GW) level from well depth. mbgl, metres below ground level. **b–f**, Trends of simulated annual groundwater recharge (**b**), groundwater abstraction (**c**), change in groundwater level (**d**), net recharge (**e**) and energy consumption (**f**). In all spatial maps of trends, zero values (no trend) represent no significant trends at a 0.05 significance level. In all spatial maps with annual trends, the null hypothesis was tested by the Mann–Kendall test, sample size = 17 for 17 yr. All district-wise maps were created using ArcMap (ArcGIS10.5).

the recharge and resulting groundwater levels (see Methods for details) using rainfall and irrigation return flow data. We used data (Table 1) from agricultural (all crops), domestic, industrial and livestock sectors to compute total groundwater abstraction (see Methods for details).

Figure 2d shows the trend in groundwater level change simulated by the GEC-97 approach and Fig. 2a shows the trend in the observed well data (measured from the ground surface). The observed well data are point data sets. The increasing trend in the observed well water depth represents groundwater depletion, which is associated with decreasing net recharge and equivalent to the decreasing trend in net change in the depth to groundwater level (or groundwater level fluctuation). We found spatial consistency in the sign of trends between observed (Fig. 2a) and simulated (Fig. 2d) data, that is, regions showing increasing trends in Fig. 2a and decreasing trends in Fig. 2d and vice versa. For example, central Uttar Pradesh, central Bihar and south-eastern West Bengal show depleting groundwater levels in both observations and simulations.

As the observed data are taken from well locations and the simulated data are at a district level, one-to-one comparison is difficult. We compared the simulated groundwater recharge with reference data provided by the Central Ground Water Board, Government of India, in the report 'Dynamic Ground Water Resources of India'[27]. We generated a scatter plot to quantify the spatial match at the district level between the simulated and reference data for the entire study region (Supplementary Fig. 3), showing good agreement (correlation coefficient of 0.65) for the financial year 2012–2013 (FY2012–2013).

Results from the optimal crop switching model

The recent trends show that the current water management practices in the IGP are not sustainable. Changes in existing cereal crops may provide a solution; however, the problem is complex, considering multiple conflicting objectives. A solution for cereal cropping practice should lead to more calorie production with water saving. Implementing such a solution involves convincing the farmers, which is impossible if they do not see increases in their profits. Hence, maximizing farmers' profits should be an additional objective with maximizing calorie production and minimizing irrigation water. Here, farmers' profits were calculated using the minimum support price (MSP) of crops. Due to the non-availability of data on the fraction of crop production covered by the MSP, we used the MSP for the entire cereal production to calculate total profit (see Methods for details). We developed a multi-objective optimization model (see Methods for details) with all the objectives mentioned above and the fractions of cereal cropped area in a district as decision variables. We solved the optimization model individually for all the districts in Uttar Pradesh, Bihar and West Bengal and compared the results and the values of the objectives with existing practices. The observed values for the 2014–2015 financial year were considered as reference values for comparison. We considered the Kharif cereal crops rice, maize, sorghum and millet (pearl millet), and the Rabi cereal crops wheat, sorghum and barley.

The optimization model was solved for three different cases based on different yield datasets, as detailed below:

1. Optimization with observed yield (OOY): the optimization model was solved with the observed yield values, which are partitioned yield values for rainfed and irrigated conditions obtained from observed yield datasets (see Methods for details).
2. Optimization with simulated yield (OSY): the optimization model was solved with simulated crop yield values (simulations performed with the AquaCrop model of the United Nations' Food and Agricultural Organization (FAO), see Methods for details).
3. Optimization after meeting yield gap (OMYG): the optimization model was solved for a district with 90th percentile observed yield values for the agroclimatic zone to which it belongs.

We first considered the observed yield of different crops (See Table 1 for details) in the optimization model (OOY). Figure 3 shows the proposed changes in the cropped area of individual crops for both rainfed and irrigated croplands obtained by the optimization model compared with existing practices. For both rainfed and irrigated croplands, there is a widespread reduction in the paddy area of 47% and 83%, respectively (Fig. 3a(ix)–(xii)), over the study region in the Kharif season. The reductions are more prominent over the irrigated lands for the obvious reason of minimizing water application. The rice areas are replaced by less water-intensive maize, millet and sorghum. The increases in maize and sorghum areas (31% and 47% increase in irrigated maize and sorghum areas, respectively) are greater than the increase in millet area (5% increase in irrigated millet area) for the Kharif season (Fig. 3a(ix)–(xii)). The changes in the Rabi season show the widespread switching of wheat to sorghum and barley (71% and 7% increase in irrigated sorghum and barley areas, respectively,

Table 1 | Descriptions and sources of the datasets

Data type	Description and sources
Observed meteorological datasets	The observed gridded rainfall data (resolution of 0.25°) and temperature data (resolution of 1°) at a daily scale were obtained from the IMD[25] for the period 1998–2015 (https://dsp.imdpune.gov.in).
Soil data	Gridded datasets for soil texture were obtained from the Harmonized World Soil Database[48] (https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/).
Groundwater well data	Groundwater data are available at the India Water Resources Information System portal (https://indiawris.gov.in/wris/).
Specific yield data	The map and specific yield values are presented in the Ground Water Resource Estimation Committee report[45] (http://cgwb.gov.in/sites/default/files/MainLinks/Manual-on-Aquifer-Mapping.pdf). The specific yield data are considered as the spatial average value for each state based on the aquifer type (GEC-97) according to the CGWB (http://cgwb.gov.in/ground-water-resource-assessment-0).
Crop parameters	Crop phenology, soil water stress and temperature stress parameters were availed from FAO datasets[38] (https://www.fao.org/fileadmin/user_upload/faowater/docs/AquaCropV40Annexes.pdf).
Crop and irrigation data	Data on district- and crop-specific production, harvested area and source-specific irrigated area were taken from agricultural census datasets[23] (https://www.aps.dac.gov.in/LUS/Public/Reports.aspx). We obtained the standard water application practices for flood and drip irrigation from the literature[9,14] and agricultural census.
Yield data	District-level yield data were obtained from ICRISAT (https://www.icrisat.org/tag/district-level-data/)
Cost of cultivation datasets	State-wise cost of cultivation data in India for each crop are available from *Agricultural Statistics at a Glance* 2017 (ref. 7) (https://desagri.gov.in/wp-content/uploads/2021/04/Agricultural-Statistics-at-a-Glance-2017.pdf).
Calorie values and other nutrition values	The calorie values per 100 g and other nutritional values for each cereal were taken from the Indian Food Composition Tables[49], the National Institute of Nutrition, Nutrient Requirements and Recommended Dietary Allowances for Indians (https://www.nin.res.in/)
MSP	MSP data for FY2014–2015 for Kharif and Rabi crops were availed from the 'FARMERS' PORTAL', GOI (https://farmer.gov.in/mspstatements.aspx).
Water withdrawal and consumption data for domestic, industrial and livestock purposes	Global water use model (WaterGAP, v2.2d) (ref. 26) outputs were used to compute domestic, industrial and livestock water consumption in the study region. These gridded datasets were aggregated to represent the district-wise values in our study region (https://hs.pangaea.de/model/WaterGAP_v2-2d/watergap_22d_WFDEI-GPCC_histsoc_plivuse_yearly_1901_2016.nc4, https://hs.pangaea.de/model/WaterGAP_v2-2d/watergap_22d_WFDEI-GPCC_histsoc_pdomww_yearly_1901_2016.nc4, https://hs.pangaea.de/model/WaterGAP_v2-2d/watergap_22d_WFDEI-GPCC_histsoc_pindww_yearly_1901_2016.nc4, https://hs.pangaea.de/model/WaterGAP_v2-2d/watergap_22d_WFDEI-GPCC_histsoc_pdomuse_yearly_1901_2016.nc4 and https://hs.pangaea.de/model/WaterGAP_v2-2d/watergap_22d_WFDEI-GPCC_histsoc_pinduse_yearly_1901_2016.nc4).

The values obtained for each variable along with results are provided in Supplementary Data 1.

Fig. 3b(iv),(v)). Supplementary Fig. 4 shows the changes in the simulated objectives (OOY) after introducing the proposed crop changes. For both seasons, the reductions in water consumption are widespread, with greater reductions in Uttar Pradesh, currently severely affected by water scarcity and groundwater depletion. The farmers' profits are also improved almost everywhere, except in the Rabi season in West Bengal. The major reason behind the improvements in profit is the lower cost of cultivation of the replacing crops (millets and sorghum) compared with rice (Supplementary Table 1). Furthermore, sorghum has a higher MSP than rice (Supplementary Table 2), which improves the profit for the Kharif season, when the dominant replacing crop is sorghum. Similarly, for the Rabi season, the improvements in profit are largely governed by the lower cost of cultivation of the replacing crops (barley and sorghum) compared with wheat (Supplementary Table 1). The MSP of sorghum is also higher than that of wheat (Supplementary Table 2). However, we did not find any improvement in the calorie production in 41 and 35 districts out of 124 districts in the Kharif and Rabi seasons, respectively. The low calorie production could be attributed to the lower observed yield of low-water-intensive crops in many districts. The low yields could be due to poor crop suitability in a specific area or yield gaps. We further used the FAO AquaCrop model[28] to simulate the crop yield and understand whether significant yield gaps exist.

Yield gap and its role in the optimization model

Comparison of the simulated and observed yield values (separately obtained for rainfed and irrigated croplands) revealed a large yield gap for all the crops (Supplementary Figs. 5 and 6). Here, yield gap can be defined as the difference between attainable yield (which is simulated with FAO's AquaCrop model) and landscape-level observed yield[29]. The yield gaps are high for millet and sorghum, likely due to poor management practices or inconsistency in sampling during data collection. As millets and sorghums are grown in more marginal conditions, the high yield gaps for these crops are expected.

To understand the sensitivity of the optimization model to the yield gap, we used the simulated yield for the Kharif and Rabi seasons (OSY). The results (Supplementary Fig. 7) for the Kharif season show that rice is now replaced more by millet (80% rice area is replaced by millet) than by maize or sorghum. These switchings are more prominent in the irrigated areas due to the use of the objective associated with water savings. For the Rabi season, wheat is replaced more by sorghum than by barley (80% wheat area is replaced by sorghum). The use of higher simulated yields for non-water-intensive crops resulted in increased profits and calorie production in every district with water savings (Supplementary Fig. 8). These results indicate that improvements in yield, specifically for non-water-intensive crops, may play an important role in water and food sustainability. It should be noted that to simulate the yield, we kept the water use the same as that practised in the districts. Hence, the computed yield gap is not affected by water use. Crop models tend to overestimate the yields by considering ideal conditions and hence the use of yield values obtained directly from the simulations may not be very practical. To address the yield gap realistically, we ran the optimization using the 90th percentile of yield (OMYG) within an agroecological zone. Here, we considered three agroecological zones: the lower Gangetic plain zone with 18 districts, the middle Gangetic plain zone with 60 districts and the upper Gangetic plain zone with 46 districts. Four districts of the central plateau region were considered under the upper Gangetic plain region to calculate the 90th percentile yield data in that region (Supplementary Fig. 9).

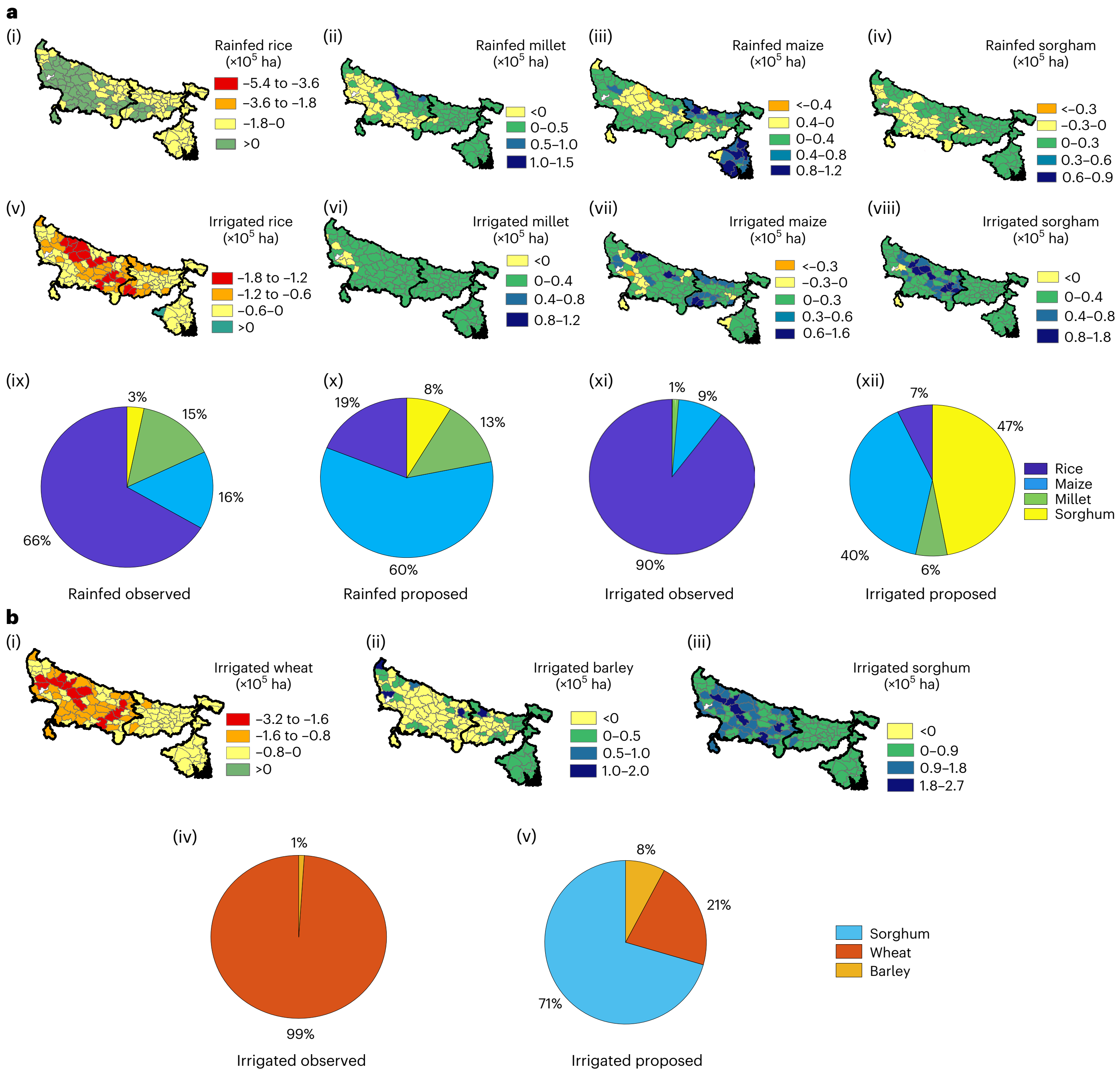

Fig. 3 | Optimized changes in crop area in the Kharif and Rabi seasons. **a**,**b**, Optimization of crop area with district-wise observed yield values (OOY). **a**, Optimized changes in rainfed (i–iv) and irrigated crop areas (v–viii) in the Kharif season for rice (i,v), millet (ii,vi), maize (iii,vii) and sorghum (iv,viii), and fractions of observed (ix,xi) and optimized (x,xii) cereal crop areas in rainfed (ix,x) and irrigated (xi,xii) cropped areas. **b**, Optimized changes in irrigated crop areas for wheat (i), barley (ii) and sorghum (iii) in the Rabi season, and fractions of observed (iv) and optimized (v) cereal crop areas in irrigated cropped areas. Rainfed areas are negligibly small in the Rabi season as irrigation is essential; thus, the proposed changes for rainfed regions in the Rabi season are not presented. All district-wise maps were created using ArcMap (ArcGIS10.5).

The results from the optimization model (OMYG) are presented in Fig. 4. We found that millet and sorghum largely replace rice in the Kharif season. In rainfed conditions, rice is replaced by millet and maize (36% reduction in rice area, 19% increase in millet area and 16% increase in maize area), while sorghum is the dominant replacing crop in irrigated conditions because of its higher yield compared with other replacing crops in irrigated conditions (85% reduction in rice area and 82% increase in sorghum area, Fig. 4). In the Rabi season, sorghum is the dominant crop to replace wheat in the irrigated region (80% increase in sorghum area). These switching patterns are a result of the lower water requirement of sorghum compared with barley. Figure 5 shows the changes in outcomes (OMYG) compared with those obtained with existing practices. For both the Kharif and Rabi seasons, very high water savings are clearly visible everywhere in the IGP. We found 55% and 9% water savings in the Kharif and Rabi seasons, respectively, in the IGP with the replaced crop. The increases in profit (139% and 152% for Kharif and Rabi, respectively) and calorie production (19% and 38% for Kharif and Rabi, respectively) are widespread, except for a very few districts

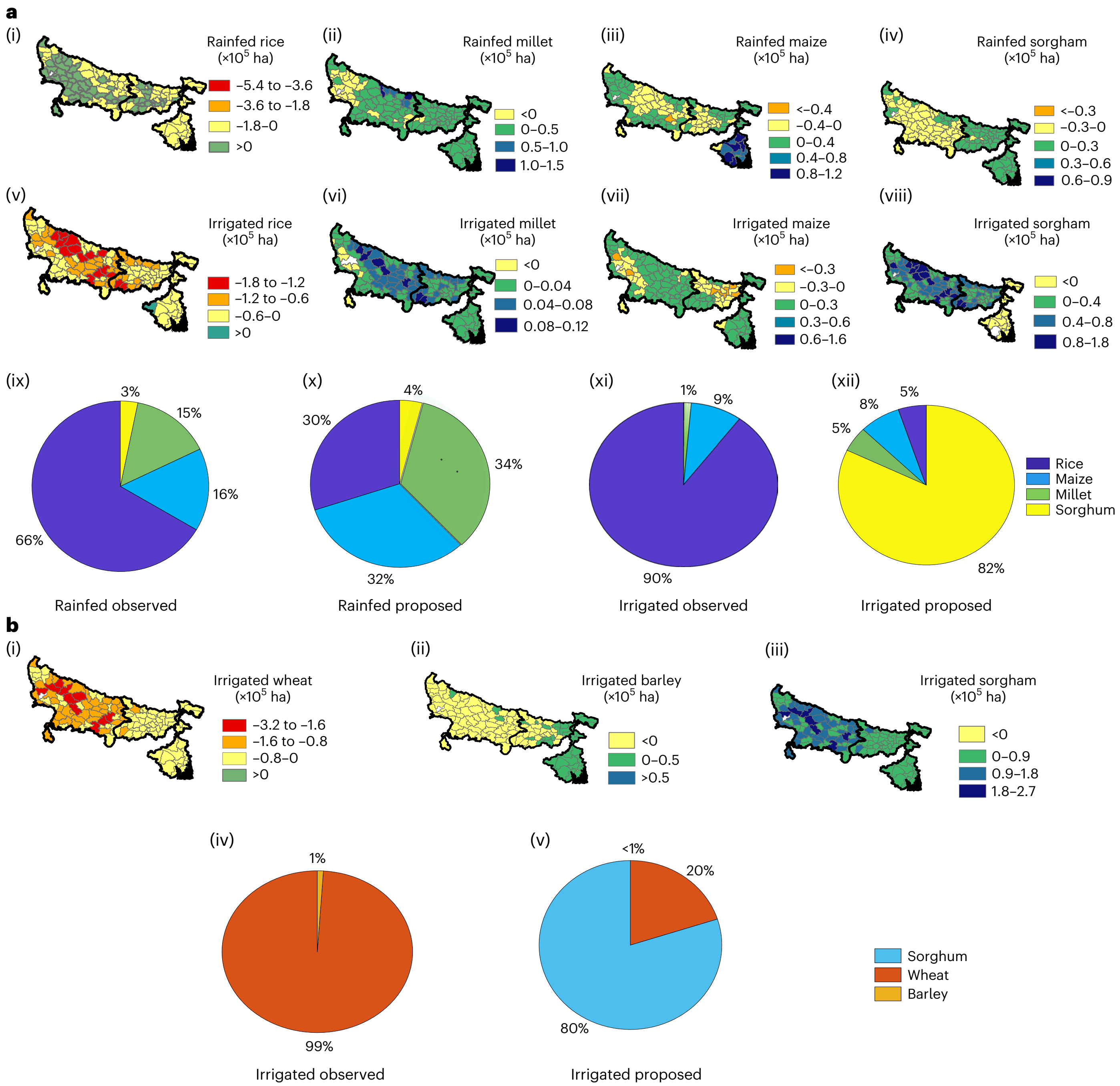

Fig. 4 | Optimized changes in crop area for the Kharif and Rabi seasons. **a**,**b**, Optimization of crop area with 90th percentile observed yield values for each agroclimatic zone (OMYG). **a**, Optimized changes in rainfed (i–iv) and irrigated (v–viii) crop areas in the Kharif season for rice (i,v), millet (ii,vi), maize (iii,vii) and sorghum (iv,viii), and fractions of observed (ix,xi) and optimized (x,xii) cereal crop areas in rainfed (ix,x) and irrigated (xi,xii) cropped areas. **b**, Optimized changes in irrigated crop areas for wheat (i), barley (ii) and sorghum (iii) in the Rabi season, and fractions of observed (iv) and optimized (v) cereal crop areas in irrigated cropped areas. Rainfed areas are negligibly small in the Rabi season as irrigation is essential; thus, the proposed changes for rainfed region in the Rabi season are not presented. All district-wise maps were created using ArcMap (ArcGIS10.5).

for the Kharif season. The calorie production and profits for existing crop practices were computed with 90th percentile yields from the agroecological zone to enable these comparisons. Hence, the improvements in objectives presented in Fig. 5 are entirely due to crop switching and not due to yield improvements beyond raising yields to the 90th percentile of yield for each cereal within the respective agroecological zone. The use of observed yield in individual districts for existing crop practices would have resulted in much greater improvements in yield and profit for the proposed scenarios. The improvement in profit is due to the high yield of non-water-intensive cereals, the low cultivation cost of the replacing crops and the high MSP for sorghum, a major replacing crop. A limitation of this work is that we did not make any changes to the cost of production that may be needed to close the yield gap because of the non-availability of data. Here, we assumed that the changes in yield are independent of the cost of cultivation. Field surveys are needed to understand the association between yield and cost of production, which is a potential area of future research. For the Rabi season, all three objectives show improvements for the proposed

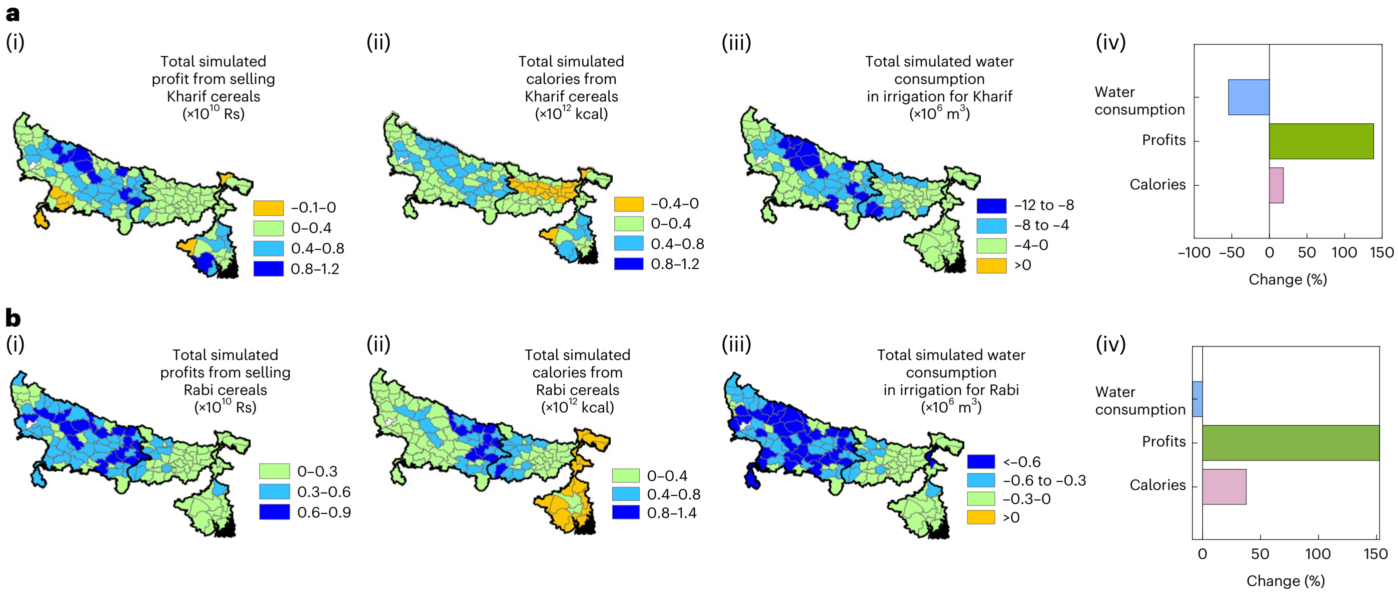

Fig. 5 | Optimized changes in the objective parameters of total profit, calorie production and irrigation water consumption. a,**b**, Optimization of the objective parameters with 90th percentile observed yield values for each agroclimatic zone (OMYG). **a**, Optimized changes in profit (i), calorie production (ii) and irrigation water consumption (iii) for crops in the Kharif season, and percentage changes in profit, calorie and water consumption summed over the study region in the Kharif season (iv). **b**, Optimized changes in profit (i), calorie production (ii) and irrigation water consumption (iii) for crops in the Rabi season, and percentage changes in profit, calorie and water consumption summed over the study region in the Rabi season (iv). Rs, Indian Rupees. All district-wise maps were created using ArcMap (ArcGIS10.5).

scenarios for all districts. The optimization results clearly show that there is a need for widespread switching of rice to millet and sorghum in the Kharif season and to barley and sorghum in the Rabi season if yield gaps can be closed. It is possible to improve all the objectives associated with water security, food security and farmers' profits with the proposed crop switching with a reduced yield gap.

Post-optimality analysis

We performed a Pareto trade-off analysis and generated Pareto fronts for districts by assigning varying weights to the objectives; the multi-objective optimization yielded Pareto optimal solutions. Ideally, a Pareto optimal solution refers to a non-inferior solution, where an objective cannot be further improved without compromising at least one of the other objectives. As a demonstration, we present the set of Pareto optimal solutions (blue lines) for one district (Araria in Bihar) in Extended Data Fig. 2. To solve the multi-objective optimization, we used a max–min approach; the result is shown by the red line, which is a compromised solution. Further improvement of one of the objectives from that solution will compromise at least one of the other objectives. We also performed a post-optimality sensitivity analysis to address the uncertainty in the input to the optimization model. We performed the sensitivity analysis considering a ±10% variation in the input, cost of cultivation, crop yield, MSP and irrigation water use. The results are presented in Extended Data Figs. 3 and 4. We found no significant changes in the values of decision variables (that is, the allocated crop fractions for both rainfed and irrigated areas), except for sorghum and barley in the Rabi season for rainfed areas. The key conclusion of our study remains unchanged, which suggests a widespread replacement of rice by millets and sorghum.

Changing irrigation practices versus crop switching

Flood irrigation practices are often blamed for the groundwater depletion in the Gangetic basin[30] and hence, policy recommendations of widespread conversion from flood to drip irrigation have been made over this region. Fishman et al.[9] suggested that improving irrigation efficiency could significantly reduce groundwater extraction over this region. However, the literature also reports that improving irrigation efficiency results in a reduction in groundwater recharge[13]. Hence, the overall impacts of introducing heavily subsidized drip irrigation on large-scale water savings are questionable[31–33].

Here, we compared the simulated net groundwater recharge for three cases: (1) shifting from flood to drip irrigation without changing crop practices, (2) changing crop practices with conventional flood irrigation and (3) changing both crop practices and irrigation method from flood to drip. We computed the net recharge for flood and drip irrigation using the GEC-97 approach (see Methods for details). We found that changing from flood to drip irrigation improves the net groundwater recharge (recharge − abstraction) marginally, despite a decrease in a few districts (Supplementary Fig. 11a). Changing crop practices improves net recharge in all districts (Supplementary Fig. 11b), although the improvements are not very high (7% increase in net recharge while adopting crop switching instead of the drip irrigation method). Spatial averaging shows that changing crop scenarios results in greater groundwater recharge for the three states than introducing drip irrigation, which demands huge government subsidies (Supplementary Fig. 10). Furthermore, continuing with the same crop with drip irrigation (case 1) will not improve the calorie production or farmers' profits. Changing from flood to drip irrigation improves net recharge by 34%, whereas changing crop practices improves it by 41% (Fig. 6b and Supplementary Figs. 10 and 11). Consideration of case 3 shows the greatest improvements in net recharge at a district level. Changing the crop scenario and introducing drip irrigation together reduces groundwater depletion by 78% (Fig. 6b and Supplementary Figs. 10 and 11) over the IGP. The energy use in the IGP for groundwater pumping is another major concern[15]. The results obtained for the simulated energy savings from groundwater pumping for the three cases are presented in Fig. 6a and Supplementary Fig. 11. Cases 1 and 2 show similar energy savings (14% and 21%, respectively), but together they result in significant energy savings (36%).

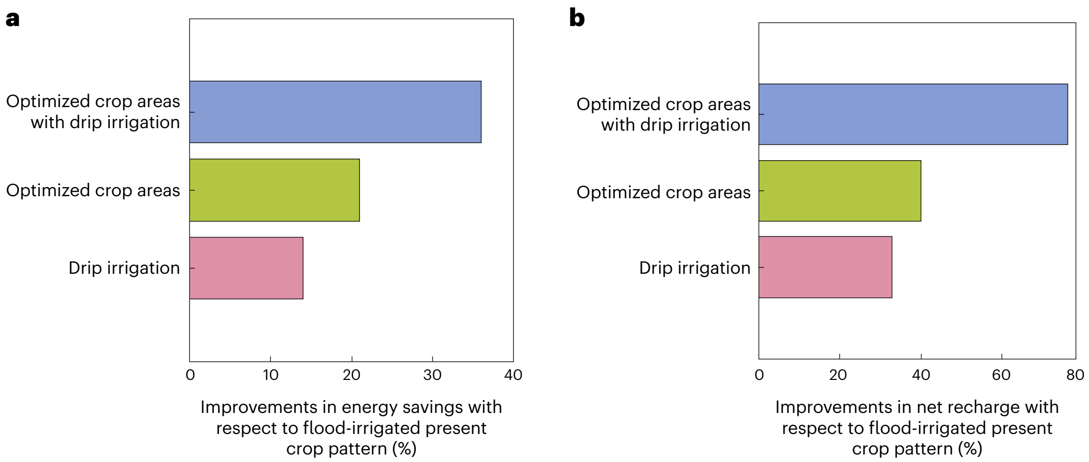

Fig. 6 | Improvements in energy savings and net recharge. a,**b**, Improvements in energy savings (**a**) and net recharge (**b**) when adopting drip irrigation practices instead of flood irrigation (case 1), shifting to optimized cropping pattern with flood irrigation (case 2) and shifting to optimized cropping pattern with drip irrigation (case 3).

Shifting from the rice–wheat system to nutri cereals improves irrigation water savings and provides more micronutrients and proteins than rice and wheat (Supplementary Table 3). Our results show that sorghum and millets are the dominant crops to replace rice and wheat. We conclude that there would be a greater production of protein and other micronutrients (iron and zinc) in the replacement scenario, with 46% increased production of protein and 353% and 82% increased production of iron and zinc, respectively. This is another benefit of shifting from rice to nutri cereals from the consumer perspective.

Summary

Historical observations and simulations over the Ganga basin showed decreasing trends of rainfall and increasing trends of agricultural water consumption. Both trends together resulted in groundwater depletion in the IGP. However, we could not find any spatially consistent improvements in total calorie production and calorie production per unit water consumption over the districts. The observed well data showed widespread groundwater depletion, specifically over the western side of the region, consistent with the simulated groundwater scenario for 1998–2014. The crop replacement scenario designed by the proposed multi-objective optimization approach revealed a widespread replacement of rice with millet and sorghum in the Kharif season and of wheat with sorghum in the Rabi season. With the optimized crop replacement scenario, we found 55% and 9% water savings in the Kharif and Rabi seasons, respectively, compared with present practices. The increases in profit from the proposed alternatives are 139% and 152% for the Kharif and Rabi seasons, respectively. Similarly, calorie production will increase by 19% and 38% in the Kharif and Rabi seasons, respectively. The optimized cropping pattern will result in a greater production of protein and other micronutrients (iron and zinc), with 46% increased production of protein and 353% and 82% increased production of iron and zinc. The optimized cropping pattern can contribute to a 41% improvement in net recharge without changing irrigation practices, whereas changing the irrigation practice (shifting from flood to drip irrigation) alone may improve net recharge by 34%. Implementing the change in irrigation practice along with the optimized cropping pattern results in a 78% improvement in net recharge. The improvement in energy savings with the proposed crop replacement scenario was computed to be 36% with simultaneous changes in crop and irrigation practices, while implementing them alone may result in 21% and 14% improvement in energy savings, respectively.

India's crop mix has changed since the 'green revolution', which began around the year 1960. The production of nutri cereals has declined with the promotion of the water-intensive rice–wheat system due to low input subsidies and revenues for the nutri cereals and the highly subsidized supply of rice and wheat through the Public Distribution System (PDS). However, water scarcity with groundwater depletion due to agricultural intensification is a matter of concern in the 'Food Bowl of India', the IGP. While these challenges are well described in the literature, solutions are largely missing. Here, we have presented alternative cropping patterns derived from a unique multi-objective optimization framework that maximizes production and farmers' profits while minimizing water use. We propose the widespread replacement of rice with millet and sorghum in the Kharif (monsoon) season, and of wheat with sorghum in the Rabi (winter) season. If crop switching is carried out on the basis of only one objective of water consumption minimization, water savings can be increased by 4%. At the same time, there will be a reduction in the improvements in calorie production and profit by 23% and 126%, respectively, compared with the proposed solutions. Similarly, when the maximization of profit was considered as the only objective, the entire cropped area will be replaced by the highest profit-making crop, that is, sorghum, as it has the highest MSP and lowest cost of cultivation. This scenario will increase profits by 58% compared with the proposed solution from the multi-objective framework but, simultaneously, reduce calorie production by 18.5% with a marginal increase in water savings of 2%. Our proposed switching from the rice–wheat system to alternative cereals supports the Sustainable Development Goal 2 to "end hunger, achieve food security and improved nutrition and promote sustainable agriculture".

Our proposed solutions also align with recent government and United Nations initiatives. In 2018 (National Year of Millets), the Indian government started a mission, 'Nutri cereal', within the National Food Security Mission (NFSM). The year 2023 has been declared as the International Year of Millets by the United Nations and initiatives are being taken to promote nutri cereals in view of their high nutritional content (proteins, vitamins and micronutrients), low water requirement and climate resilience. We have also demonstrated the efficacy of our proposed solution for water security by comparison with other proposed alternatives, such as changing from flood to drip irrigation. Our framework is easily applicable in different agroclimatic regions (Extended Data Fig. 1).

The suitability of our solution also depends on the demand for alternative cereals. The majority of the population in India, specifically in the IGP, consider rice and wheat to be the major cereals. The policy of switching crops can be successfully implemented only when the mindset of the population in selecting cereals changes, probably systematically with time. The catalyst for this change might be awareness and promotional activity, such as the United Nations Development Programme declaring 2023 as the International Year of Millets. In the global market, the demand for nutri cereals is increasing. Also, rice and wheat exports from India are quite small compared with the production of these crops, so selective crop switching towards millets and/or sorghum would likely have little impact on the capacity to export rice or wheat. Hence, there is an opportunity arising for farmers to switch from water-intensive rice and wheat to nutri cereals, leading to water and food sustainability.

Despite the lower cost of cultivation and thus the higher profit from alternative cereals (nutri cereals), farmers currently prefer to cultivate rice and wheat. There might be several factors that need to be considered from the farmers' perspective, such as the post-harvest processing of cereals, access to agricultural markets, and challenges in converting paddy field to suitable cropland for millets and other nutri cereals. Thus, the implementation of crop switching strategies requires interactions with farmers and consideration of farmers' input in policy framing. Promoting the cultivation and inclusion of nutri cereals in the PDS, procuring nutri cereals through the MSP and providing incentives to the farmers growing nutri cereals are potential ways to enhance the adoption of these crops by farmers. Subsidized supply of nutri cereals through the PDS may also change (and increase) consumer demand. However, implementation through the PDS might be difficult considering the political, economic and cultural aspects of a particular region. While such approaches are already being implemented in a few states and are also planned to be implemented as part of the NFSM of the Government of India (GOI) for promoting nutri cereals, such implementation will need to account for the political, economic and cultural differences between regions to better ensure their feasibility and success. The districts showing the largest potential benefits from implementing optimized cropping patterns could be considered as potential first targets for the procurement of cereals through the PDS system to incentivize farmers.There is scope for future work on policy framing with the proposed solution considering the multiple dimensions of subsidies, irrigation efficiency, yield gap and technological improvements. Also, in our optimization of cropped areas, we did not put any constraints on the degree of substitution of rice and wheat areas by alternative crops. Considering this point, we ran additional optimization scenarios for the Kharif season in which rice areas were restricted to reductions of 20% and 40%. We found a 17% reduction in the improvement of calorie production in both cases compared with the scenario of putting no constraints on the degree of reduction in rice area (Supplementary Fig. 12). The reductions in water savings were 44% and 32% when the constraints on the degree of reduction in rice area were set as 20% and 40%. Finally, the reductions in the improvements of profit were 123% and 10%, respectively, in both cases (Supplementary Fig. 12).

Decision-making can be restrictive when considering one district at a time, while a scenario with across-district switching can resolve this issue. However, across-district switching will increase the number of decision variables 124 times, as there are 124 districts, and achieving a global optimum of optimization through a trial-and-error approach will not be feasible. In future, this work might be extended by considering the total production of cereals for a geographical location as constant but with specific crops reallocated within that geographical region. This future extension might be in line with the study of Devineni et al.[10], in which the single objective of maximizing national net revenue was considered. A shift in the geographical location of crops, whereby the present spatial pattern of crop area allocation changes while keeping the total production constant in a multi-objective optimization framework needs to be investigated. Data non-availability limits the spatial resolution of the analysis to the district level. Ideally, crop switching scenarios should consider local crop suitability at a much more granular scale. Implementing crop switching strategies also requires more detailed granular-scale stakeholder interviews, surveys and crop suitability studies. The sustainability of the proposed solution depends on the future RCP-SSP (Representative Concentration Pathways-Shared Socio-economic Pathways) climate scenarios, the projected population, and their water and calorie demand. This needs to be explored in future studies for the policy framing of improved agricultural interventions to develop a sustainable food–water–energy system.

Methods

Present scenario for water availability and food production

Significant trends in rainfall (IMD gridded rainfall data of 0.25° resolution at a daily scale) were mapped spatially over the study region (Fig. 1b). The annual mean (1998–2015) of daily rainfall data were considered to compute the significant trend at a 0.05 significance level. Significant trends were also plotted for monsoon rainfall (June–September, Supplementary Fig. 1).

The crop-wise seasonal water consumption for irrigation was computed using the values of water consumption for both flood and drip irrigation[9]. The specific amounts of water used for flood and drip irrigation for different crops approximately averaged for different regions in India were taken from the literature[9,34] and agricultural census data.

The district-wise seasonal water consumption by cereals through irrigation ($\mathrm{WC}_{\mathrm{irr}}$) was computed for all cereals (rice, wheat, maize, millets, sorghum and barley) for both the Kharif and Rabi seasons (equation (1)) for a financial year. In equation (1), for crop i, $c_{i,\mathrm{irr}}$ denotes irrigated cropped area and w_i denotes the seasonal water consumption (flood irrigation or drip irrigation) in millimetres, which were taken from the literature[9].

$$\mathrm{WC}_{\mathrm{irr}} = \sum_{i=1}^{n} c_{i,\mathrm{irr}} \times w_i \tag{1}$$

To compute the percentage fractions of water consumption (Fig. 1c) by cereals and other crops (non-cereal crops are those that are cultivated in the study region as per agricultural census data), we used the depth of seasonal irrigation (flood irrigation) in millimetres (ref. 9) multiplied by the irrigated crop areas (equation (1)). Water consumption data for domestic, industrial and livestock sectors were taken from the output data available from water consumption model simulations (WaterGAP, v2.2d) (ref. 26). Here, domestic and industrial water use were computed as the difference between withdrawal water and return flow (wastewater). Withdrawal water for livestock use was computed annually by multiplying the number of animals per grid cell by the livestock-specific water use intensity. The resulting water consumption data were aggregated sector-wise (irrigation for cereal and other crops, domestic, industrial and livestock) summing over the entire study region and averaging over the entire study period (from FY1998–1999 to FY2014–1015) to compute the fractions for each sector (Fig. 1c).

The district-wise calorie production data (Kcal) were computed as per equation (2).

$$\mathrm{Kcal} = \sum_{i=1}^{n} \mathrm{cp}_i \times \mathrm{kc}_i \tag{2}$$

Here, cp_i is the crop production value (in tonnes) and kc_i is the calorie value (kilocalories per tonne) for crop i. The calorie production per unit water consumption by cereal was computed by dividing the district-wise calorie production by the water consumption of cereals.

Crop modelling

We used the model AquaCrop[28,35], developed by the Land and Water Division of the FAO, to simulate crop growth. The AquaCrop software was originally point-location based. Here, we used the AquaCrop-OS module[36] to simulate the yield of all cereal crops over the IGP. The simulations were performed at a grid scale and then mapped onto all the districts for rainfed and irrigated conditions. The inputs to simulate biomass production and yield (response to water) consisted of weather data (minimum and maximum temperatures, rainfall data and evaporative demand of the atmosphere), crop parameters, soil characteristics (for example, soil texture) and management practices (field and irrigation management), which define the environment in which the crop will develop. The evaporative demand (reference evapotranspiration) was estimated in the Variable Infiltration Capacity (VIC) model, which applies the FAO's Penman–Monteith equation[37]. To compute reference evapotranspiration for the study period (1998–2015), wind data were obtained from the European Centre for Medium-Range Weather Forecasts interim reanalysis. Observed daily precipitation data were taken from the IMD. The soil parameters were procured directly from the VIC website. The land use information was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) Land Use Land Cover.

The crop parameters for simulating yields, comprising crop phenology, soil water stress and temperature stress, were based on an FAO dataset[38]. The limitation of the AquaCrop simulations is the unavailability of real data related to day-to-day applications of irrigation and fertilizer. The district-wise simulated yields are mapped in Supplementary Fig. 6 and compared with the observed yield data for rainfed and irrigated conditions. The spatial average values of observed and simulated yield data for rainfed and irrigated conditions are compared in Supplementary Fig. 5.

Partitioning of observed yields

The district-level observed yields (y_i) from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) were partitioned into district-level rainfed and irrigated yields ($y_{i,\mathrm{ra}}$ and $y_{i,\mathrm{irr}}$) following the methodology suggested by Davis et al.[39]:

$$y_{i,\mathrm{ra}} = \frac{y_i \times c_i}{c_i - c_{i,\mathrm{irr}} + (Z_i \times c_{i,\mathrm{irr}})} \tag{3}$$

$$Z_i = \frac{1}{n}\sum \frac{\text{Weighted average irrigated yield values considering all states for crop } i}{\text{Weighted average rainfed yield values considering all states or crop } i} \tag{4}$$

$$y_{i,\mathrm{irr}} = y_{i,\mathrm{ra}} \times Z_i \tag{5}$$

The rainfed yield ($y_{i,\mathrm{ra}}$) for crop i was calculated using equation (3), where y_i, c_i and $c_{i,\mathrm{irr}}$ are the observed yield, crop area and irrigated area for crop i, respectively, in a district, Z_i denotes the national average ratio of irrigated-to-rainfed yields (equation (4)) and n is the number of states for which yield data are available from the Cost of Cultivation dataset for crop i. The weighted average state-level yields for irrigated and rainfed conditions were calculated using plot-level data of crop production and harvested area multiplied by a factor (from the Cost of Cultivation survey datasets), the 'cluster weight', to estimate representative yield at the state level. Information on whether a plot is rainfed or irrigated was gathered from reported values of either irrigation pumping hours or canal fee. If the value of pumping hours or canal fee was greater than zero for a plot, the plot was considered as irrigated, otherwise rainfed. The weighted average of state-level rainfed and irrigated yield values were estimated considering those rainfed and irrigated plots separately. The irrigated yield ($y_{i,\mathrm{irr}}$) is defined as the product of rainfed yield ($y_{i,\mathrm{ra}}$) and Z_i (equation (5)).

Optimization model development for crop switching

We developed an optimization model in which the decision variables are the fractions of crop areas in a district to maximize the calorie production (Kcal) and farmers' profits (FP) and to minimize the irrigation water consumption (WC). The optimization model is presented below:

$$\text{Maximize FP} \tag{6}$$

$$\text{Minimize WC} \tag{7}$$

$$\text{Maximize Kcal} \tag{8}$$

Subject to

$$c_i = c_{i,\mathrm{ra}} + c_{i,\mathrm{irr}} \tag{9}$$

$$\mathrm{cp}_i = c_{i,\mathrm{ra}} \times y_{i,\mathrm{ra}} + c_{i,\mathrm{irr}} \times y_{i,\mathrm{irr}} \tag{10}$$

$$\mathrm{FP} = \sum_{i=1}^{n} \mathrm{cp}_i \times S_i - c_{i,\mathrm{ra}} \times \mathrm{CC}_{i,\mathrm{ra}} - c_{i,\mathrm{irr}} \times \mathrm{CC}_{i,\mathrm{irr}} \tag{11}$$

$$\mathrm{Kcal} = \sum_{i=1}^{n} \mathrm{cp}_i \times \mathrm{kc}_i \tag{12}$$

$$\mathrm{WC}_{\mathrm{irr}} = \sum_{i=1}^{n} c_{i,\mathrm{irr}} \times w_i \tag{13}$$

In equation (9), c_i denotes the cropped area of crop i (computed as the product of the fraction for crop i and the total crop area), $c_{i,\mathrm{ra}}$ denotes the rainfed cropped area of crop i (computed as the product of the fraction for crop i and the total rainfed crop area) and $c_{i,\mathrm{irr}}$ denotes the irrigated cropped area of crop i (computed as the product of the fraction for crop i and the total rainfed crop area).

$y_{i,\mathrm{ra}}$ and $y_{i,\mathrm{irr}}$ are the yield values of crop i for rainfed and irrigated conditions, respectively. The crop production cp_i was computed by multiplying the rainfed and irrigated crop areas by the respective yield values (equation (10)).

All objective functions are defined by equations (11)–(13) as a function of crop area c_i and summed for n crops, where n is the total number of crops harvested in a particular district.

S_i and CC_i denote the MSP (in Indian rupees per kg) and the cost of cultivation (in Indian rupees per ha) for crop i, respectively. The cost of cultivation for the rainfed area $\mathrm{CC}_{i,\mathrm{ra}}$ was estimated by subtracting the irrigation charges from the cost of cultivation data provided and multiplied by the rainfed crop area $c_{i,\mathrm{ra}}$. Similarly, the cost of cultivation for the irrigated area $\mathrm{CC}_{i,\mathrm{irr}}$ was calculated including the irrigation charges. The farmers' profits use the selling price (MSP) multiplied by the crop production cp_i. Farmers' profits (FP) were estimated by subtracting the cost of cultivation from the profit (equation (11)). Crop price can vary significantly according to demand. We considered MSP in our study because it is the only reliable minimum crop price data available from the GOI and is not subjected to variability as is the case with open market prices.

Calorie production (Kcal) was computed following Davis et al.[40] according to equation (12), where cp_i is the crop production (tonnes) and kc_i is the calorie value (kilocalories per tonne) for crop i. Irrigation water consumption (WC) was computed according to equation (13), where w_i denotes the seasonal water consumption for crop i.

Here, we used the max–min approach of multi-objective optimization[41,42]. The goal was to maximize the minimum satisfaction (γ) of all the objectives (equation (14)). This approach will in turn maximize all the objectives (equations (15)–(17)).

$$\text{Maximize } \gamma \tag{14}$$

subject to

$$\frac{\mathrm{FP}-\mathrm{FP}_{\mathrm{min}}}{\mathrm{FP}_{\mathrm{max}}-\mathrm{FP}_{\mathrm{min}}} \geq \gamma \tag{15}$$

$$\frac{\mathrm{Kcal}-\mathrm{Kcal}_{\mathrm{min}}}{\mathrm{Kcal}_{\mathrm{max}}-\mathrm{Kcal}_{\mathrm{min}}} \geq \gamma \tag{16}$$

$$\frac{\mathrm{WC}_{\mathrm{max}}-\mathrm{WC}}{\mathrm{WC}_{\mathrm{max}}-\mathrm{WC}_{\mathrm{min}}} \geq \gamma \tag{17}$$

$$0 < \gamma < 1 \tag{18}$$

$$c_i = c_{i,\mathrm{ra}} + c_{i,\mathrm{irr}} \tag{19}$$

$$\mathrm{cp}_i = c_{i,\mathrm{ra}} \times y_{i,\mathrm{ra}} + c_{i,\mathrm{irr}} \times y_{i,\mathrm{irr}} \tag{20}$$

$$\mathrm{FP} = \sum_{i=1}^{n} \mathrm{cp}_i \times S_i - c_{i,\mathrm{ra}} \times \mathrm{CC}_{i,\mathrm{ra}} - c_{i,\mathrm{irr}} \times \mathrm{CC}_{i,\mathrm{irr}} \tag{21}$$

$$\mathrm{Kcal} = \sum_{i=1}^{n} \mathrm{cp}_i \times \mathrm{kc}_i \tag{22}$$

$$\mathrm{WC} = \sum_{i=1}^{n} c_{i,\mathrm{irr}} \times w_i \tag{23}$$

In the constraints (equations (15)–(17)), the goals related to farmers' profits, calorie production and water consumption were made greater than or equal to γ to represent this max–min model. It should be noted that, as we needed to minimize WC, WC was subtracted in the numerator in equation (17), in contrast to equations (15) and (16), where the goal was to maximize the objective functions.

The maximum and minimum values of FP, Kcal and WC are defined on the basis that the entire crop area is being replaced by the specific crop that produces maximum and minimum FP, Kcal and WC, respectively.

The decision variables are the area fractions for the cereal crops, provided that the irrigated and rainfed area fractions will not change with respect to current practice.

The optimization model (developed using the MATLAB programming language) was solved using Probabilistic Global Search Laussane (PGSL), a direct stochastic algorithm for global search[43]. The PGSL algorithm is based on the assumption that better results can be obtained by focusing more on the neighbourhood of good solutions. It works better than genetic and advanced algorithms in solving benchmark optimization problems where the solution can be generated efficiently by sampling the search space without any special operators or gradient[43]. Gradients are not needed and no special characteristics of the objective functions (such as convexity) are required for PGSL.

The search space is defined by reading the minimum and maximum values for each variable given by the user. The PDF (probability density function) of each variable at the beginning of the search is created by assuming a uniform distribution over the entire domain. The PDFs are updated after the completion of each cycle. In every iteration, the algorithm increases the probability of obtaining a solution from the range of good solutions of the previous iteration. Thus, the search space is narrowed down until it converges to the optimum solution. PGSL is different from other methods as it uses four nested cycles, which helps to improve the search, and thus more focus could be given to areas around good solutions in the nested cycles. The four cycles of PGSL are detailed below.

In the sampling cycle, samples are generated randomly from the current PDF of each variable. Each point is evaluated according to the objective functions, and the best point is selected.

In the probability updating cycle, the probability of neighbourhood of good solutions increases and that of bad solutions decreases, and the PDFs of each variable are updated accordingly after each cycle.

In the focusing cycle, search is focused on an interval containing better solutions after a number of probability updating cycles. This is done by dividing the interval containing the best solution for each variable.

In the subdomain cycle, the search space continues to narrow by selecting only a subdomain of the region of good points.

As the four nested cycles take care of the global search, in the inner cycle, the sampling cycle, more focus is given to the areas around good solutions. The outer cycle makes sure that such processes happen around the entire search space so that the possibility of generating a good solution is improved without getting trapped in local minima.

This optimization model was run for all 124 districts individually in the study area for both the Kharif and Rabi seasons separately. The district-wise input data used in the model were as follows:

- Yield data for all crops in rainfed and irrigated conditions
- Total crop area (summation of cultivated areas under all cereal crops considered in the study)
- Total irrigated crop area (summation of irrigated areas under all cereal crops considered in the study)
- Cost of cultivation data for all crops

Crop-specific inputs such as MSP (MSP data for FY2014–2015 were used in this study as the observed crop area for FY2014–2015 was used in this study as the reference for comparision), calorie values and water consumption values did not vary district-wise.

The district-wise optimized crop area fractions for rainfed and irrigated regions were multiplied by the total rainfed and irrigated areas to determine the optimized crop areas. The proposed changes in the areas were computed by substracting the observed crop areas (for FY2014–2015) from the proposed crop areas. Similarly, the objective functions (farmers' profits, calorie production and water consumption) were computed with the optimized crop areas using equations (21)–(23).

Groundwater modelling

Groundwater abstraction (Abs, in ha m) was estimated according to equation (24).

$$\mathrm{Abs} = \mathrm{WC}_{\mathrm{irr}} \times \mathrm{GW}_{\mathrm{frac}} + D \tag{24}$$

Here, $\mathrm{WC}_{\mathrm{irr}}$ is the total Irrigation water consumption (in ha m), $\mathrm{GW}_{\mathrm{frac}}$ is the groundwater use fraction and D is the groundwater draft for domestic, industrial and livestock purposes (in ha m). The groundwater draft data were obtained from water use model (WaterGAP, v2.2d) simulations[26].

$\mathrm{GW}_{\mathrm{frac}}$ was estimated using district-level data according to equation (25).

$$\mathrm{GW}_{\mathrm{frac}} = \frac{\mathrm{Area}_{\mathrm{irr,GW}}}{\mathrm{Area}_{\mathrm{irr,GW}} + \mathrm{Area}_{\mathrm{irr,SW}}} \tag{25}$$

Here, $\mathrm{Area}_{\mathrm{irr,SW}}$ is the area irrigated by surface water (SW) sources (in ha) and $\mathrm{Area}_{\mathrm{irr,GW}}$ is the area irrigated by groundwater sources (in ha). The estimation of areas irrigated by different sources are as per the agricultural census data.

The groundwater recharge was estimated according to the methodology adopted by the CWC, GOI, detailed in the GEC-97 report[44]. The methodology is based on recharge from rainfall infiltration and other sources, such as recharge from irrigation return flow, tanks, ponds, canals and water conservation structures. In this study, recharge from canal, tank, ponds and water conservation structures were not considered due to the non-availability of data in the study region; however, the amount of recharge from these components is very low compared with the recharge from rainfall and return flow from irrigation[45]. The GEC-97 approach is a simplified representation of very complex hydrological processes in the human–natural environment of the IGP. The present study may be extended in the future to use a more detailed method, involving India-specific irrigation and paddy fields and a coupled surface–groundwater system, as performed by Joseph and Ghosh[13,46].

The empirical values of the return flow factor (RFF) are indicated in the CWC[44] as percentages of irrigation water application depending on the type of crop (paddy or non-paddy) and irrigation source (groundwater or surface water). The RFF values suggested for paddy (45–50%) in the manual[44] are overestimated because the formation of 'hard pan', a low permeability layer in the base of flood-irrigated paddy fields, was not considered, so they are multiplied by a factor 0.001 to take into account the effect of tilling and the formation of 'hard pan'[47]. RFF values for non-paddy fields are 25–30% following the CWC guidelines[44]. The RFF for non-paddy considering surface irrigation ($\mathrm{RFF}_{\mathrm{SRF}}$) and groundwater irrigation ($\mathrm{RFF}_{\mathrm{GRF}}$) are 30% and 25%, respectively, where the depth of the water table is assumed to be within 10 m of ground level[44]. The recharge from the return flow of surface water (R_{SRF}) and groundwater irrigated land (R_{GRF}) were estimated using equations (26) and (27), respectively.

$$R_{\mathrm{SRF}} = I_{\mathrm{SRF}} \times \mathrm{RFF}_{\mathrm{SRF}} \tag{26}$$

$$R_{\mathrm{GRF}} = I_{\mathrm{GRF}} \times \mathrm{RFF}_{\mathrm{GRF}} \tag{27}$$

Here, I_{SRF} is the irrigation water applied from surface water sources (in ha m) and I_{GRF} is the irrigation water applied from groundwater sources (in ha m).

I_{SRF} and I_{GRF} were computed using equations (28) and (29), respectively. The total recharge due to return flow from applied irrigation water (R_{RF}) was estimated using equation (30).

$$I_{\mathrm{SRF}} = \mathrm{WC}_{\mathrm{irr}} \times (1 - \mathrm{GW}_{\mathrm{frac}}) \tag{28}$$

$$I_{\mathrm{GRF}} = \mathrm{WC}_{\mathrm{irr}} \times \mathrm{GW}_{\mathrm{frac}} \tag{29}$$

$$R_{\mathrm{RF}} = R_{\mathrm{SRF}} + R_{\mathrm{GRF}} \tag{30}$$

Recharge due to rainfall (R_{rain}, in ha m) was estimated according to equation (31) as district-wise recharge due to rainfall computed by aggregating the gridded rainfall data for a district and considering the district areas as the command areas. The total recharge (R, in ha m) due to return flow and rainfall was computed using equation (32).

$$R_{\mathrm{rain}} = \mathrm{RIF} \times A \times P \tag{31}$$

$$R = R_{\mathrm{RF}} + R_{\mathrm{rain}} \tag{32}$$

Here, RIF is the rainfall infiltration factor, A is the command area (in ha), P is the rainfall (in m) and R_{RF} is the recharge due to return flow. The empirical value recommended for RIF for the Indo-Gangetic area (alluvial areas) in the CWC manual[44] is 22%.

The change in storage or net recharge was computed by subtracting the abstraction (Abs) from the recharge (R), which is equivalent to the change in groundwater level ($\mathrm{GWL}_{\mathrm{fluc}}$, in m) multiplied by the specific yield (SP) and command area (A; equation (33))[44].

$$R - \mathrm{Abs} = \mathrm{GWL}_{\mathrm{fluc}} \times \mathrm{SP} \times A \tag{33}$$

A positive net recharge suggests an increase in groundwater level and a negative recharge suggests a decrease in groundwater level. The specific yield values, which represent the actual amount of water that can be extracted by pumping from a unit volume of aquifer, are based on the aquifer map of India and guidelines set out by the Central Ground Water Board (CGWB)[45].

Estimation of energy used for irrigation

The power consumption (in W) was estimated using equation (34).

$$\mathrm{Power} = \frac{Q\rho g h}{\eta} \tag{34}$$

Here, the power is the power consumed in a district to pump groundwater, Q is the flow rate of the pump (in $\mathrm{m^3\,s^{-1}}$), ρ is the density of water (1,000 $\mathrm{kg\,m^{-3}}$), $g = 9.8\ \mathrm{m\,s^{-2}}$, h is the 'head of the pump' (in m), which is equivalent to the depth to the groundwater level (in mbgl), and η is the efficiency of the pump (assumed to be 85%),

The energy consumption was estimated annually (in kWh), assuming that the pump runs on average for 8 h each day for the entire year. The flow rate of the pump was estimated from the groundwater abstraction information.

The district-wise map of annual energy consumption for pumping groundwater from wells is presented in Fig. 2f.

Reporting summary

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

Data availability

The data used in the study are accessible from the websites reported in Table 1.

Code availability

The MATLAB version for the PGSL algorithm[43], which was used to solve the optimization problem, is available at https://bennyraphael.com/PGSL/MATLAB-PGSL-Release1.0.zip. The open source version of FAO's AquaCrop model (AquaCrop-OS[36], coded in MATLAB) is available at https://github.com/aquacropos/aquacrop-matlab.

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Author contributions

S.G. conceived the idea and designed the problem. R.C., K.F.D., R.D., N.D.R., J.J. and S.G. designed the solution. R.C. and S.G. wrote the

code and performed the analysis. R.C., K.F.D., R.D., N.D.R., J.J. and S.G. analysed the results. S.G. and R.C. wrote the manuscript with input from K.F.D., R.D., N.R. and J.J. R.C., K.F.D., R.D., J.J. and S.G. reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s44221-023-00135-z.

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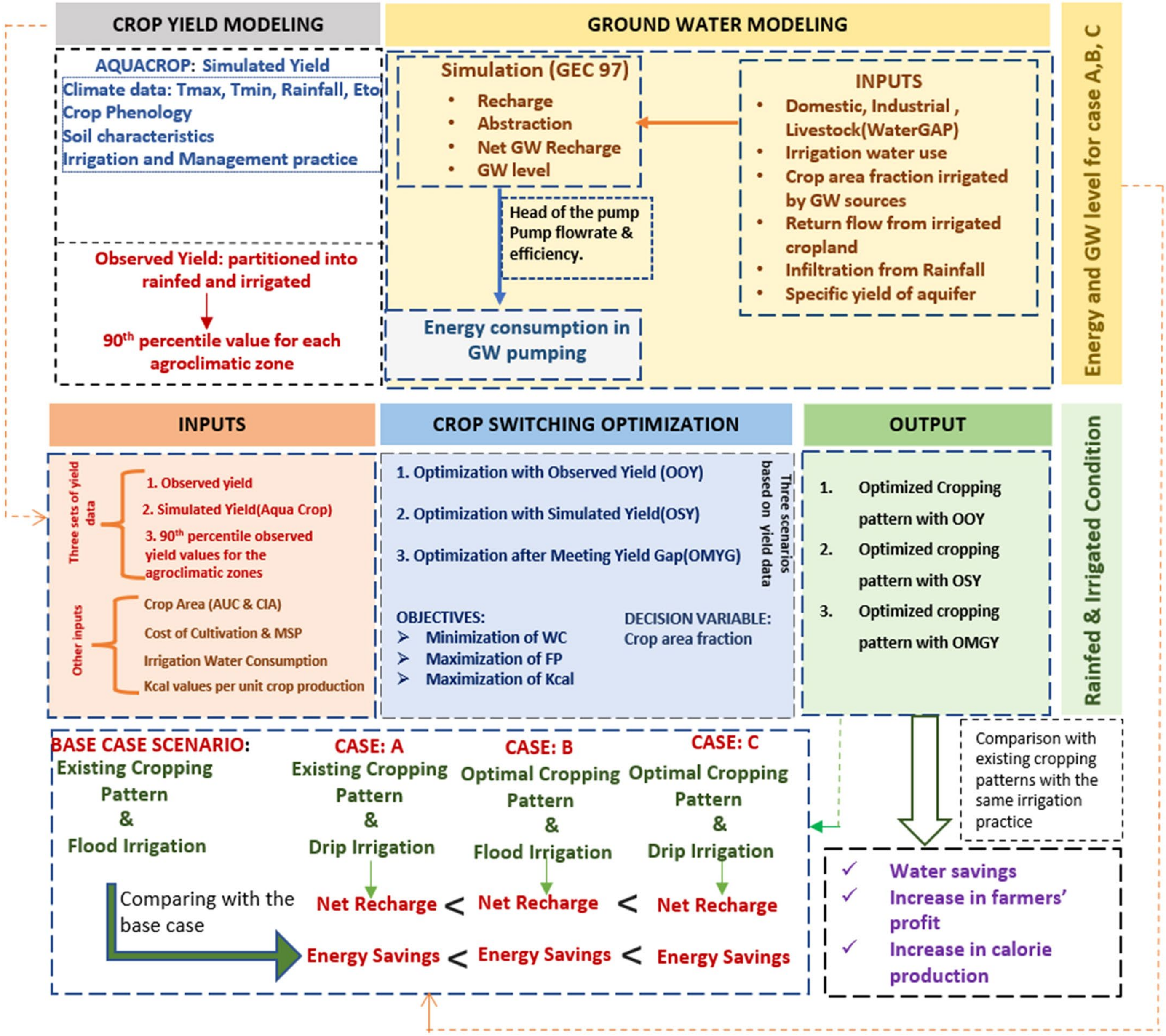
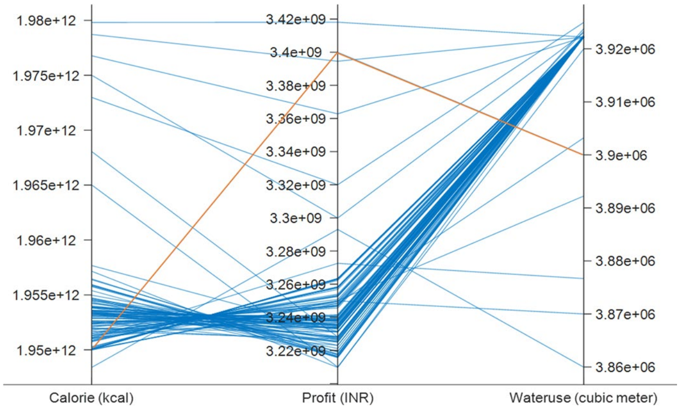
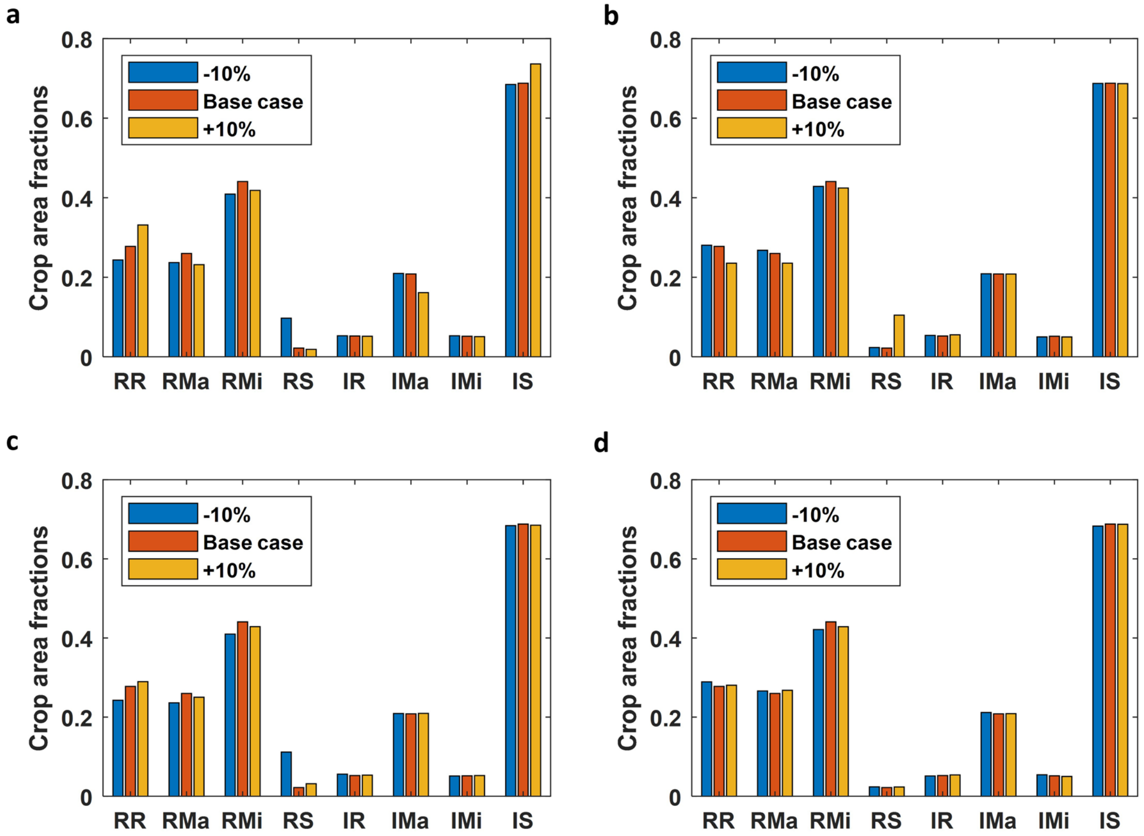


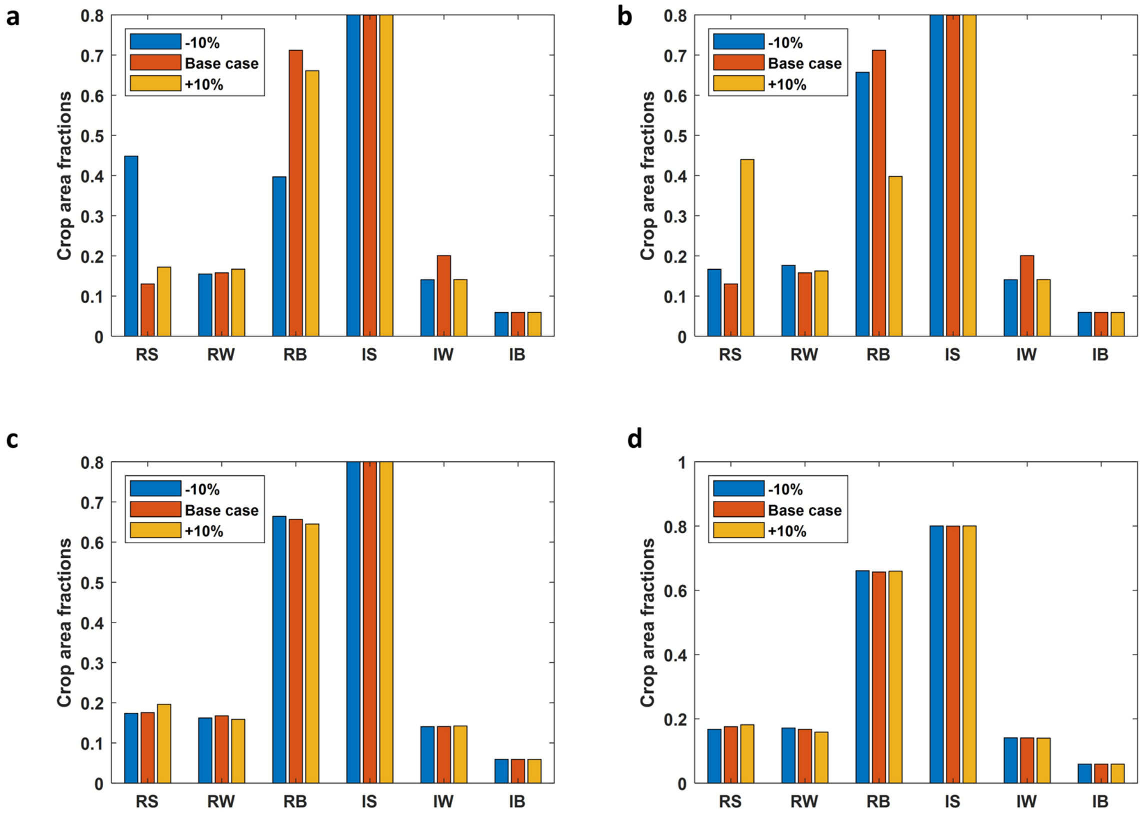
Extended Data Fig. 1 | Methodological framework. Methodology presenting different model components and information exchange between them.



Extended Data Fig. 2 | Trade off analysis. Trade off analysis for a district considering multiple objective spaces (red line represents solution from max-min optimization approach).



Extended Data Fig. 3 | Sensitivity analysis for Kharif crops. a. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in yield data as input to the optimization model **b**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in cost of cultivation data as input **c**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in MSP data as input **d**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in Irrigation Water Use data as input. (RR: Rainfed Rice, RMa: Rainfed Maize, RMi: Rainfed Millet, RS: Rainfed Sorghum, IR: Irrigated Rice, IMa: Irrigated Maize, IMi: Irrigated Millet, IS: Irrigated Sorghum).



Extended Data Fig. 4 | Sensitivity analysis for Rabi crops. a. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in yield data as input **b**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in cost of cultivation data as input **c**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in MSP data as input **d**. Optimum Crop area fractions (for both rainfed and irrigated separately) with ±10% change in Irrigation Water Use data as input. (RS: Rainfed Sorghum, RW: Rainfed Wheat, RB: Rainfed Barley, IS: Irrigated Sorghum, IW: Irrigated Wheat, IB: Irrigated Barley).

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection. All data are accessible through the links of the websites provided in the manuscript('Table 1' in Data section)
Data analysis	The MATLAB version for PGSL algorithm which is used to solve the optimization problem is available at: https://bennyraphael.com/PGSL/MATLAB-PGSL-Release1.0.zip .The open source version of FAO Aqua crop model (Aqua crop-OS, coded in MATLAB) is available at https://github.com/aquacropos/aquacrop-matlab

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Study description	The Indo-Gangetic Plain (IGP) is facing severe groundwater depletion due to agricultural intensification. One of the suggested strategies to deal with this unsustainable water usage is crop switching. However, its potential to provide co-benefits or trade-offs for other sustainability dimensions (such as food supply, farmer profit) remains largely unquantified. Here, we design and apply an optimization model for crop switching to cereals in the IGP, with the goal of maximising calorie production, farmer profit, and water efficiency. Our solution offer a larger reduction in groundwater depletion and energy savings in comparison to improving irrigation efficiency (i.e. from flood to drip).
Research sample	NA
Sampling strategy	NA
Data collection	NA
Timing and spatial scale	NA
Data exclusions	NA
Reproducibility	NA
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