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Crop switching can enhance environmental sustainability and farmer incomes in China

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Achieving food-system sustainability is a multidimensional challenge. In China, a doubling of crop production since 1990 has compromised other dimensions of sustainability[1,2]. Although the country is promoting various interventions to enhance production efficiency and reduce environmental impacts[3], there is little understanding of whether crop switching can achieve more sustainable cropping systems and whether coordinated action is needed to avoid tradeoffs. Here we combine high-resolution data on crop-specific yields, harvested areas, environmental footprints and farmer incomes to first quantify the current state of crop-production sustainability. Under varying levels of inter-ministerial and central coordination, we perform spatial optimizations that redistribute crops to meet a suite of agricultural sustainable development targets. With a siloed approach—in which each government ministry seeks to improve a single sustainability outcome in isolation—crop switching could realize large individual benefits but produce tradeoffs for other dimensions and between regions. In cases of central coordination—in which tradeoffs are prevented—we find marked co-benefits for environmental-impact reductions (blue water (−4.5% to −18.5%), green water (−4.4% to −9.5%), greenhouse gases (GHGs) (−1.7% to −7.7%), fertilizers (−5.2% to −10.9%), pesticides (−4.3% to −10.8%)) and increased farmer incomes (+2.9% to +7.5%). These outcomes of centrally coordinated crop switching can contribute substantially (23–40% across dimensions) towards China's 2030 agricultural sustainable development targets and potentially produce global resource savings. This integrated approach can inform feasible targeted agricultural interventions that achieve sustainability co-benefits across several dimensions.

The Green Revolution brought about unprecedented increases in global food supply to meet rapidly rising demand. Yet the promotion of relatively few high-yielding crops and accompanying input-intensive practices has led to serious compromises for nutrition security and the environment[4]. The development of agriculture in China has followed these same patterns. The country has made marked gains in its agricultural productivity over the past several decades, increasing national crop production by +107% since 1990 alone[1]. Despite a population of more than 1.4 billion people, the increase in China's food demand has largely been met by domestic increases in agricultural production, except for soybean[1]. Yet attaining these high levels of food production has meant mounting environmental challenges across the country. In recent decades, groundwater levels have dropped at alarming rates[2], agricultural GHG emissions have increased[1], the intensity of fertilizer application has increased substantially[1] and pesticide pollution has become more widespread[1].

In recognition of these clear tradeoffs, the Chinese government is considering a suite of interventions to improve the sustainability of agriculture without compromising the sector's high levels of production[3]. These strategies include developing 'high-standard farmland' to improve agriculture productivity while reducing input use (for example, water, fertilizer), implementing 'water-saving projects' to improve water-use efficiency and extending technologies for soil testing and nutrient recommendations to reduce fertilizer use, among others. Although all of these solutions promise to reduce the environmental burden of agriculture, they tend to focus on singular outcomes and are based on the assumption that crops are already grown in the locations in which they are most agro-climatically suited and most resource-efficient. Yet recent research has made it increasingly clear that current cropping patterns are suboptimal across several outcomes and that crop switching (that is, changes in crop distribution and/or crop rotations) may offer promise for improving agricultural sustainability. Recent global studies[5–8] have shown that crop redistribution can reduce irrigation (that is, blue) water demand (−12% to −21%) and blue-water scarcity and protect the natural environment and biodiversity while improving or maintaining food production. Several other

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analyses have recently been performed at the country level, which is necessary to account for policy-relevant factors that can influence the extent to which an agricultural solution is feasible. In India, crop redistribution has been shown to improve dietary nutrient supply, climate resilience and net farmer incomes and reduce natural-resource use and GHG emissions[9–11]. In the United States, studies found that crop switching can reduce blue-water demand[12] and climate-related crop losses[13]. Other research has shown the promise of diversifying crop rotations[14,15]. In China, field-based experiments in the North China Plain have shown that crop rotations alternative to conventional maize–wheat systems can reduce groundwater depletion and increase economic output[14]. Long-term evidence from North America has also shown the superior climate resilience of more diversified rotations[15]. Yet whether and to what extent crop switching would yield similar benefits for agricultural sustainability for the entire country of China remains unquantified.

Crop switching is a promising strategy to complement other sustainable farm-management solutions. The Chinese government has also recognized redistributing crops as a way to enhance the sustainable development of the agriculture sector[3,16]. For example, in early 2000, a crop-switching research project led by the National Development and Reform Commission (NDRC) put forward regional agriculture development directions based on historical analysis[16]. More recently, China's National Sustainable Agriculture Development Plan (2015–2030) also gave general directions by dividing China into three regions: with more emphasis on food production than sustainability (for example, in the Yangtze River region), with equal emphasis on food production and sustainability (for example, in the Northwest) and more emphasis on sustainability than food production (for example, in the Tibetan Plateau)[3]. To meet these policy priorities, it is therefore essential to quantitatively evaluate where and to what extent crop switching—in an economically feasible way—may contribute to China's sustainable development targets without compromising food supply. Furthermore, because China alone accounts for large fractions of the global population (19%)[1], primary crop production (19%)[1], natural-resource use (for example, fertilizers (25%), pesticides (10%), irrigation (13%), cropland (9%))[1,17], agrifood-system-related GHGs (12%)[1] and farmers (16%)[1], efforts undertaken in China to improve its sustainable development goals will have far-reaching implications towards addressing global food security and sustainability challenges.

Here we quantify and assess opportunities for crop switching across China, focusing on 13 crops that collectively account for 94% of China's primary crop production and 90% of its harvested area[18]. We combine gridded (5 arcmin) crop-specific data (circa the year 2010) on rainfed and irrigated yields and harvested areas[19] with each crop's water-requirement estimates, GHGs intensity[20], fertilizer application rate[21], pesticide use[21] and farmer net profit[21]. Using these data, we estimate several sustainability dimensions prioritized in China's sustainable agriculture plans[22], namely, production quantity, water demand, GHG emissions, fertilizer use, pesticide use and economic output of current crop production. We then construct a linear optimization model to simulate the contribution of crop switching to sustainable agricultural development and assess tradeoffs and co-benefits across several dimensions and different regions. Each optimization run assigns priority to one of the following objectives: minimize water demand; minimize GHGs; minimize fertilizer use; minimize pesticides; maximize farmer incomes; or maximize benefits across all dimensions simultaneously—based on three different levels of governmental cooperation (that is, siloed, cross-ministry coordination and central government coordination) (Table 1). Our optimizations reallocate harvested areas between crops and alter cropping rotations with the constraints that: (1) national supply of all crops cannot decrease—a constraint reflecting national self-sufficiency targets; (2) farmer incomes within each grid cell cannot decrease—ensuring that farmer profitability is not adversely affected; (3) only crops grown at present within a grid cell can be planted there; (4) the harvested area within each grid cell is held constant—preventing

Table 1 | Scenario summaries

| Scenarios	Sustainability dimension of objective function	Other sustainability dimensions	Farmer incomes	Crop production
G1	Optimized individually	May degrade on both national and grid levels		
G2	Optimized individually	May not degrade on national/grid levels	May not decrease at grid level	May not decrease on national level
G3	All sustainable dimensions are optimized			

G1 (no coordination): siloed approach assigning priority to a single sustainability objective at a time; G2 (cross-ministry coordination): assigning priority to one sustainability dimension while not degrading outcomes for the other sustainability dimensions at the national/grid levels; G3 (central coordination): assigning priority to the improvement margins in all dimensions being as high as possible while their between-dimension differences are as low as possible.

agricultural expansion; and (5) cropping calendars of rotating crops cannot overlap in time. We also test the uncertainties of relaxing these constraints. Finally, we quantify the outcomes of optimized crop switching and compare the magnitude of benefits to relevant sustainable development targets for China. Such evaluations of several outcomes are essential for identifying interventions capable of improving the multidimensional sustainability of agriculture.

Sustainability outcomes of potential crop switching

Different sustainability outcomes are administrated by separate government departments in China (for example, the Ministry of Water Resources—irrigation; the Ministry of Ecology and Environment—GHG emissions; the Ministry of Agriculture and Rural Affairs—fertilizers, pesticides and farmer incomes). Consequently, the narrower focus of each department on specific outcomes may work at counter-purposes towards achieving other sustainability goals. With this siloing of ministries in mind, we first explored the extent to which a single dimension of agricultural sustainability could be improved through crop switching (hereinafter referred to as G1 simulations of no coordination; Table 1). We find that there is considerable potential for crop switching to enhance sustainable development. When assigning priority to a single sustainability objective, crop switching can reduce the demand for blue water by as much as −27.8%, green water by −12.6%, GHGs by −17.1%, nitrogen fertilizers by −15.9%, phosphorous fertilizers by −15.5%, potash fertilizers by −20.6% and pesticides by −15.6% relative to current levels—without expanding cropland, reducing the production of any crop or reducing farmer incomes (Fig. 1 and Table S14). However, because a ministry assigns priority to only the sustainability objectives under its mandate, it may not necessarily consider the outcomes of other sustainability objectives for which other ministries are responsible. Accordingly, when our model optimizes an individual dimension of sustainability, we allow other dimensions to potentially degrade. Indeed, we find that, under this scenario (G1), several tradeoffs emerge between different dimensions of agricultural sustainability and between different regions (Fig. 1). We also observe a clear tradeoff with environmental outcomes when attempting to maximize farmer incomes. Under this scenario, crop switching can increase farmer incomes by as much as 90.5%, though at the cost of other environmental outcomes (Figs. S5 and S6). This suggests that efforts to increase farmer profitability under current crop-price structures would probably produce clear environmental tradeoffs.

To address this shortcoming, we examined a set of optimization scenarios in which cross-ministry coordination was enhanced to avoid sustainability tradeoffs. To reflect this, we imposed the constraints that optimizing one sustainability dimension would not degrade outcomes for the other sustainability dimensions (hereinafter referred to as G2
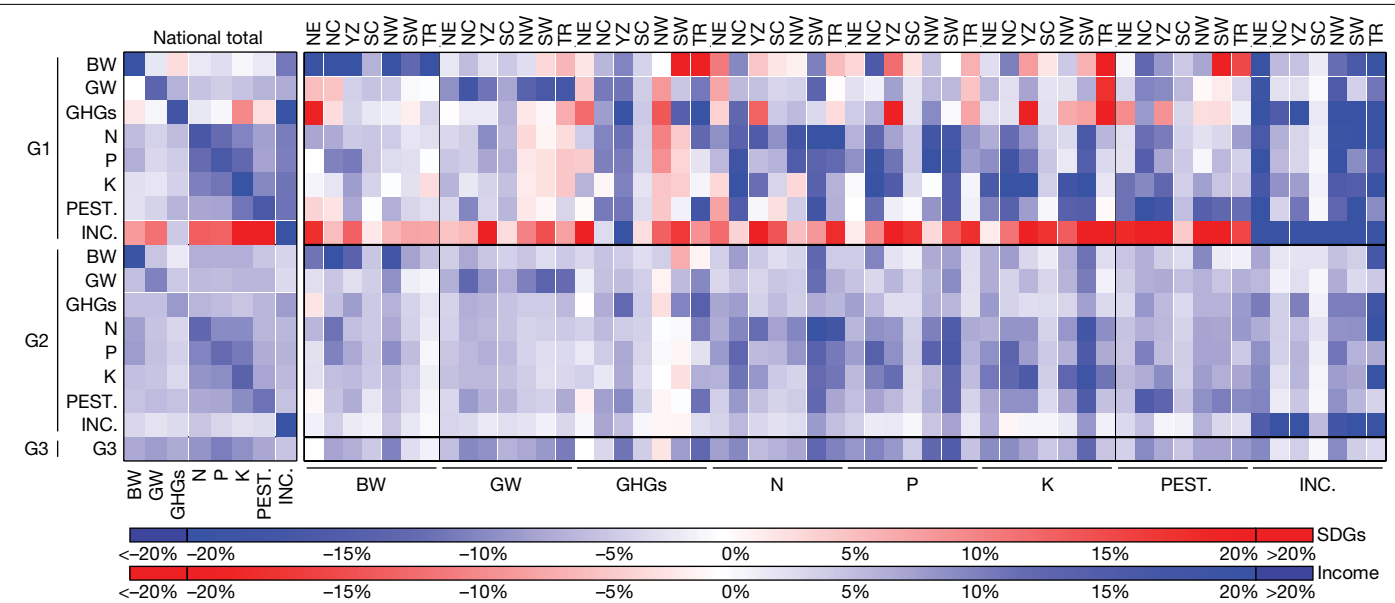
Fig. 1 | National and regional changes in resource use, environmental losses and farmer incomes through crop switching under varying levels of government coordination. Each row represents a different optimization objective and each column represents the outcome for each sustainability dimension. G1 (simulation of no coordination) shows the changes in resource use, environmental losses and farmer incomes under the siloed approach, assigning priority to a single sustainability objective at a time. G2 (simulation of cross-ministry coordination) corresponds to the scenarios in which assigning priority to one sustainability dimension would not degrade the outcomes for the other sustainability dimensions. G3 (simulation of central

coordination) represents the optimization that ensures that the improvement margins in all dimensions are as high as possible while their between-dimension differences are as low as possible. See Extended Data Figs. 1 and 2 for uncertainty analysis. BW, blue water; GW, green water; GHGs, greenhouse gas emissions; N, nitrogen fertilizers; P, phosphorus fertilizers; K, potash fertilizers; PEST., pesticides; INC., farmer incomes. The top row shows the seven regions of China: NE, Northeast Plain; NC, North China Plain; YZ, the Yangtze River Plain; SC, Southern China; NW, Northwest Region; SW, Southwest Region; TR, Tibet Region (see Fig. S3 and Table S2 for regional divisions). SDGs, sustainable development goals.

simulations of cross-ministry coordination; Table 1). Under these conditions, we found that crop switching can still achieve sizeable benefits across all dimensions—changes by as much as −18.5% (blue water), −9.5% (green water), −7.9% (GHGs), −12.0% (N fertilizer), −11.4% (P fertilizer), −13.0% (K fertilizer), −10.8% (pesticides) and +20.2% (farmer incomes). Yet, although tradeoffs are avoided between sustainability dimensions and different regions under G2, the optimization of any one objective with cross-ministry coordination would still lead to minimal benefits for other outcomes (Fig. 1 and Table S14).

To this end, we performed a multiobjective optimization to examine to what extent co-benefits can emerge for all sustainability dimensions simultaneously under a scenario in which China's central government leads the coordination (hereinafter referred to as G3 simulation of central coordination; Table 1). Under these conditions, we optimized for all sustainability dimensions such that the improvement margins in all dimensions are as high as possible while their between-dimension differences are as low as possible. In doing so, we take an agnostic position on the relative importance of each outcome. We also adapt our approach to place different weights on the outcomes to demonstrate different levels of government's political will (see Extended Data Fig. 1). Under this set of results, we found that crop switching can still achieve considerable benefits: −6.5% (−4.5% to −18.5%) for blue water; −7.5% (−4.4% to −9.5%) for green water; −6.5% (−1.7% to −7.7%) for GHGs; −8.1% (−5.2% to −12.0%) for N fertilizer; −9.8% (−5.1% to −11.4%) for P fertilizer; −8.3% (−4.5% to −13.0%) for K fertilizer; −6.7% (−4.3% to −10.8%) for pesticides; +4.5% (+2.9% to +7.5%) for farmer incomes (Fig. 1 and Table S14).

Comparing across all three levels of coordination highlights cases in which certain sustainability outcomes are similar in magnitude, whereas others can differ substantially at the national level (Table S14). As an example of the former, minimizing P fertilizer use under G1 leads to a modest (6% relative to G3) enhancement in P fertilizer savings while other outcomes are comparable in magnitude (−4% to +5% relative to

G3). Conversely, minimizing blue water under G1 leads to 23% greater blue-water savings relative to G3 but produces several losses for other outcomes (−10% to −5% relative to G3). Furthermore, the G1 scenario allows for degradation of certain sustainability criteria in some locations, which does not occur in G2 and G3. These contrasting examples point to an interesting tension between the amount of extra effort accompanying greater levels of coordination, the relative difference in benefits associated with greater coordination and the willingness to accept tradeoffs along some sustainability outcomes and among some regions. Nevertheless, our findings show that crop switching can be used as an effective strategy to address current conditions of resource depletion or unsustainable use (for example, blue-water scarcity) (Fig. 2) and the location of crop switching can be targeted on the basis of a variety of definitions and measures of sustainability (see Fig. S7 for other sustainability dimensions and Table S12 for boundaries of sustainable resource use).

Across the optimization scenarios examined here, we also find certain consistent regional changes in the distributions of specific crops. For instance, regardless of the optimization objective, we observe substantial recommended shifts, for example, wheat decrease in both the North China Plain and the Northwest Region and increase in the Yangtze River Plain; rice decrease in the Yangtze River Plain; maize increase in the Northwest Region; rapeseed decrease in the Yangtze River Plain and cotton decrease in the Northwest Region (see Figs. 3 and S9–S11). These findings point to regions in which shifts in certain crops can lead to robust outcomes for several sustainability dimensions without compromising national food production or requiring more cropland. Taken together, all of these regional and national results—accompanied by modest changes in crop rotations (Fig. S8)—demonstrate real opportunities for crop switching to improve environmental sustainability and farmer incomes (Fig. S4). We have also shown the feasibility of the proposed crop switching by comparing it with recent rates of change in crop distributions across China (see Extended Data Figs. 3–6 and
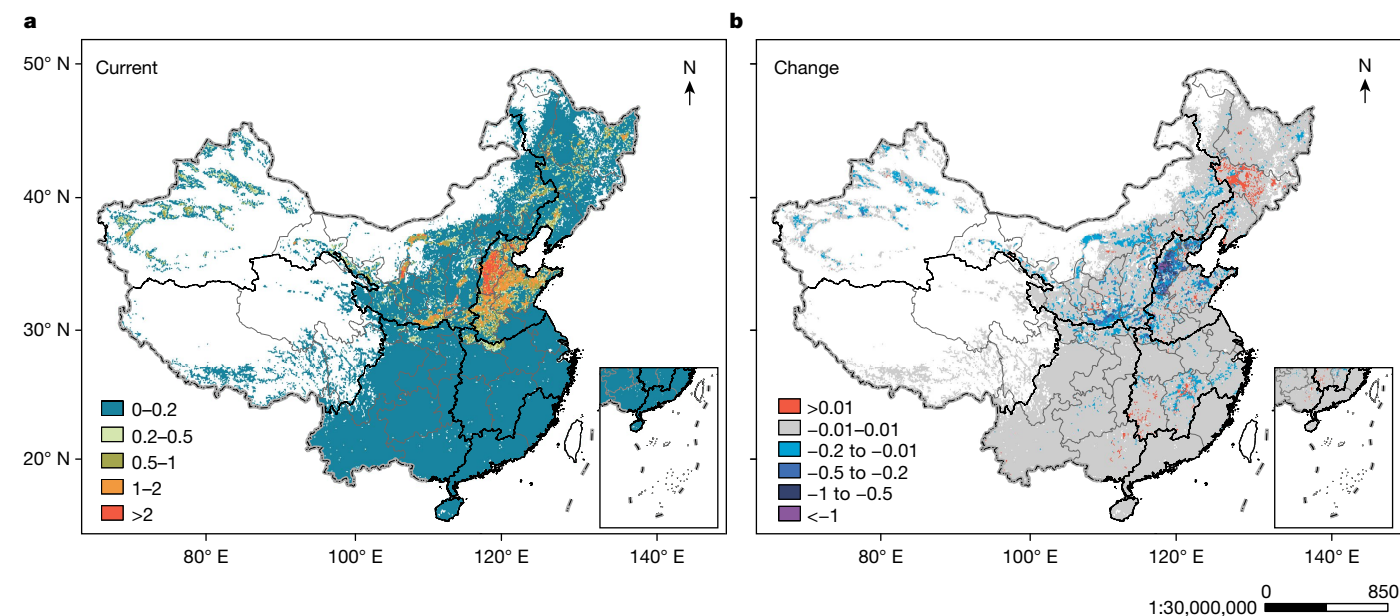
Fig. 2 | Changes in blue-water scarcity through optimized crop switching. Changes in the spatial distribution of water scarcity under the optimization scenario (G3) that simultaneously saves resources, reduces environmental losses and increases farmer incomes. **a**, Ratio of current blue-water use to water availability (that is, water scarcity)[35]. **b**, Changes in blue-water scarcity after crop switching. The base map was applied without endorsement using data from the National Geomatics Center of China (NGCC; http://www.ngcc. cn/ngcc/) and the Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences (IARRP; https://iarrp.caas.cn/).

Figs. S12–S14). Although this demonstrates that such changes may be feasible in the near future, unprecedented events such as the COVID-19 pandemic could slow the pace of domestic-policy change and implementation. On the other hand, the increasingly consolidated ability of the central government—combined with China's emphasis on domestic food supply and demonstrated ability to alter cropping patterns in the face of recent past events (for example, SARS and the global financial crisis)—could also mean that change can occur more quickly than has historically occurred if there is political will to do so.

## Meeting China's agricultural sustainable development targets

Different agencies in China set specific reduction targets for selected sustainability dimensions as a measure of progress towards achieving certain sustainable development goals. Realizing any one of the goals requires a combination of investments, technological and infrastructural improvements, policy reforms and, ultimately, a suite of interventions that will probably be necessary to fully meet sustainability targets. To explain the relative impact magnitudes of crop switching, we compare its potential benefits (that could be realized in the coming decades depending on the government's political will to do so) with China's 2030 sustainable development goals in a counterfactual way (Figs. 4 and S15). According to the agricultural water-demand projections[23] and the sustainable development goal[3], China needs to save 30 km³ of blue water by 2030, and our crop switching can save 7.8 (5.4–22.1) km³—equivalent to 26% (18–74%) for this goal under the G3 simulation of central coordination. For GHGs, China's government aims to peak emissions around 2030 and realize a net-zero emissions target before 2060. Although there is no specific target for agricultural GHG abatement, we assume no further increase after 2020 as a strict mitigation goal. Accordingly, we estimate that crop switching can contribute 24% (6–29%) towards achieving this goal. For fertilizers and pesticides, China has adopted a zero-increase plan[24,25]. Compared with these targets, savings from crop switching would also be substantial—equivalent to 40% (24–51%) for fertilizers and 23% (15–37%) for pesticides by 2030. Increasing farmer incomes is also

an important goal for the government. The Chinese Academy of Social Sciences projects that farmers' personal disposable income in 2030 will double from its 2020 level of US$2,600 per year (ref. [26]). Most of the increase in farmer incomes will be from non-agricultural industries and high-value-added agricultural activities rather than traditional crop production. Our estimates still show that crop switching not only aids in realizing environmental sustainability goals in China but can also increase farmers' personal income by US$6.3 to US$126.

## Potential contribution to global resource savings

Agricultural trade has clear implications for food security, livelihoods and the environment in both exporting and importing countries[27]. The already large agricultural trade flows into and out of China, combined with its projected future food demand, mean that the country will play an important (and growing) role in determining global agricultural sustainability outcomes[28]. A prime example of this is China's soybean imports, which have not only markedly altered the country's cropping systems and damaged its environment[29] but also placed reliance on remote natural-resource use[30,31]. By redistributing soybean production to regions with high yields and lower resource-use intensities in China, crop switching can help the country use natural resources more efficiently and, at the same time, produce more soybeans. The increased production of soybean and other main crops in China has the potential to cascade through the global trade network (through China's reduced import demand) and may lead to global resource savings (Table S15; see Supplementary Information Section 1.2.4 for the estimation method) and other indirect environmental and ecological benefits (see, for example, Folberth et al.[8])—depending on how the trade partners would respond to China's decreased international crop demand (for example, decreased production, sale of crops elsewhere etc.). If China's trade partners did in fact reduce production and exports in response to China's crop switching, we estimate that this could lead to substantial resource savings for China's trade partners of blue water (0.3 to 102.9 km³), GHGs (0.5 to 24.6 million tonnes CO_2 eq) and fertilizers (0.1 to 14.0 million tonnes) (Table S15).
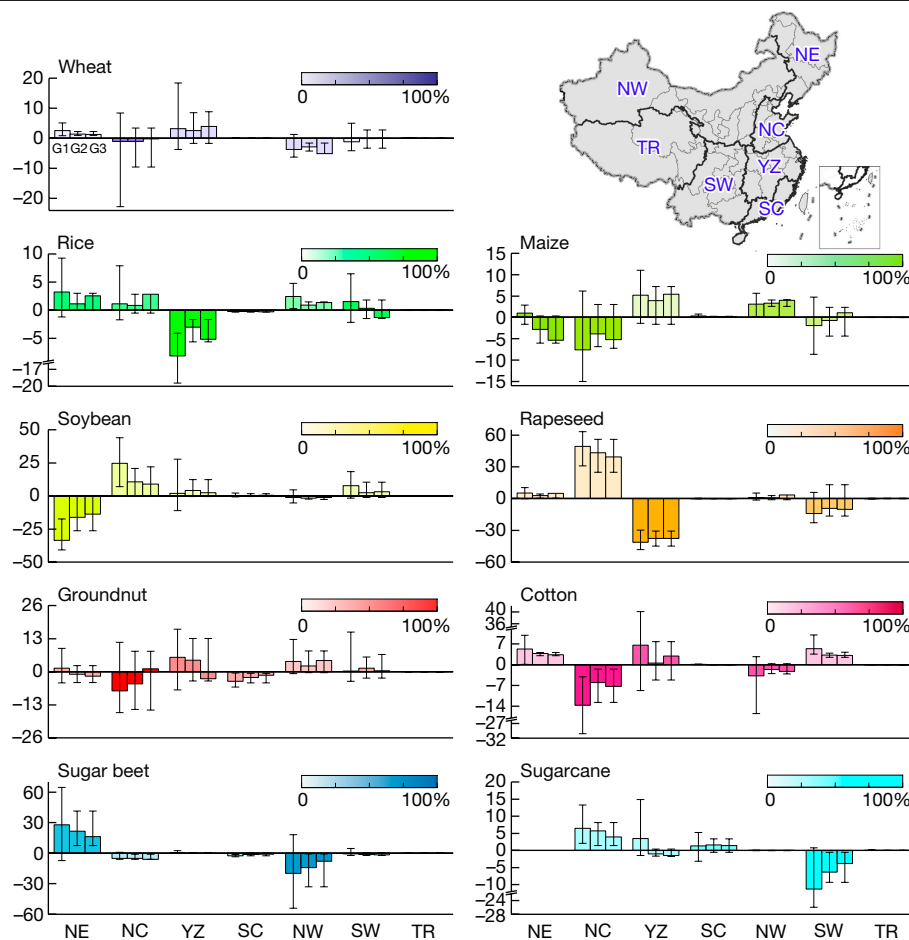
Fig. 3 | Proposed changes in crop-production distribution. The *y* axis indicates the percentage point differences between the shares (%) in the national production of a specific crop in each region before and after crop switching. In each group of three bars, the left, middle and right bars are the average change of regional crop-production share under G1 (eight scenarios), G2 (eight scenarios) and G3 (one scenario), respectively. The whiskers indicate the minimum and maximum of all changes; whiskers for G3 bars represent the range of Pareto-optimal outcomes (see Extended Data Fig. 1). The colour scale of the bars corresponds to the share of current crop production of each region to the national total; for instance, the darker shades of the bars for wheat in the

North China Plain (NC) and rice in the Yangtze River Plain (YZ) indicate that these regions account for large shares in the total national production of those crops. The map in the top-right corner shows the distribution of the seven regions of China: NE, Northeast Plain; NC, North China Plain; YZ, Yangtze River Plain; SC, Southern China; NW, Northwest Region; SW, Southwest Region; TR, Tibet Region (see Fig. S3 and Table S2 for regional divisions). The base map for China was applied without endorsement using data from the National Geomatics Center of China (NGCC; http://www.ngcc.cn/ngcc/) and the Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences (IARRP; https://iarrp.caas.cn/).
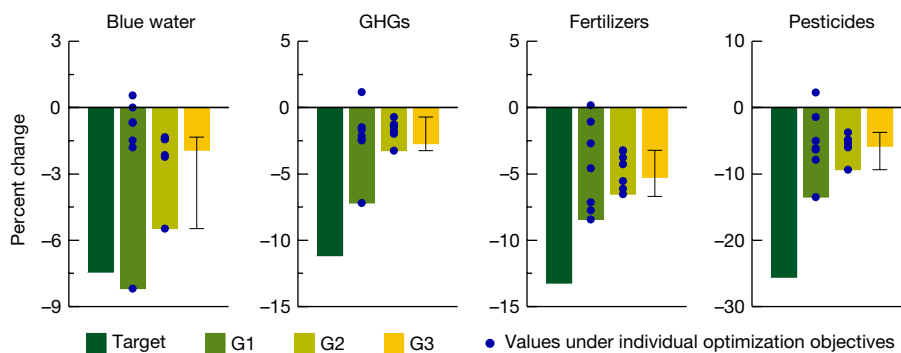
Fig. 4 | Comparison of crop-switching benefits with China's 2030 official agricultural sustainability targets. The dark-green bars ('Target') show the difference between the baseline projection and China's official agricultural sustainability targets in 2030. Under the baseline, the projection of blue water is based on existing literature[23]. As the projections of other sustainable dimensions for China were unavailable in the literature, we multiplied projected crop production in 2030 (ref. [36]) and current resource-use intensities

(see 'Current state of sustainability outcomes' in Methods) to estimate their baseline projections. The other three bars represent the crop-switching benefits of the G1, G2 and G3 scenarios. The blue points represent the crop-switching benefits/costs of individual optimization objectives. The whiskers for the G3 bars represent the range of Pareto-optimal outcomes (see Extended Data Fig. 1).

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A scientific basis for sustainable agricultural interventions

This study shows that crop switching is an important measure that can help achieve several sustainable development targets in China while improving farmer incomes and maintaining national production on existing croplands. We also show that siloed efforts by individual ministries (based on their narrow individual definitions of sustainability) may lead to substantial tradeoffs for other sustainability outcomes and work at counter-purposes to the goals of other ministries. As such, coordination is essential for avoiding tradeoffs and, more desirably, realizing several co-benefits, and for a country such as China with a large central planner government, such large-scale coordination is indeed feasible. Further, because sustainability outcomes are dependent on location, our study can enable the provision of spatially detailed solutions for different areas of China based on local conditions and sustainability priorities (Fig. 3). For instance, the consistent shifts that we observe away from some maize and towards soybean, sugar beet and rice in the Northeast Plain (NE) would benefit farmer incomes (as well as reducing the overuse of fertilizers and pesticides and preventing black-soil degradation) (Table S14) and point to initial opportunities for policymakers to implement crop switching. Similarly, in the Yangtze River Plain, sustainability co-benefits can be realized by reducing rapeseed and rice and increasing cultivation of wheat and maize, especially for GHG emissions. In the North China Plain, increases in soybean, rapeseed and rice in lieu of some wheat, maize, cotton and groundnut (Figs. S10 and S11) can also contribute to more sustainable cropping patterns and contribute substantially to alleviating regional water scarcity and excessive fertilizer use (Figs. 2 and S7). Such spatially explicit quantifications (such as those produced here) can thus play an important role in evaluating where agricultural interventions—and which specific cropping switches—can offer the greatest benefits.

This study provides detailed, actionable scientific evidence as the Chinese government increases efforts to implement crop switching as a means of achieving more sustainable agriculture. Critical to realizing these changes will be the challenge of encouraging farmers to adopt new cropping choices. However, such changes are potentially realistic and achievable (Figs. S12–S14), especially considering that China has previously had success in incentivizing farmers at the provincial level[32] and even county level[33] to choose crops intended to achieve national food-security targets. The spatially detailed results of our analysis also directly meet the information needs described in recent government plans, which seek to address agricultural sustainability issues related to cultivated land, water resources, ecological protection and national food production and food security[3]. Further, our findings demonstrating the benefits of increased inter-ministry cooperation are in line with recent plans by the Chinese government to strengthen coordination and enhance close cooperation among different agencies through the 'Plan for Green Agricultural Development'[34]. Taken together, our quantitative multidimensional assessment provides an objective, science-based foundation for ensuring the feasibility of potential solutions for more sustainable agricultural systems.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-023-05799-x.

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Methods

The crop-switching method for improving different (or several) sustainability outcomes across China involved the use of diverse datasets and cross-disciplinary techniques. The overall framework of our methods is summarized in Fig. S2. Our approach followed four main tasks. First, we defined the crops to be included in the study. Second, we calculated green and blue water demand using a process-based crop water model (in four steps). Third, we quantified the current state of sustainability outcomes in China. Fourth, we developed and implemented single-objective and multiobjective crop-switching optimization models.

Crop definitions

We focus on 13 main crops, wheat (spring wheat; winter wheat), rice (early rice; middle-season rice; late rice), maize (spring maize; summer maize), soybean, rapeseed, groundnut, cotton, sugar beet and sugarcane, which account for 94% of China's primary crop production and 90% of its harvested area[18]. For the crops we did not consider owing to data limitations, such as vegetables and fruits, we assumed that their harvest area and production remain constant and unaffected under our crop switching. Spatial data (5 arcmin; 1/12°; about 10 km resolution; dividing China into 72,000 grids) on crop-specific irrigated/rainfed yields (kg ha^{-1}) and harvested areas (ha) were taken from the latest Spatial Production Allocation Model (SPAM) database (version 1.1, year 2010) of the International Food Policy Research Institute[19]. Note that the areas with higher yields in 2010 are still more productive than other places in the past few years (Fig. S1), so our results are not sensitive to using the year 2010 SPAM maps.

For each grid, the current (year 2010) production of irrigated (Production$_{Cur,irr,z}$) and rainfed (Production$_{Cur,ra,z}$) crops were calculated as:

$$\text{Production}_{\text{Cur,irr/ra},z} = \sum_i \text{HA}_{\text{irr/ra},i,z} \times \text{YLD}_{\text{irr/ra},i,z} \tag{1}$$

in which HA is harvested area (ha), YLD is yield (kg ha^{-1}), the subscripts irr and ra represent irrigated and rainfed cropping systems, respectively, i represents the grids (i = 1, 2, ..., 72,000) and z is crops. The national combined irrigated and rainfed production of each crop agrees well with that reported in FAOSTAT[1] (Tables S1 and S9–S11).

Calculation of green and blue water using a process-based crop water model

In our approach, consumptive blue and green water requirements and demand are estimated directly by us using a process-based crop water model based on the Penman–Monteith equation. Green water refers to the effective precipitation consumed during the growing period of a crop. Blue water refers to the amount of water that needs to be supplemented by irrigation when natural, effective precipitation during the crop-growing season is insufficient to maintain the normal growth of the crop. We first calculated the water requirements of different crops (ET$_z$) based on the Penman–Monteith equation and the crop coefficient method recommended by the FAO[37]. This method is widely used for calculating crop water requirements (equations (2)–(4)). We then calculated crop-specific and grid-level green water and blue water demand (equations (5)–(8)). We used a long-term climatic dataset (1987–2016) from more than 800 weather stations in China and calibrated the crop coefficients (K_z) for the selected crops in different regions of China (equation (3)). All climate-related parameters were based on daily observed data from weather stations (see data sources in Table S16). To avoid the unrepresentative impact of extreme weather in a single year on the crop water requirements, we used 30-year (1987–2016) average values of climate data rather than single-year values to calculate the ET$_z$, GW$_z$ and BW$_z$ of each crop.

Step 1: calculating the potential evapotranspiration
Potential evapotranspiration ET$_0$ (mm) was calculated as

$$\text{ET}_0 = \frac{0.498\Delta(R_\text{n} - G) + \gamma\frac{900}{T_\text{mean} + 273}u_2(e_\text{s} - e_\text{a})}{\Delta + \gamma(1 + 0.34u_2)} \tag{2}$$

in which R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), T_mean is the daily average temperature (°C), u_2 is the wind speed at 2 m height (m s^{-1}), e_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa), Δ is the slope of the vapour pressure–temperature curve (kPa °C^{-1}) and γ is the psychrometric constant (kPa °C^{-1}).

Step 2: calibration of crop coefficients and calculation of crop water requirement

Crop coefficients were calculated using the single-valued averaging method recommended by Allen et al.[38]. In general, their recommended K_z is applicable for average semi-humid climate conditions (with a minimum relative humidity of 45% and an average wind speed of 2 m s^{-1}). The K_z therefore needs to be revised according to local conditions. In this study, we calibrated the crop coefficients of selected crops according to the climatic conditions in the specific study areas of China based on the calibration equation suggested by Allen et al.[38] (equation (3)):

$$K_z = K_{z(\text{tab})} + [0.04(u_2 - 2) - 0.004(\text{RH}_{\min} - 45)](h/3)^{0.3} \tag{3}$$

in which $K_{z(\text{tab})}$ is the crop coefficient under the standard conditions at different growth stages (based on Allen et al.[38]), RH$_{\min}$ is the average value of the daily minimum relative humidity during a particular growth stage (%) and h is the average height of the crop during a particular growth stage (m). After making this adjustment, the crop water requirement (ET$_z$) was then calculated as the product of K_z and ET$_0$.

$$\text{ET}_z = K_z\text{ET}_0 \tag{4}$$

Step 3: calculation of crop-specific green and blue water demand
Crop-specific green and blue water demands were calculated as:

$$\text{GW}_z = 10 \times \sum \min(0, \text{ET}_{z,t}, P_{\text{eff},t}) \tag{5}$$

$$\text{BW}_z = 10 \times \sum \max(0, \text{ET}_{z,t} - P_{\text{eff},t}) \tag{6}$$

in which GW$_z$ is the green-water use of crop z, BW$_z$ is the blue-water demand of crop z, ET$_{z,t}$ refers to the water requirement in the tth growth period of the crop and $P_{\text{eff},t}$ is the effective precipitation in the tth growth stage of the crop calculated following Yin et al.[39]. To compare crops with different lengths of growing periods, we converted into annual values as GW$_z$ and BW$_z$ of crops (expressed in m^3 ha^{-1}).

On rainfed cropland, we can only obtain the data for green-water demand (GW$_z$). On irrigated cropland, however, we can obtain the data for both green-water demand (GW$_z$) and blue water demand (BW$_z$) for crop z, which was initially calculated from weather station data. We then interpolated the GW$_z$ and BW$_z$ values into grid-cell (5-arcmin) data as GW$_{i,z}$ and BW$_{i,z}$ using the 'inverse distance weighted' tool in ArcGIS 10.2 software.

Step 4: current green and blue water demand at the grid level
Current total green-water demand (TGW$_{\text{irr/ra},i}$) and total blue-water demand (TBW$_{\text{irr},i}$) of each grid were calculated as:

$$\text{TGW}_{\text{irr/ra},i} = \sum_z \text{HA}_{\text{irr/ra},i,z} \times \text{GW}_{i,z} \tag{7}$$

$$\text{TBW}_{\text{irr},i} = \sum_z \text{HA}_{\text{irr},i,z} \times \text{BW}_{i,z} \tag{8}$$

Article

Current state of sustainability outcomes

Unlike the process-based modelling required to estimate crop water demand above, fertilizer use, pesticide use and farmer incomes are assessed directly on the basis of official statistical data, whereas the GHG intensity data are from previous literature[20].

Current fertilizer use. Current nitrogen fertilizer use in grid i ($TFN_{irr/ra,i}$) was calculated as:

$$TFN_{irr/ra,i} = \sum_z HA_{irr/ra,i,z} \times FN_{i,z} \tag{9}$$

in which $FN_{i,z}$ is the nitrogen fertilizer use intensity of different crops (kg ha^{-1}). Current phosphorus ($TFP_{irr/ra,i}$) and potash ($TFK_{irr/ra,i}$) fertilizer use was calculated by changing $FN_{i,z}$ to phosphorus ($FP_{i,z}$) or potash ($FK_{i,z}$) fertilizer use intensity. Owing to unavailable data at finer spatial scales, we perform the analysis using provincial average fertilizer-use intensities as input data to represent these intensities in each grid, taken from Cost-benefit of Agricultural Products in China[21]. In our uncertainty analysis, we also improved the resolution of fertilizer-use data, for which we constructed the intensity of fertilizer use for different crops at the county level by using the total amount of chemical fertilizer application at the county level[40] and the intensity of fertilizer application for different crops at the provincial level[21] (Fig. S17). It is noted that the fertilizer data from NDRC cover four parts, that is, nitrogen, phosphorus, potash and compound fertilizer. We divide the compound fertilizer into nitrogen, phosphorus and potash fertilizer according to its chemical composition: for the diammonium hydrogen phosphate ((NH_4)$_2$HPO$_4$), we divide it into N and P$_2$O$_5$ according to the ratio 1:2.56; for the other compound fertilizers, we divide it into N, P$_2$O$_5$ and K$_2$O according to the ratio 1:1:1.

Current pesticide use. Current pesticide use in grid i ($TPT_{irr/ra,i}$) was calculated as:

$$TPT_{irr/ra,i} = \sum_z HA_{irr/ra,i,z} \times PT_{i,z} \tag{10}$$

in which $PT_{i,z} = PTC_{i,z}/pc$, $PTC_{i,z}$ is the crop-specific pesticide cost per hectare (US\$ ha^{-1}) in grid i, which was taken in the same way as fertilizer-use intensity and pc (US\$ kg^{-1}) is the price per unit of fertilizer, which was taken from the National Bureau of Statistics of China[18].

Farmer incomes. Farmer incomes at the grid level ($TFI_{irr/ra,i}$) were calculated as:

$$TFI_{irr/ra,i} = \sum_z HA_{irr/ra,i,z} \times YLD_{irr/ra,i,z} \times NetProfit_{i,z} \tag{11}$$

in which $NetProfit_{i,z}$ is the farmer's net profit (US\$ kg^{-1}) acquired for crop z in grid i. The farmer incomes coefficient information was taken from the NDRC[21] and processed in the same way as fertilizer-use intensity.

Current GHG emissions. Current GHG emissions in grid i ($TGHG_{irr/ra,i}$) were calculated as:

$$TGHG_{irr/ra,i} = \sum_z HA_{irr/ra,i,z} \times GHG_{i,z} \tag{12}$$

in which $GHG_{i,z}$ is the crop-specific GHG intensity (Mg CO$_2$ eq ha^{-1}) in grid i, taken from Carlson et al.[20]. Because the crop-specific GHG intensities from Carlson et al. are for the year 2000, we used the FAO's crop emissions data[1] to estimate the percent changes in China's GHG emissions from 2000 to 2010 and update grid-level crop-specific GHG intensities for 2010.

The crop-switching model

To evaluate different degrees of coordination in government management, we developed three groups of crop-optimization scenarios (Tables 1 and S5) and solved them using the software GAMS (version 22.8). (1) The first group, G1 (no coordination), simulates the potential behaviour of different independent government departments with a narrow focus on their own political responsibility. Specifically, the first group contains eight optimization scenarios that assign priority to a single sustainability objective in each scenario to explore the extent to which a single dimension of agricultural sustainability could be improved through crop switching. (2) The second group, G2 (cross-ministry coordination), aims to enhance cross-ministry coordination by considering other sustainability objectives. Specifically, the second group ensures that assigning priority to one sustainability dimension cannot degrade outcomes for the other sustainability dimensions. There are also eight scenarios in G2 for eight agricultural sustainability dimensions. (3) The third group, G3 (central coordination), examines whether co-benefits can emerge for all sustainability dimensions simultaneously when the central government of China leads the coordination. Specifically, the third group only includes one scenario that optimizes all sustainability dimensions such that the improvement margins in all sustainable dimensions are as high as possible while their between-dimension differences are as low as possible.

(1) G1 (no coordination): siloed approach assigning priority to a single sustainability objective each time.

Min/max SDG$_{Dim}$ (minimize national use of blue water or other six sustainable dimensions or maximize national farmer incomes) such that

$$\sum_{\{irr,ra\},i,j} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \geq \sum_{\{irr,ra\}} Production_{Cur,irr/ra,z} \tag{13}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\}} TFI_{irr/ra,i} \tag{14}$$

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z} \geq \sum_{\{irr,ra\},i} CURRENT_{Dim,irr/ra,i} \tag{15}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z} \leq \begin{cases} \sum_{\{irr,ra\}} CURRENT_{Dim,irr/ra,i}|(Ind_{Dim,i} \geq BD_{Dim,i}) \\ UPBOUND_{Dim,i}|(Ind_{Dim,i} < BD_{Dim,i}) \end{cases} \tag{16}$$

$$\sum_j x_{irr/ra,i,j} \leq 1 \tag{17}$$

$$\sum_{j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} = \sum_z HA_{irr/ra,i,z} \tag{18}$$

$$SDG_{Dim} = \sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z} \tag{19}$$

in which Dim represents the eight agricultural sustainability dimensions and SDG$_{Dim}$ is the total national use of Dim; $CA_{irr/ra,i}$ is the cultivated area of irrigated or rainfed croplands in grid i that was calculated by the harvested area and the growth-stage information of crops in each grid; j is the rotation number ($j = s1, s2, …, s153$) (Tables S4 and S13); $x_{irr/ra,i,j}$ is the proportion of the irrigated or rainfed cultivated land applying crop rotation j in grid i; $R_{j,z}$ represents the number that crop z is planted per year in rotation j, which are built using the crop-rotation model (Supplementary Information Section 1.2.2) according to the crop-specific growth-stage information in each region of China (Tables S2 and S3 and Fig. S3); $UI_{Dim,i,z}$ is the use (or emissions) intensity

of a specific sustainability dimension (Dim) in grid i of crop z; $\text{CURRENT}_{\text{Dim,irr/ra},i}$ represents the current use (or emissions) of a specific sustainability dimension (Dim) across all crops in grid i; $\text{UPBOUND}_{\text{Dim},i}$ represents the upper boundary of the total use (or emissions) across all crops in grid i, which is greater than $\sum_{\{\text{irr,ra}\}} \text{CURRENT}_{\text{Dim,irr/ra},i}$ when $\text{Ind}_{\text{Dim},i} \leq \text{BD}_{\text{Dim},i}$. $\text{Ind}_{\text{Dim},i}$ represents an indicator to evaluate the scarcity or stress of a sustainability dimension (Dim) in grid i and $\text{BD}_{\text{Dim},i}$ is a scientifically defined sustainability boundary. Taking blue water as an example, $\text{UPBOUND}_{\text{BW},i} = \text{BD}_{\text{BW},i}/\text{Ind}_{\text{BW},i} \cdot \text{CURRENT}_{\text{BW,irr},i}$, in which $\text{Ind}_{\text{BW},i}$ is the blue-water-scarcity indicator, which is equal to blue-water use divided by irrigation water availability, taken from the work of Zhou et al.[35] (with boundary equal to 0.2), which is a presumptive standard for environmental flow requirements following Richter et al.[41]. For nitrogen and phosphorus fertilizer, $\text{UPBOUND}_{\text{N/P},i} = \sum_{\{\text{irr,ra}\}} \text{CURRENT}_{\text{N/P,irr/ra},i} - \text{Ind}_{\text{N/P},i}$, in which $\text{Ind}_{\text{N/P},i}$ is the nutrient balance indicator representing the excess nitrogen and phosphorus nutrients in the soil (kg)—meant to prevent nutrient loading and eutrophication—taken from West et al.[42] and the boundaries $\text{BD}_{\text{N/P},i}$ are all 0. For green water and pesticides, we impose the constraint that they cannot degrade at the grid level. For GHGs and potash, considering that the distribution of GHG emissions across grids is inconsequential from a climate change perspective and that the application of potash fertilizer has little adverse impact on the local environment, we impose constraints at the national level on these two dimensions.

Equation (13) represents the constraint on crop production at the national level. Equation (14) is the constraint of farmer incomes at the grid level. Equations (15) and (16) represent the constraints of resource use and environmental footprints on the national and grid levels, respectively. For the grids experiencing unsustainable resource use at present ($\text{Ind}_{\text{Dim},i} \geq \text{BD}_{\text{Dim},i}$), we do not allow resource use to increase; for the grids in which resource use is not beyond the sustainability boundary ($\text{Ind}_{\text{Dim},i} < \text{BD}_{\text{Dim},i}$), we allow resource use to increase but only up to the sustainability boundary. For the scenario that minimizes national total GHG emissions or potash fertilizer use, we omit the estimation of equation (16), as there are no grid-level constraints for these two dimensions. Equations (17) and (18) are constraints of cultivated land and harvested land, respectively. The harvested area is held constant at the grid level. Equation (19) is the overall optimization object.

(2) G2 (cross-ministry coordination): assigns priority to one sustainability dimension while not degrading outcomes for the other sustainability dimensions.

Min/max SDG_{Dim} (minimize national use of blue water or other six sustainable dimensions or maximize national farmer incomes) such that

$$\sum_{\{\text{irr,ra}\},i,j} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \geq \sum_{\{\text{irr,ra}\}} \text{Production}_{\text{Cur,irr/ra},z} \tag{20}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \cdot \text{NetProfit}_{i,z} \geq \sum_{\{\text{irr,ra}\},i} \text{TFI}_{\text{irr/ra},i} \tag{21}$$

$$\sum_{i,j,z} \text{CA}_{\text{irr},i} \cdot x_{\text{irr},i,j} \cdot R_{j,z} \cdot \text{BW}_{i,z} \leq \sum_{i} \text{TBW}_{\text{irr},i} \tag{22}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GW}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TGW}_{\text{irr/ra},i} \tag{23}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GHG}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TGHG}_{\text{irr/ra},i} \tag{24}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FN}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFN}_{\text{irr/ra},i} \tag{25}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FP}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFP}_{\text{irr/ra},i} \tag{26}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FK}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFK}_{\text{irr/ra},i} \tag{27}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{PT}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TPT}_{\text{irr/ra},i} \tag{28}$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \cdot \text{NetProfit}_{i,z} \geq \sum_{\{\text{irr,ra}\}} \text{TFI}_{\text{irr/ra},i} \tag{29}$$

$$\sum_{j,z} \text{CA}_{\text{irr},i} \cdot x_{\text{irr},i,j} \cdot R_{j,z} \cdot \text{BW}_{i,z} \leq \begin{cases} \text{TBW}_{\text{irr},i} | (\text{Ind}_{\text{BW},i} \geq \text{BD}_{\text{BW},i}) \\ \text{UPBOUND}_{\text{BW},i} | (\text{Ind}_{\text{BW},i} < \text{BD}_{\text{BW},i}) \end{cases} \tag{30}$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GW}_{i,z} \leq \sum_{\{\text{irr,ra}\}} \text{TGW}_{\text{irr/ra},i} \tag{31}$$

$$\begin{aligned} &\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FN}_{i,z} \\ &\leq \begin{cases} \sum_{\{\text{irr,ra}\}} \text{TFN}_{\text{irr/ra},i} | (\text{Ind}_{\text{N},i} \geq \text{BD}_{\text{N},i}) \\ \text{UPBOUND}_{\text{N},i} | (\text{Ind}_{\text{N},i} < \text{BD}_{\text{N},i}) \end{cases} \end{aligned} \tag{32}$$

$$\begin{aligned} &\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FP}_{i,z} \\ &\leq \begin{cases} \sum_{\{\text{irr,ra}\}} \text{TFP}_{\text{irr/ra},i} | (\text{Ind}_{\text{P},i} \geq \text{BD}_{\text{P},i}) \\ \text{UPBOUND}_{\text{P},i} | (\text{Ind}_{\text{P},i} < \text{BD}_{\text{P},i}) \end{cases} \end{aligned} \tag{33}$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{PT}_{i,z} \leq \sum_{\{\text{irr,ra}\}} \text{TPT}_{\text{irr/ra},i} \tag{34}$$

$$\sum_{j} x_{\text{irr/ra},i,j} \leq 1 \tag{35}$$

$$\sum_{j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} = \sum_{z} \text{HA}_{\text{irr/ra},i,z} \tag{36}$$

$$\text{SDG}_{\text{Dim}} = \sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{UI}_{\text{Dim},i,z} \tag{37}$$

Compared with the G1 scenarios, we set constraints on all sustainable dimensions at the national (equations (21)–(28)) and grid (equations (29)–(34)) levels (except GHG emissions and potash fertilizer at the grid level).

(3) G3 (central coordination): optimizes all sustainability dimensions such that the improvement margins in all dimensions are as high as possible while their between-dimension differences are as low as possible.

Max Aver(G_{Dim})/Var(G_{Dim}) such that

$$\sum_{\{\text{irr,ra}\},i,j} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \geq \sum_{\{\text{irr,ra}\}} \text{Production}_{\text{Cur,irr/ra},z} \tag{38}$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \cdot \text{NetProfit}_{i,z} \geq \sum_{\{\text{irr,ra}\},i} \text{TFI}_{\text{irr/ra},i} \tag{39}$$

$$\sum_{i,j,z} \text{CA}_{\text{irr},i} \cdot x_{\text{irr},i,j} \cdot R_{j,z} \cdot \text{BW}_{i,z} \leq \sum_{i} \text{TBW}_{\text{irr},i} \quad (40)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GW}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TGW}_{\text{irr/ra},i} \quad (41)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GHG}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TGHG}_{\text{irr/ra},i} \quad (42)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FN}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFN}_{\text{irr/ra},i} \quad (43)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FP}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFP}_{\text{irr/ra},i} \quad (44)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FK}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TFK}_{\text{irr/ra},i} \quad (45)$$

$$\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{PT}_{i,z} \leq \sum_{\{\text{irr,ra}\},i} \text{TPT}_{\text{irr/ra},i} \quad (46)$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{YLD}_{\text{irr/ra},i,z} \cdot \text{NetProfit}_{i,z} \geq \sum_{\{\text{irr,ra}\}} \text{TFI}_{\text{irr/ra},i} \quad (47)$$

$$\sum_{j,z} \text{CA}_{\text{irr},i} \cdot x_{\text{irr},i,j} \cdot R_{j,z} \cdot \text{BW}_{i,z} \leq \begin{cases} \text{TBW}_{\text{irr},i} | (\text{Ind}_{\text{BW},i} \geq \text{BD}_{\text{BW},i}) \\ \text{UPBOUND}_{\text{BW},i} | (\text{Ind}_{\text{BW},i} < \text{BD}_{\text{BW},i}) \end{cases} \quad (48)$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{GW}_{i,z} \leq \sum_{\{\text{irr,ra}\}} \text{TGW}_{\text{irr/ra},i} \quad (49)$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FN}_{i,z}$$
$$\leq \begin{cases} \sum_{\{\text{irr,ra}\}} \text{TFN}_{\text{irr/ra},i} | (\text{Ind}_{\text{N},i} \geq \text{BD}_{\text{N},i}) \\ \text{UPBOUND}_{\text{N},i} | (\text{Ind}_{\text{N},i} < \text{BD}_{\text{N},i}) \end{cases} \quad (50)$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{FP}_{i,z}$$
$$\leq \begin{cases} \sum_{\{\text{irr,ra}\}} \text{TFP}_{\text{irr/ra},i} | (\text{Ind}_{\text{P},i} \geq \text{BD}_{\text{P},i}) \\ \text{UPBOUND}_{\text{P},i} | (\text{Ind}_{\text{P},i} < \text{BD}_{\text{P},i}) \end{cases} \quad (51)$$

$$\sum_{\{\text{irr,ra}\},j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{PT}_{i,z} \leq \sum_{\{\text{irr,ra}\}} \text{TPT}_{\text{irr/ra},i} \quad (52)$$

$$\sum_{j} x_{\text{irr/ra},i,j} \leq 1 \quad (53)$$

$$\sum_{j,z} \text{CAz}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} = \sum_{z} \text{HA}_{\text{irr/ra},i,z} \quad (54)$$

$$G_{\text{Dim}} = \left(1 - \frac{\sum_{\{\text{irr,ra}\},i,j,z} \text{CA}_{\text{irr/ra},i} \cdot x_{\text{irr/ra},i,j} \cdot R_{j,z} \cdot \text{UI}_{\text{Dim},i,z}}{\sum_{\{\text{irr,ra}\},i} \text{CURRENT}_{\text{Dim,irr/ra},i}}\right) \times 100\% \quad (55)$$

in which $\text{Aver}(G_{\text{Dim}})$ and $\text{Var}(G_{\text{Dim}})$ are the average and variance of the improvement of all sustainable dimensions, respectively. Here we perform a limited analysis with weights of 1 or 0 for the seven sustainability indicators to demonstrate the flexibility of our approach (see Extended Data Fig. 1). In the first step, we assign a weight of 0 or 1 to each of the seven indicators so that there are 2^7 (128) crop-switching solutions, each of which is Pareto optimal. The weights 0 and 1 represent whether the

planners consider the corresponding indicator the least or the most important, respectively. We can also simulate the options with more weights, but the solution will not have an ending. In the second step, the planners and decision-makers can choose any solution according to their prioritization of different indicators. In the G3 scenario (blue line in Extended Data Fig. 1), we choose the solution in which improvement margins in all sustainable dimensions are as high as possible while their between-dimension differences are as low as possible. This also provides a way to compare the G3 scenario with the G1 and G2 scenarios.

According to the above explanation, the G3 scenario represents a Pareto-optimal solution when setting a weight of 0 or 1 for each indicator (Extended Data Fig. 1). Of course, if we set other weights between 0 and 1 for each indicator (which can be infinite), other Pareto-optimal solutions may emerge that are closer to the Pareto frontier. As such, our approach provides flexibility by allowing planners and decision-makers to place greater weight on the sustainability outcomes that they deem most important.

Uncertainties and limitations

We performed uncertainty analyses by relaxing constraints on all sustainability dimensions and farmer incomes at the grid level (Table S6 and Fig. S16), relaxing the constraint of crop production (Tables S6 and S7) and testing the sensitivity of our outcomes to the input data (Table S6 and Fig. S17). The analysis shows that, if these constraints are lifted, there will be increased improvements in environmental sustainability and farmer incomes at the national level (Extended Data Fig. 2). However, there will be some regional tradeoffs. For example, farmer incomes would decrease in some areas (thereby potentially requiring subsidies; Table S8) or blue-water use would increase in some water-scarce areas (Fig. S16). As well as quantifying uncertainties, we note that our findings should be interpreted with several considerations in mind. First, our analysis was limited by the spatial resolution of the available underlying datasets. Specifically, we are not able to capture field-level heterogeneity in suitability for different crops (for example, flood plains versus highlands) and economies of scale that may arise (or degrade) from increases (or decreases) in monoculture cropping, which should be taken into account for the implementation of crop switching. Second, crop production is an interconnected ecological process, in which changing one input would change other inputs, for example, irrigation change would affect fertilizer use and GHG emissions. Although such interconnections are beyond the scope of this study, their potential influence (either positive or negative) on sustainability outcomes is important to take into account when seeking to responsibly implement crop-switching interventions. Moreover, our model has the limitations of not considering the switching costs and assumption of the constant harvested area under crop switching, which are discussed in detail in Supplementary Information Sections 2.6 (Table S8) and 2.7 (Figs. S18 and S19).

Reporting summary

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

Data availability

The SPAM database (version 1.1, year 2010) used in this study can be downloaded at https://mapspam.info/. We extracted China's data from the SPAM database and deposited it online (https://doi.org/10.5281/zenodo.7575266). The historical climate data for the crop water model and the crop growth stage data for the crop-rotation model are available at http://data.cma.cn/. The crop coefficients ($K_{z(\text{tab})}$) and irrigation efficiency coefficients used for calculating water use of crops are available at http://www.fao.org/3/X0490E/x0490e0b.htm and http://www.mwr.gov.cn/, respectively. Crop-specific GHG emissions data at the grid level is from Carlson et al.[20]. Crop-specific fertilizer use, pesticides use and

farmer income data are available in the Agricultural Cost and Benefit Statistical Yearbook 2011 (https://doi.org/10.5281/zenodo.7575632). The fertilizer data at the county level for uncertainty analysis was from the proprietary County-level Agricultural Database of the Chinese Academy of Agricultural Sciences (http://aii.caas.net.cn/). The irrigation water availability data used for water-scarcity calculation is taken from Zhou et al.[35]. The nutrient balance data can be downloaded from https://www.science.org/doi/10.1126/science.1246067.

Code availability

The linear programming solution procedure was used to solve our model with the equations illustrated in the Methods section of our manuscript. The standard optimization solver (CPLEX 22.1) available in open-access software (GAMS) can be used to replicate the analysis. The code and related description of CPLEX 22.1 can be accessed at https://www.gams.com/latest/docs/S_CPLEX.html.

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Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41586-023-05799-x.
Correspondence and requests for materials should be addressed to Wei Xie, Xiaoguang Chen, Feng Wu or Kyle Frankel Davis.
Peer review information *Nature* thanks Reinier de Adelhart Toorop, Xiao-Peng Song and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.
**Reprints and permissions information** is available at http://www.nature.com/reprints.
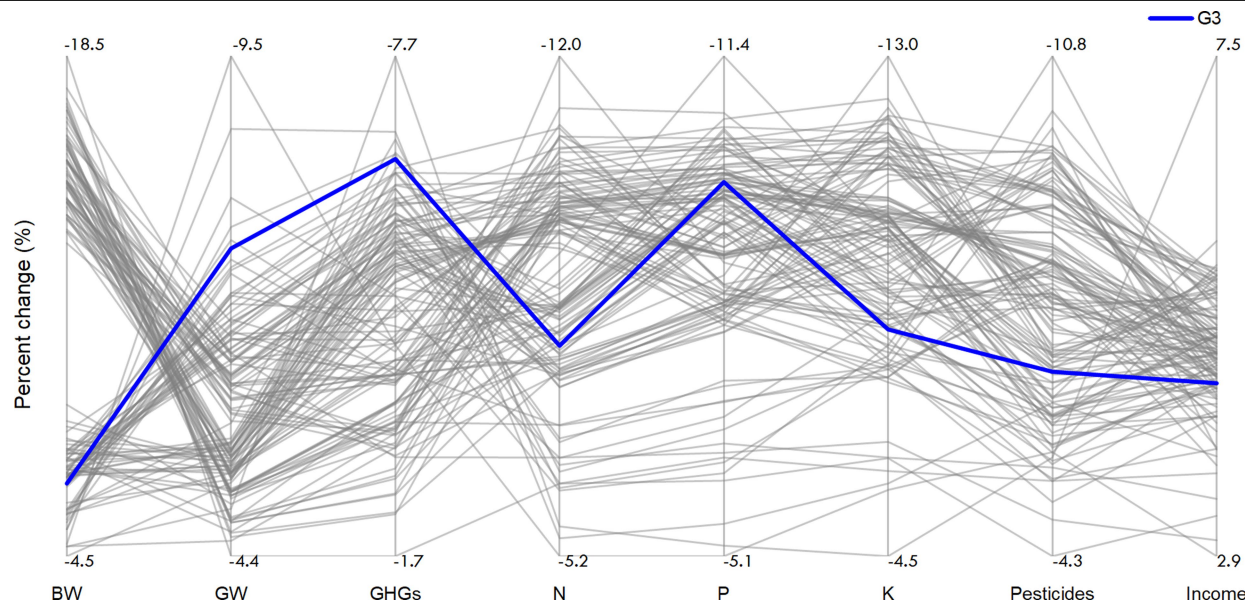
Extended Data Fig. 1 | Parallel coordinate plot with crop-switching strategies that are Pareto optimal for all dimensions. Each coordinate corresponds to a sustainability dimension and each line connecting different values between the coordinates corresponds to a single Pareto-optimal solution. The bold blue line shows the crop-switching solution under G3. BW, blue water; GW, green water; GHGs, greenhouse gas emissions; N, nitrogen fertilizers; P, phosphorus fertilizers; K, potash fertilizers.
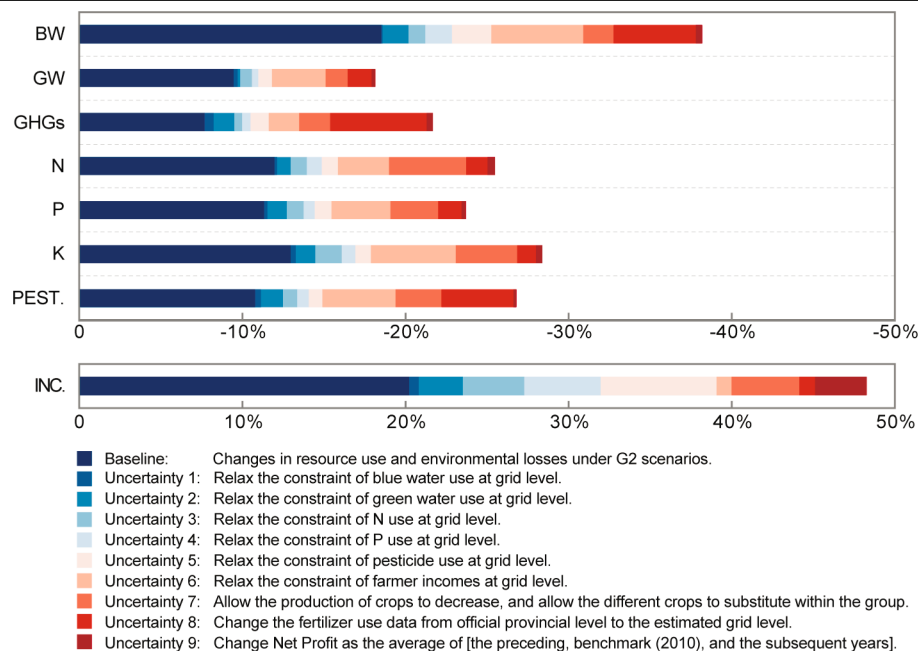
Extended Data Fig. 2 | Decomposition of the sources of uncertainty.
'Baseline' (dark blue bar) shows the reduction in resource use, reduction in environmental impacts and increase in farmer incomes under the G2 scenario. Other colours represent the difference between results of uncertainty scenarios and the baseline scenario (G2 scenario) (see Table S6 and Supplementary Information Section 2.5 for details on the varying assumptions about different uncertainty sources). BW, blue water; GW, green water; GHGs, greenhouse gas emissions; N, nitrogen fertilizers; P, phosphorus fertilizers; K, potash fertilizers; PEST., pesticides; INC., farmer incomes.
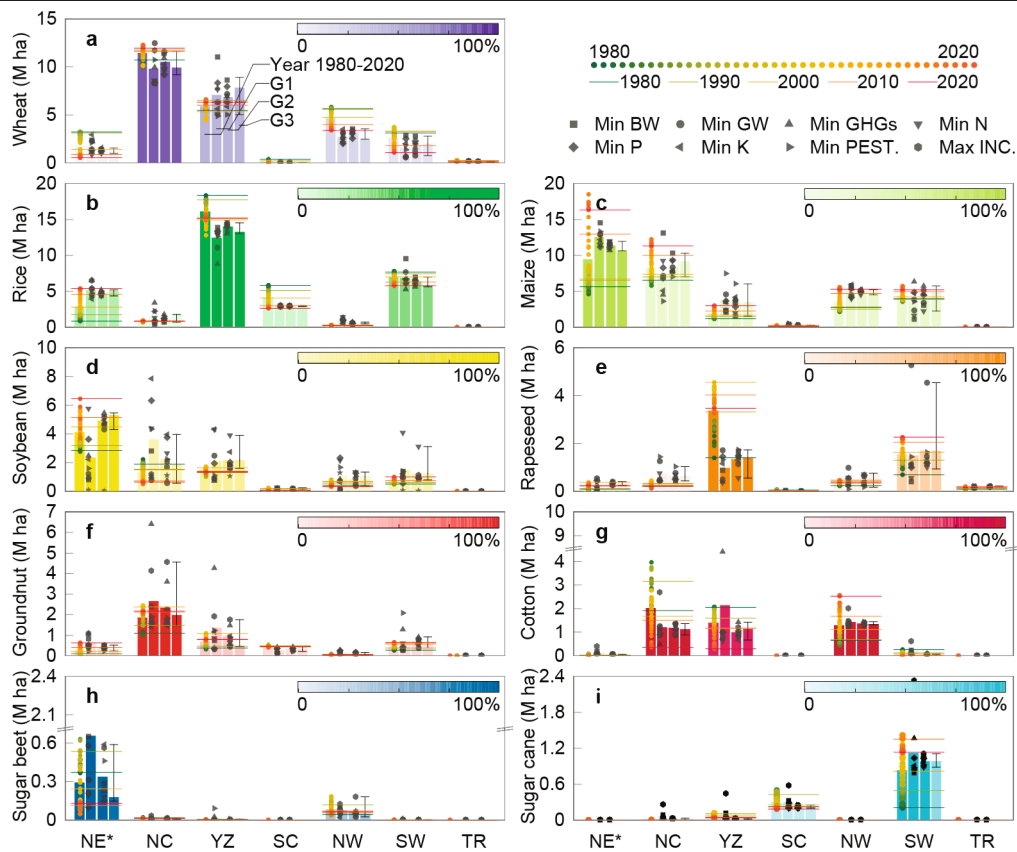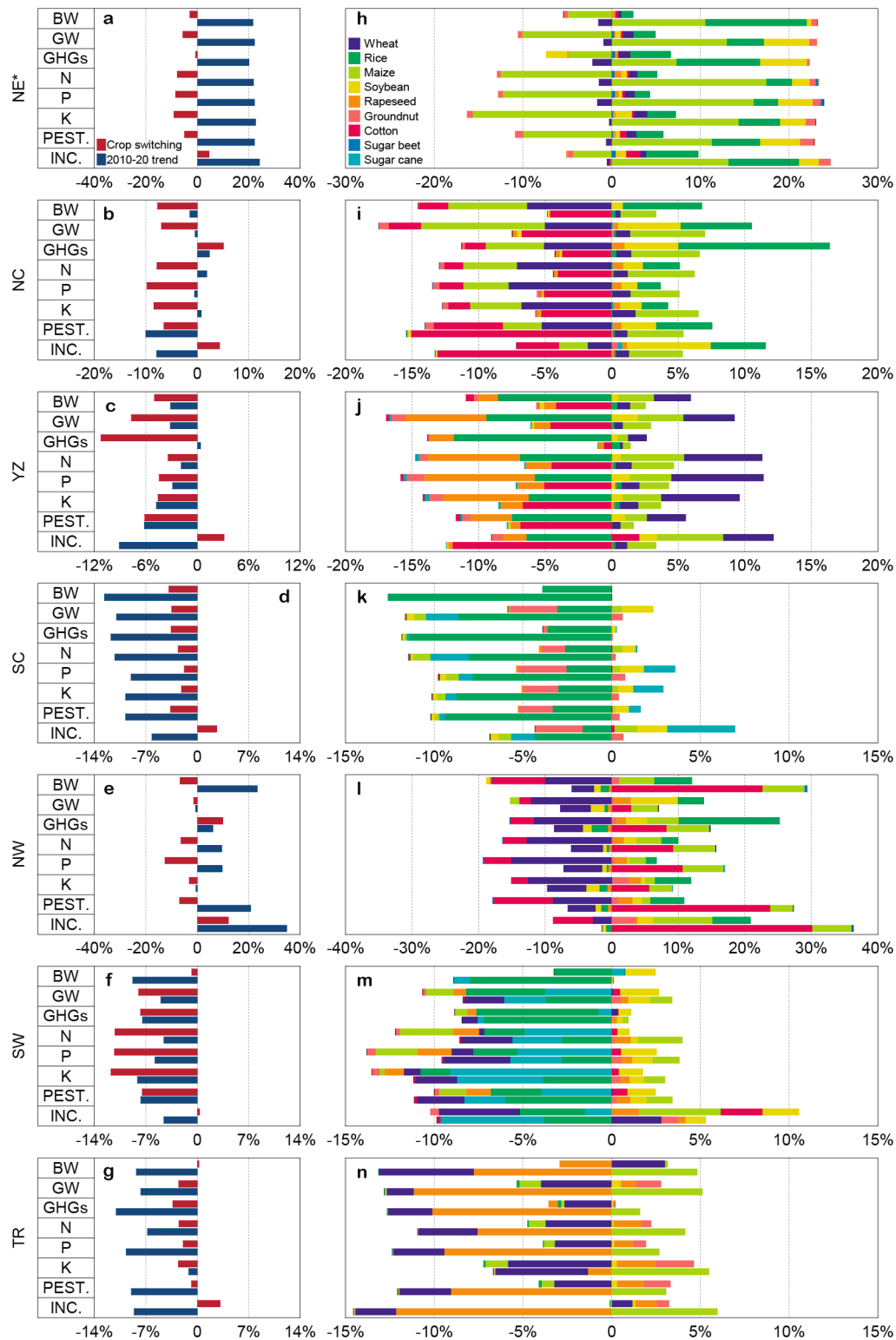
Extended Data Fig. 3 | Comparison of proposed crop switching with historical crop distribution. The five horizontal lines in each panel show crop distributions at decadal intervals (that is, between 1980 and 2020) that can be compared with our proposed crop switching. The colour scale of the bars corresponds to the share of current crop production of each region to the national total; for instance, the darker shades of the bars for wheat in North China (NC) and rice in the Yangtze River Plain (YZ) indicate that these regions account for large shares in the total national production of those crops. Min, minimize; Max, maximize; BW, blue water; GW, green water; GHGs, greenhouse gas emissions; N, nitrogen fertilizers; P, phosphorus fertilizers; K, potash fertilizers; PEST., pesticides; INC., farmer incomes. *Note that because crop distribution changes during the past ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from that used in our crop-switching model, which is based on the agricultural ecological zone. The regional coverage is Northeast Plain and Inner Mongolia (NE) = Heilongjiang, Jilin, Liaoning, Inner Mongolia; North China (NC) = Beijing, Tianjin, Hebei, Henan, Shandong; the Yangtze River Plain (YZ) = Jiangxi, Shanghai, Zhejiang, Anhui, Jiangsu, Hubei, Hunan; Southern China (SC) = Fujian, Guangdong, Hainan; Northwest Region (NW) = Xinjiang, Ningxia, Shaanxi, Gansu, Shanxi; Southwest Region (SW) = Guangxi, Chongqing, Guizhou, Sichuan, Yunnan; Tibet Region (TR) = Tibet, Qinghai.

Extended Data Fig. 4 | Trend agreement between proposed and recently observed changes in cropping patterns. Circle colours denote whether—compared with our proposed crop switching (G3)—the observed distribution change of the crop in that region during the past ten years has moved in the opposite direction and needs to reverse the direction (red), the same direction but faster rate and needs to slow down (yellow) or the same direction and the same/slower rate and needs to speed up (green). Faded circles indicate that a crop in that region accounts for a small fraction of the national production. The top signs (+, −, 0) inside each circle represent how the sowing area of the crop is proposed to change under our crop-switching scenarios, whereas the bottom signs (+, −, 0) show recent crop distribution changes during 2010–2020. We find that, in 68% (21/32) of cases, recent crop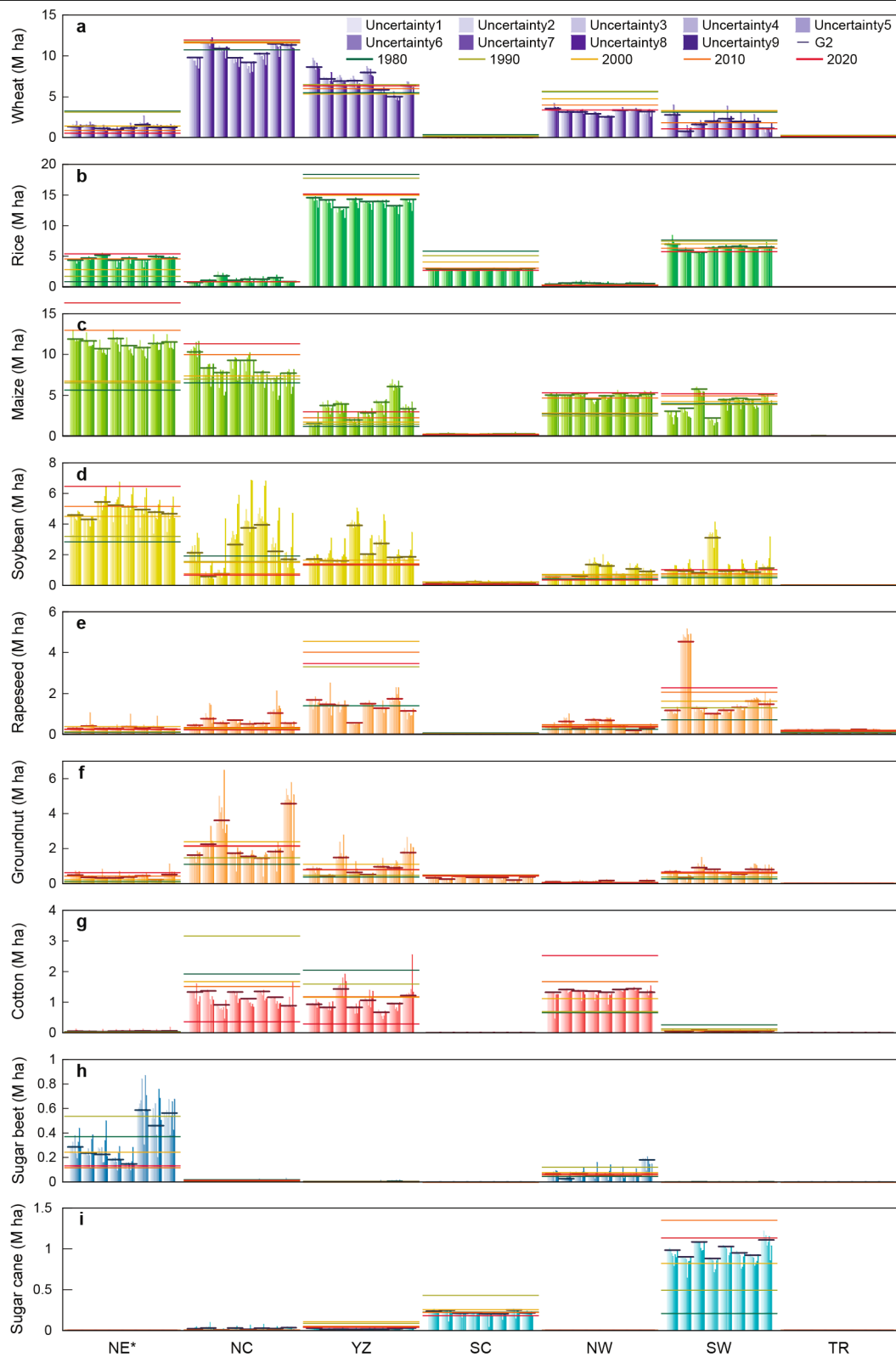ping-pattern changes are moving in the same (green or yellow) direction as our proposed switches. *Note that because crop distribution changes during the past ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from that used in our crop-switching model, which is based on the agricultural ecological zone. The regional coverage is Northeast Plain and Inner Mongolia (NE) = Heilongjiang, Jilin, Liaoning, Inner Mongolia; North China (NC) = Beijing, Tianjin, Hebei, Henan, Shandong; the Yangtze River Plain (YZ) = Jiangxi, Shanghai, Zhejiang, Anhui, Jiangsu, Hubei, Hunan; Southern China (SC) = Fujian, Guangdong, Hainan; Northwest Region (NW) = Xinjiang, Ningxia, Shaanxi, Gansu, Shanxi; Southwest Region (SW) = Guangxi, Chongqing, Guizhou, Sichuan, Yunnan; Tibet Region (TR) = Tibet, Qinghai.

Extended Data Fig. 5 | Comparison of sustainability outcomes between proposed crop switching (G2) and observed crop distribution changes during the past ten years. The baseline points for these comparisons are the sustainability outcomes in 2010. The left-hand panels (**a**–**g**) show the total net changes across all crops in the seven regions. The right-hand panels (**h**–**n**) show the specific changes for each crop in the seven regions. BW, blue water; GW, green water; GHGs, greenhouse gas emissions; N, nitrogen fertilizers; P, phosphorus fertilizers; K, potash fertilizers; PEST., pesticides; INC., farmer incomes. *Note that because crop distribution changes during the past ten years are only available based on the administrative divisions, the regional

aggregation used here is slightly different from that used in our crop switching model, which is based on the agricultural ecological zone. The regional coverage is Northeast Plain and Inner Mongolia (NE) = Heilongjiang, Jilin, Liaoning, Inner Mongolia; North China (NC) = Beijing, Tianjin, Hebei, Henan, Shandong; the Yangtze River Plain (YZ) = Jiangxi, Shanghai, Zhejiang, Anhui, Jiangsu, Hubei, Hunan; Southern China (SC) = Fujian, Guangdong, Hainan; Northwest Region (NW) = Xinjiang, Ningxia, Shaanxi, Gansu, Shanxi; Southwest Region (SW) = Guangxi, Chongqing, Guizhou, Sichuan, Yunnan; Tibet Region (TR) = Tibet, Qinghai.

Extended Data Fig. 6 | See next page for caption.

Article

Extended Data Fig. 6 | Uncertainty ranges of crop redistribution. Each short horizontal line in the group of eight bars in each panel represents, from left to right, the baseline scenarios of minimizing blue water, green water, GHGs, N, P, K, pesticides and maximizing farmer incomes under G2 (eight scenarios). The nine individual bars from left to right (light to dark shade) inside each broader bar represent uncertainty 1–9 (see Table S6 and Supplementary Information Section 2.5 for details on the varying assumptions about different uncertainty sources). The five long horizontal lines show crop distributions at decadal intervals (that is, between 1980 and 2020) that can be compared with our proposed crop switching. *Note that because crop distribution changes during the past ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from that used in our crop switching model, which is based on the agricultural ecological zone. The regional coverage is Northeast Plain and Inner Mongolia (NE) = Heilongjiang, Jilin, Liaoning, Inner Mongolia; North China (NC) = Beijing, Tianjin, Hebei, Henan, Shandong; the Yangtze River Plain (YZ) = Jiangxi, Shanghai, Zhejiang, Anhui, Jiangsu, Hubei, Hunan; Southern China (SC) = Fujian, Guangdong, Hainan; Northwest Region (NW) = Xinjiang, Ningxia, Shaanxi, Gansu, Shanxi; Southwest Region (SW) = Guangxi, Chongqing, Guizhou, Sichuan, Yunnan; Tibet Region (TR) = Tibet, Qinghai.

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☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

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 were used to collect data in this study.
Data analysis	ArcGIS 10.2 is used for analyze the crop sepecific yield and harvest data and the water use, fertilizer use, pesticide use, GHGs emission and farmers incomes data at the grid level; GAMS 22.8 is used for solving the switching model.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

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- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
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Spatially distributed irrigated/rainfed yield and harvested area of nine crops were taken from the Spatial Production Allocation Model (SPAM) database (version 1.1, the year 2010) (https://mapspam.info/), we extracted China's data from the SPAM database and deposited it online (https://doi.org/10.5281/zenodo.7575266).; Crop-specific greenhouse gas (GHG) emissions data were taken from Carlson et al. (https://doi.org/10.1038/nclimate3158);

Crop-specific fertilizer use (nitrogen, phosphorous, potash, and compound fertilizer), pesticides use, and farmer incomes data were taken from the Agricultural Cost and Benefit Statistical Yearbook 2011 (in Chinese), published by the National Development and Reform Commission (NDRC) of China (https://doi.org/10.5281/zenodo.7575632);
The fertilizer data at the county level for uncertainty analysis was from the County-level Agricultural Database of Chinese Academy of Agricultural Sciences (http://aii.caas.net.cn/);
The irrigation water availability data in different provinces in China used for blue water scarcity calculation was obtained from the National Long-term Water Use Dataset of China (https://figshare.com/articles/Zhou_et_al_2020_PNAS_dataset_xlsx/11545176);
The spatial distribution of nutrient balance data was taken from West et al. (https://www.science.org/doi/10.1126/science.1246067);
Crop growth stage data based on the weather stations were obtained from the China Meteorological Data Service Center (CMDC) (http://data.cma.cn/);
The mapping layer of cropping regions was obtained from Institute of Agricultural Resources and Regional Planning, China Academy of Agricultural Sciences;
Crop coefficients (Kz(tab)) were obtained from FAO (http://www.fao.org/3/X0490E/x0490e0b.htm) and calibrated according to the climatic conditions in China;
The irrigation efficiency coefficients in different provinces were obtained from the Ministry of Water Resources of the People's Republic of China (http://www.mwr.gov.cn/);
Historical climate data (from 1987 to 2016) at 839 weather stations in China was obtained from the China Meteorological Data Service Center (CMDC) (http://data.cma.cn/), which includes net radiation at the crop surface, soil heat flux density, daily average temperature, wind speed at 2 meters height, saturation vapor pressure, actual vapor pressure, the slope of the vapor pressure-temperature curve, psychrometric constant, average value of the daily minimum relative humidity, the average height of the crop during a particular growth stag, and effective precipitation;
All other relevant data are available from the corresponding authors.

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	*Use the terms sex (biological attribute) and gender (shaped by social and cultural circumstances) carefully in order to avoid confusing both terms. Indicate if findings apply to only one sex or gender; describe whether sex and gender were considered in study design whether sex and/or gender was determined based on self-reporting or assigned and methods used. Provide in the source data disaggregated sex and gender data where this information has been collected, and consent has been obtained for sharing of individual-level data; provide overall numbers in this Reporting Summary. Please state if this information has not been collected. Report sex- and gender-based analyses where performed, justify reasons for lack of sex- and gender-based analysis.*
Population characteristics	*Describe the covariate-relevant population characteristics of the human research participants (e.g. age, genotypic information, past and current diagnosis and treatment categories). If you filled out the behavioural & social sciences study design questions and have nothing to add here, write "See above."*
Recruitment	*Describe how participants were recruited. Outline any potential self-selection bias or other biases that may be present and how these are likely to impact results.*
Ethics oversight	*Identify the organization(s) that approved the study protocol.*

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Achieving food system sustainability is a multi-dimensional challenge. In China, a doubling of crop production since 1990 has compromised other dimensions of sustainability. While the country is promoting various interventions to enhance production efficiency and reduce environmental impacts, there is little understanding of whether crop switching can achieve more sustainable cropping systems and whether coordinated action is needed to avoid tradeoffs. Here we combine high-resolution data on crop-specific yields, harvested areas, environmental footprints, and farmer incomes to first quantify the current state of crop production sustainability. Under varying levels of inter-ministerial and central coordination, we execute spatial optimizations that redistribute crops to meet a suite of agricultural sustainable development targets.
Research sample	The crop yield and harvested area data from SPAM database and GHG emission data from Carlson et al. were selected due to its high resolution, wide variety of crops, and suitable for crop switching model. Crop growth stage data were derived from CMDC weather stations, which improved the accuracy of crop rotation model. The climate and weather data used in the crop water model were selected as they are the most commonly used and widely recognized database for water calculation.
Sampling strategy	We do not use any sampling procedure to conduct our study.

Data collection	W.X., Z.Z., X.C., F.W. and A.Z. extracted the following data from respective sources: Spatially distributed irrigated/rainfed yield and harvested area of nine crops were taken from the Spatial Production Allocation Model (SPAM) database (version 1.1, the year 2010) (https://mapspam.info/), we extracted China's data from the SPAM database and deposited it online (https://doi.org/10.5281/zenodo.7575266); crop-specific greenhouse gas (GHG) emissions data were taken from Carlson et al. (https://doi.org/10.1038/nclimate3158); crop-specific fertilizer use (nitrogen, phosphorous, potash, and compound fertilizer), pesticides use, and farmer incomes data were taken from the Agricultural Cost and Benefit Statistical Yearbook 2011 (in Chinese), published by the National Development and Reform Commission (NDRC) of China (https://doi.org/10.5281/zenodo.7575632); the fertilizer data at the county level for uncertainty analysis was from the County-level Agricultural Database of Chinese Academy of Agricultural Sciences (http://aii.caas.net.cn/); the irrigation water availability data in different provinces in China used for blue water scarcity calculation was obtained from the National Long-term Water Use Dataset of China (https://figshare.com/articles/Zhou_et_al_2020_PNAS_dataset_xlsx/11545176); the spatial distribution of nutrient balance data was taken from West et al. (https://www.science.org/doi/10.1126/science.1246067); crop growth stage data based on the weather stations were obtained from the China Meteorological Data Service Center (CMDC) (http://data.cma.cn/); the mapping layer of cropping regions was obtained from Institute of Agricultural Resources and Regional Planning, China Academy of Agricultural Sciences; crop coefficients (Kz(tab)) were obtained from FAO (http://www.fao.org/3/X0490E/x0490e0b.htm) and calibrated according to the climatic conditions in China; the irrigation efficiency coefficients in different provinces were obtained from the Ministry of Water Resources of the People's Republic of China (http://www.mwr.gov.cn/); historical climate data (from 1987 to 2016) at 839 weather stations in China was obtained from the China Meteorological Data Service Center (CMDC) (http://data.cma.cn/), which includes net radiation at the crop surface, soil heat flux density, daily average temperature, wind speed at 2 meters height, saturation vapor pressure, actual vapor pressure, the slope of the vapor pressure-temperature curve, psychrometric constant, average value of the daily minimum relative humidity, the average height of the crop during a particular growth stag, and effective precipitation.
Timing and spatial scale	The timing of crop-specific yield, harvested area, fertilizer use, pesticides use and farmer incomes are 2010; the timing of GHG emissions of nine crops is 2000, we used FAO's crop emissions data to estimate percent changes in China's GHG emissions from 2000 to 2010 and update grid-level crop-specific GHGs intensities for 2010; the timing of irrigation water availability data is 2010; the timing of crop growth stage data and historical climate data ranges over 1992 - 2014 and 1987 - 2016, respectively, we used the average values to avoid the unrepresentative data in a single year. The spatial scale of crop yield, harvested area, GHG emissions and nutrient balance data is 0.5°x0.5° horizontal resolution; the crop-specific fertilizer use, pesticides use, farmer income, irrigation water availability, and irrigation efficiency coefficients are provincial level data; the fertilizer data at the county level for uncertainty analysis are county level data; the growth stage of 13 crops and historical climate data are collected from 778 agro-meteorological stations and 839 weather stations, respectively.
Data exclusions	No data were excluded from the analyses
Reproducibility	Our study did not involve comparisons of treatment groups or populations so we did not employ traditional experimental design and ANOVA techniques. Therefore, replication of experimental units is not applicable to our study design. The reliability of our results was evaluated based on reported uncertainty analyses.
Randomization	We used crop switching model in this study, so randomization is not relevant.
Blinding	This study used a crop switching model, so no relationship with blinding.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒ ☐	Antibodies
☒ ☐	Eukaryotic cell lines
☒ ☐	Palaeontology and archaeology
☒ ☐	Animals and other organisms
☒ ☐	Clinical data
☒ ☐	Dual use research of concern

Methods

n/a	Involved in the study
☒ ☐	ChIP-seq
☒ ☐	Flow cytometry
☒ ☐	MRI-based neuroimaging