Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

Crop switching can enhance environmental sustainability and farmer incomes in China

Authors: Wei Xie[1,8*], Anfeng Zhu[1,8], Tariq Ali[2,8], Zhengtao Zhang[3], Xiaoguang Chen[4*], Feng Wu[5*], Jikun Huang[1], Kyle Frankel Davis[6,7*]

Affiliations:

[1]China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China

[2]School of Economics and Management, Jiangxi Agricultural University, Nanchang, China

[3]School of National Safety and Emergency Management, Beijing Normal University, Beijing, China

[4]Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, 610074, China

[5]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China

[6]Department of Geography and Spatial Sciences, University of Delaware, Newark, Delaware, USA

[7]Department of Plant and Soil Sciences, University of Delaware, Newark, Delaware, USA

[8]These authors contributed equally: Wei Xie, Anfeng Zhu, Tariq Ali

* Correspondence to Wei Xie (xiewei.ccap@pku.edu.cn), Xiaoguang Chen (cxg@swufe.edu.cn), Feng Wu(wufeng@igsnrr.ac.cn) or Kyle Frankel Davis (kfdavis@udel.edu).

Achieving food system sustainability is a multi-dimensional challenge. In China, a doubling of crop production since 1990 has compromised other dimensions of sustainability[1,2]. While 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 execute 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 cobenefits for environmental impact reductions [blue water (-4.5% to -18.5%), green water (-4.4% to -9.5%), 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 multiple 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 over 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 greenhouse gas (GHGs) emissions have increased[1], the intensity of fertilizer application has increased dramatically[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 (e.g., 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. While 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 where they are most agro-climatically suited and most resource-efficient. Yet recent research has made it increasingly clear that current cropping patterns are sub-optimal across multiple outcomes and that crop switching (i.e., changes in crop distribution and/or crop rotations) may offer promise for improving agricultural sustainability. Recent global studies[5,6,7,8] have shown that crop redistribution can reduce irrigation (i.e., 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 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 [9,10,11]. 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[16,3]. For example, in early 2000, a crop-switching research project led by the National Development and Reform Commission 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 (e.g., in the Yangtze River region), with equal emphasis on food production and sustainability (e.g., in Northwest), and more emphasis on sustainability than food production (e.g., in Tibet 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. In addition, because China alone accounts for large fractions of the global population (19%)[1], primary crop production (19%)[1], natural resource use [e.g., fertilizers (25%), pesticides (10%), irrigation (13%), cropland (9%)][1,17], agrifood-system-related GHGs (12%)[1], and farmers (16%)[1], efforts taken in China to improve its sustainable development goals (SDGs) 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 arcminute) 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 multiple 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 multiple dimensions and different regions. Each optimization run prioritizes one of the following objectives: minimize water demand; minimize GHGs; minimize fertilizer; minimize pesticides; maximize farmer incomes; or maximize benefits across all dimensions simultaneously – based on three different levels of governmental cooperation (i.e., 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 currently grown within a grid cell can be planted there; 4) harvested area within each grid cell is held constant—preventing 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 multiple outcomes are essential for identifying interventions capable of improving the multi-dimensional sustainability of agriculture.

Sustainability outcomes of potential crop switching

Different sustainability outcomes are administrated by separate government departments in China (e.g., 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 toward 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 prioritizing 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 (Figure 1; Table S14). However, because a ministry prioritizes 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), multiple tradeoffs emerge between different dimensions of agricultural sustainability and between different regions (Figure 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%, nevertheless, at the cost of other environmental outcomes (Figures S5-S6). This suggests that efforts to increase farmer profitability under current crop price structures would likely 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 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% (pesticide); +20.2% (farmer incomes). Yet while 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 (Figure 1; Table S14).

To this end, we performed a multi-objective 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 Figure 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 pesticide; +4.5% (+2.9% to +7.5%) for farmer incomes (Figure 1; Table S14).

Comparing across all three levels of coordination highlights cases in which certain sustainability outcomes are similar in magnitude while 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 multiple losses for other outcomes (-10% to -5% relative to G3). Additionally, the G1 scenario allows for degradation of certain sustainability criteria in some locations, while that does not occur in G2 and G3. These contrasting examples point to an interest tension between the amount of additional 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 (e.g., blue water scarcity) (Figure 2), and the location of crop switching can be targeted based on a variety of definitions and measures of sustainability (see Figure 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, e.g., wheat decrease in both North China Plain (NC) and Northwest Region (NW) and increase in Yangtze River Plain (YZ); rice decreases in Yangtze River Plain (YZ); maize increases in Northwest Region (NW); rapeseed decrease in Yangtze River Plain (YZ) and cotton decrease in Northwest Region (NW) (see Figure 3, Figures S9-S11). These findings point to regions where shifts in certain crops can lead to robust outcomes for multiple 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 (Figure S8) – demonstrate real opportunities for crop switching to improve environmental sustainability and farmer incomes (Figure S4). We have also shown the feasibility of the proposed crop switching by comparing it to recent rates of change in crop distributions across China (see Extended Data Figures 3-6; Figures S12-S14). While 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 power 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 (e.g., SARS, 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 toward 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 likely be necessary to fully meet sustainability targets. To elucidate 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 SDGs in a counterfactual way (Figure 4; Figure S15). According to the agricultural water demand projections[23] and the sustainable goal[3], China needs to save 30 km^3 of blue water by 2030, and our crop switching can save 7.8 (5.4 to 22.1) km^3 – equivalent to 26% (18% to 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. While there is no specific target for agricultural greenhouse gas abatement, we assume no additional increase after 2020 as a strict mitigation goal. Accordingly, we estimate that crop switching can contribute 24% (6% to 29%) towards achieving this goal. For fertilizers and pesticides, China has adopted a zero-increase plan[24,25]. Compared to these targets, savings from crop switching would also be substantial - equivalent to 40% (24% to 51%) for fertilizers and 23% (15% to 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$ 2600/year[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 a significant (and growing) role in determining global agricultural sustainability outcomes[28]. A prime example of this is China's soybean imports, which have not only dramatically 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 major crops in China has the potential to cascade through the global trade network (via China's reduced import demand) and may lead to global resource savings (Table S15; see Supplementary Information section 1.2.4 for estimation method) and other indirect environmental and ecological benefits (see, e.g., Folberth *et al*., 2020)[8] – depending on how the trade partners would respond to China's decreased international crop demand (e.g., 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 resources savings for China's trade partners of blue water (0.3 to 102.9 km^3), GHGs (0.5 to 24.6 million tonnes CO_2 eq), and fertilizers (0.1 to 14.0 million tonnes) (Table S15).

A scientific basis for sustainable agricultural interventions

This study reveals that crop switching is an important measure that can help achieve multiple 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 multiple 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 location-dependent, our study can enable the provision of spatially detailed solutions for different areas of China based on local conditions and sustainability priorities (Figure 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 (in addition to reducing the overuse of fertilizer and pesticide and preventing black soil degradation) (Table S14) and point to initial opportunities for policy-makers to implement crop switching. Similarly, in the Yangtze River Plain (YZ), 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 (NC), increases in soybean, rapeseed and rice in lieu of some wheat, maize, cotton, and groundnut (Figure S10 and S11) can also contribute to more sustainable cropping patterns and contribute substantially to alleviating regional water scarcity and excessive fertilizer use (Figure 2; Figure S7). Such spatially explicit quantifications (like the ones produced here) can thus play an important role in evaluating where agricultural interventions – and which specific cropping switches – can offer the largest 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 (Figures S12-S14), especially considering that China has previously had success in incentivizing farmers at the provincial[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 via the 'Plan for Green Agricultural Development'[34]. Taken together, our quantitative multi-dimensional assessment provides an objective, science-based foundation for ensuring the feasibility of potential solutions for more sustainable agricultural systems.

References

1. FAOSTAT Database. http://www.fao.org/faostat.
2. Dalin, C., Wada, Y., Kastner, T., & Puma, M. J. Groundwater depletion embedded in international food trade. *Nature* **543**(7647), 700-704 (2017).
3. Ministry of Agriculture and Rural Affairs of China. National Sustainable Agriculture Development Plan (2015-2030). http://www.gov.cn/xinwen/2015-05/28/content_2869902.htm (2015) (in Chinese).
4. Pingali, P. L. Green revolution: Impacts, limits, and the path ahead. *Proc. Natl. Acad. Sci. U.S.A.* **109**, 12302–12308 (2012).
5. Davis, K. F., Rulli, M. C., Seveso, A., & D'Odorico, P. Increased food production and reduced water use through optimized crop distribution. *Nat. Geo.* **10**(12), 919-924 (2017).
6. Chouchane, H., Krol, M. S., & Hoekstra, A. Y. Changing global cropping patterns to minimize national blue water scarcity. *Hydrol. Earth Syst. Sci*. **24**(6), 3015-3031 (2020).
7. Karandish, F., Hoekstra, A. Y., & Hogeboom, R. J. Reducing food waste and changing cropping patterns to reduce water consumption and pollution in cereal production in Iran. *J. Hydrol.* **586**, 124881 (2020).
8. Folberth, C. *et al*. The global cropland-sparing potential of high-yield farming. *Nat. Sustain.* **3**, 281–289 (2020).
9. Davis, K. F. *et al*. Alternative cereals can improve water use and nutrient supply in India. *Sci. adv.* **4**(7), eaao1108 (2018).
10. Davis, K.F. *et al*. Assessing the sustainability of post-Green Revolution cereals in India. *Proc. Natl.*

Acad. Sci. U.S.A. **116**, 25034-25041 (2019).

11. Devineni, N., Perveen, S. & Lall, U. Solving groundwater depletion in India while achieving food security. *Nat. Commun.* **13**, 3374 (2022).
12. Davis, K. F., Seveso, A., Rulli, M. C., & D'Odorico, P. Water savings of crop redistribution in the United States. *Water* **9**(83), (2017).
13. Rising, J., & Devineni, N. Crop switching reduces agricultural losses from climate change in the United States by half under RCP 8.5. *Nat. Commun.* **11,** 4991 (2020).
14. Yang, X. *et al*. Diversified crop rotations enhance groundwater and economic sustainability of food production. *Food and Energ. Secur.* **10(**4), e311 (2021).
15. Bowles, T. M. *et al*. Long-Term Evidence Shows that Crop-Rotation Diversification Increases Agricultural Resilience to Adverse Growing Conditions in North America. *One Earth* **2**, 284-293 (2020).
16. Liu, J., & Du, Y. *The research of China's Agricultural Productivity Layout*. (China Econ. Press, Beijing, 2010).
17. Hoekstra, A. Y., & Mekonnen, M. M. The water footprint of humanity. *Proc. Natl. Acad. Sci. U.S.A.* **109**(9), 3232-3237 (2012).
18. National Bureau of Statistics of China, http://www.stats.gov.cn/ (2021).
19. International Food Policy Research Institute. Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.1, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PRFF8V&version=3.0, Harvard Dataverse, V3 (2019).

20. Carlson, K. M. *et al*. Greenhouse gas emissions intensity of global croplands. *Nat. Clim. Change* **7**, 63–68 (2017).

21. NDRC (National Development and Reform Commission of China). Cost-benefit of Agricultural Products in China. (China Statistics Press, China, 2011) (in Chinese).

22. Government of China. National Agricultural Sustainable Development Plan (2015-2030). State Council of the People's Republic of China. http://www.gov.cn/foot/site1/20150528/99261432789977448.doc (2015).

23. Zhang, D. Study on Problems and Countermeasures of Agricultural Water Saving Irrigation. *J. Water Resour. Res.* **06**(1), 49-54 (2017) (in Chinese).

24. Ministry of Agricultural and Rural Affairs of China. Action Plan for Zero Growth in Fertilizer Use by 2020. http://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923401.htm (2017) (In Chinese).

25. Ministry of Agricultural and Rural Affairs of China. Action Plan for Zero Growth in Pesticide Use by 2020. http://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923401.htm (2017) (In Chinese).

26. Chinese Academy of Social Sciences. *China's Rural Development Report (2021): Agricultural and Rural Modernization towards 2035*. (China Soc. Sci. Press, Beijing, 2021).

27. MacDonald, G.K. *et al*. Rethinking agricultural trade relationships in an era of globalization, *BioScience* **65**, 275–289 (2015).

28. Zhao, H. *et al*. China's future food demand and its implications for trade and environment. *Nat. Sustain.* **4**, 1042–1051 (2021).

29. Sun, J. *et al*. Importing food damages domestic environment: Evidence from global soybean trade. *Proc. Natl. Acad. Sci. U.S.A.* **115**, 5415-5419 (2018).

30. Ali, T., Huang, J., Wang, J., & Xie, W. Global footprints of water and land resources through China's food trade. *Glob. Food secure*. **12**, 139-145 (2017).

31. Ali, T., Xie, W., Zhu, A., & Davis, K. F. Accounting for re-exports substantially reduces China's virtual water demand through agricultural trade. *Environ. Res. Lett*. **16**, 045002 (2021).

32. State Council of the People's Republic of China. Some opinions of the State Council on establishing and improving the governor's responsibility system for food security. http://www.gov.cn/zhengce/content/2015-01/22/content_9422.htm (2015) (in Chinese).

33. Zhejiang Provincial Government. Opinions of the People's Government of Zhejiang Province on further strengthening the responsibility system of city and county governors for food security and strengthening the capability of food security. http://www.lswz.gov.cn/html/zt/szzrz/2018-06/14/content_236168.shtml (2015) (in Chinese)

34. Government of China. 14th Five-Year National Plan for Green Agricultural Development. http://www.gov.cn/zhengce/zhengceku/2021-09/07/content_5635867.htm (2021) (in Chinese).

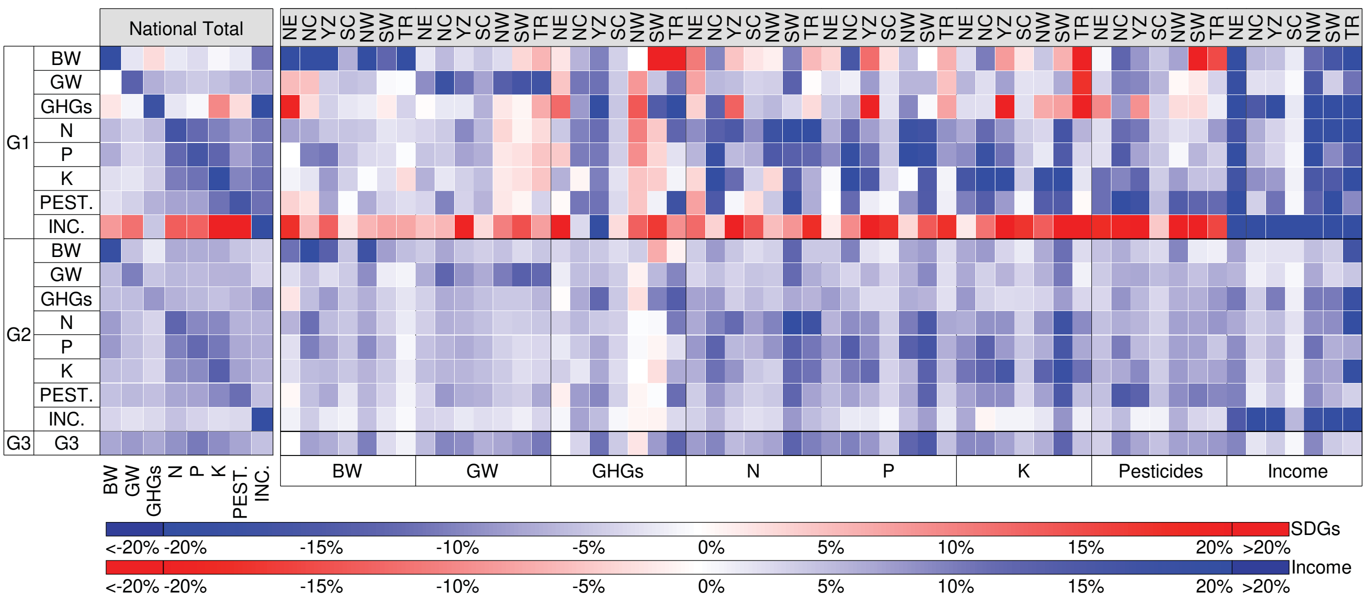
35. Zhou F. *et al*. Deceleration of China's human water use and its key drivers. *Proc. Natl. Acad. Sci. U.S.A.* **117** (14), 7702-7711 (2020).

36. Government of China. *China's Agricultural Outlook Report (2020-2030)*. Market Early Warning Expert Committee of the Ministry of Agriculture and Rural Affairs (China Agri. Sci. Technol. Press, Beijing, 2021) (in Chinese).

Table 1. Scenario summaries. G1 (No coordination): Siloed approach prioritizing a single sustainability objective at a time; G2 (Cross-ministry coordination): prioritizes one sustainability dimension while not degrading outcomes for the other sustainability dimensions at the national/grid levels; G3 (Central coordination): prioritizes that the improvement margins in all dimensions are as high as possible while their between-dimension differences are as low as possible.

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

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x



Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

Figure 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 prioritizing a single sustainability objective at a time. G2 (simulation of cross-ministry coordination) corresponds to the scenarios where prioritizing 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 Figures 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 China’s seven regions: NE = Northeast Plain; NC = North China; YZ = the Yangtze River Plain; SC = Southern China; NW = Northwest Region; SW = Southwest Region; TR = Tibet Region (see Figure S3 and Table S2 for regional division).

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

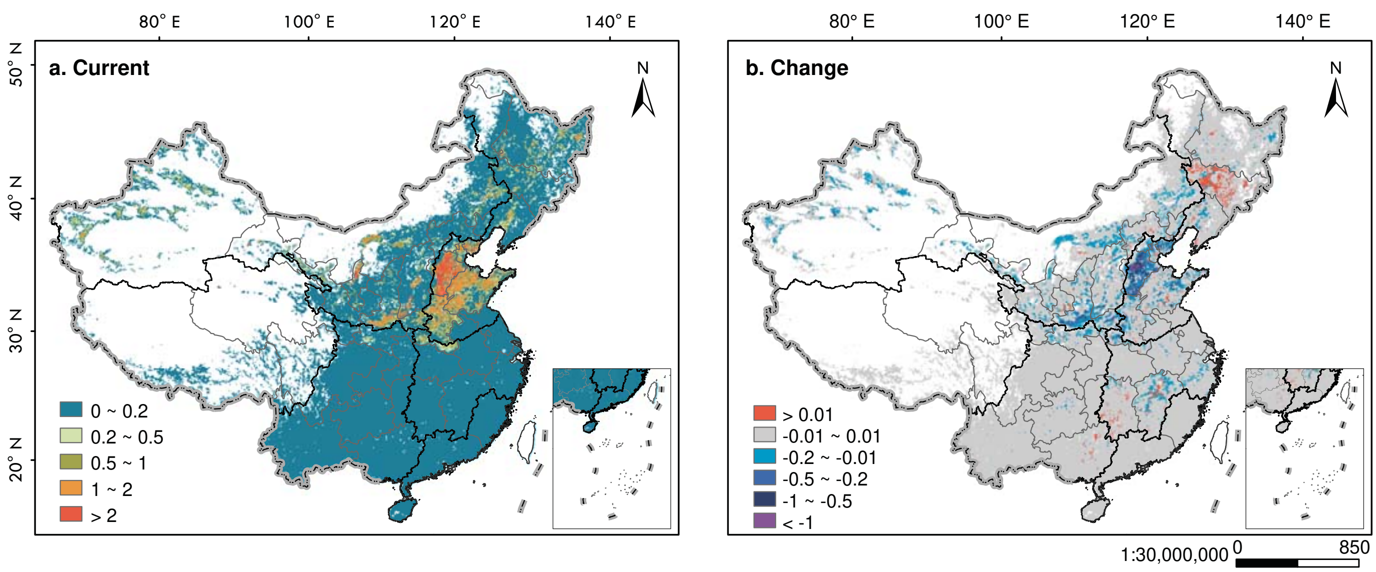


Figure 2 | Changes in blue water scarcity through optimized crop switching. Changes in the spatial distribution of water scarcity under the optimization scenario (G3) that simultaneously saves resources, reduces environmental losses and increases farmer incomes. **a**, Ratio of current blue water use to water availability (i.e., 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, China Academy of Agricultural Sciences (IARRP; https://iarrp.caas.cn/).

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

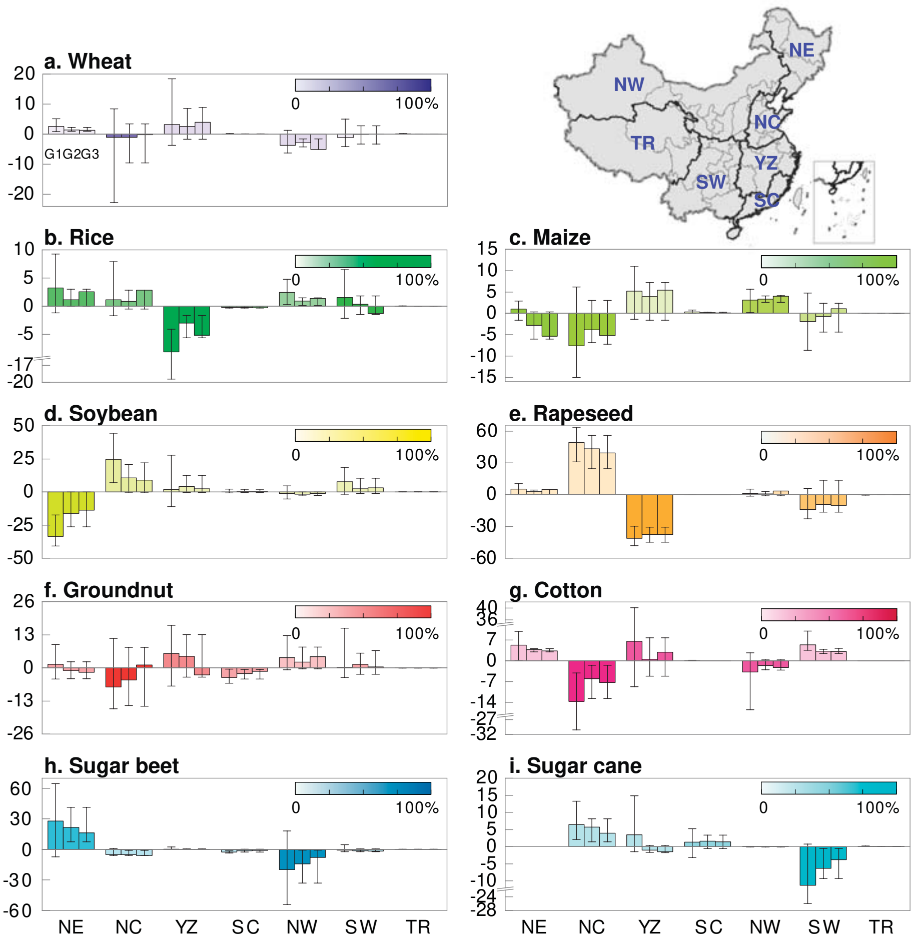


Figure 3 | Proposed changes in crop production distribution. The y-axis indicates the percentage point differences between the shares (%) in the national production of a specific crop in each region before and after crop switching. In each group of three bars, the left, middle, and right bars are the average change of regional crop production share under G1(8 scenarios), G2 (8 scenarios), and G3 (1 scenario), respectively. Whiskers indicate the minimum and maximum of all changes; whiskers for G3 bars represent the range of Pareto optimal outcomes (see Extended Data Figure 1). The color 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. The map in the top right corner shows the distribution of China's seven regions. NE = Northeast Plain; NC = North China; YZ = the Yangtze River Plain; SC = Southern China; NW = Northwest Region; SW = Southwest Region; TR = Tibet Region (see Figure S3 and Table S2 for regional division). 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, China Academy of Agricultural Sciences (IARRP; https://iarrp.caas.cn/).

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

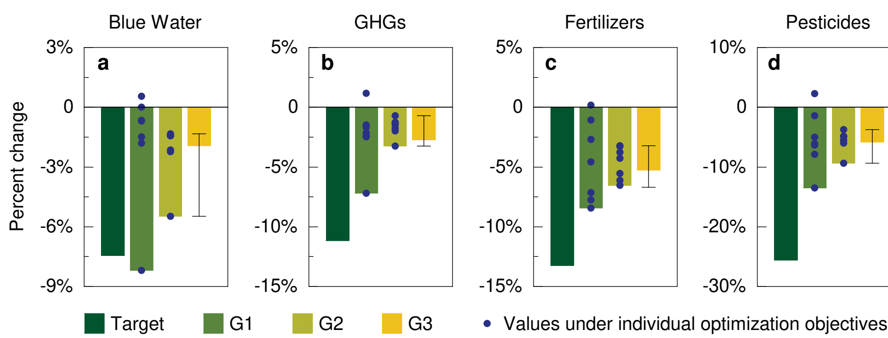


Figure 4 | Comparison of crop switching benefits with China's 2030 official agricultural sustainability targets. The dark green color bars (Target) show the difference between the baseline projection and China's official agricultural sustainability targets in 2030. Under the baseline, the projection 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[36] and current resource use intensities (see "Current state of sustainability outcomes" in the Method section) 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. Whiskers for G3 bars represent the range of Pareto optimal outcomes (see Extended Data Figure 1).

Methods

The crop switching method for improving different (or multiple) sustainability outcomes across China involved the use of diverse datasets and cross-disciplinary techniques. The overall framework of our methods is summarized in Figure 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- and multi-objective crop switching optimization models.

Crop definitions

We focus on 13 major 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 sugar cane – that account for 94% of China's primary crop production and 90% of harvested area[18]. For the crops we did not consider due 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 arc minute; 1/12°; ~10-km resolution; dividing China into 72000 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, the year 2010) of International Food Policy Research Institute (IFPRI)[19]. Note that the areas with higher yields in 2010 are still more productive than other places in the last few years (Figure S1), so our results are not sensitive to using the year 2010 SPAM maps.

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

$$Production_{Cur,irr/\mathrm{ra},z} = \sum_i HA_{irr/ra,i,z} * YLD_{irr/ra,i,z} \quad (1)$$

where HA is harvested area (ha), YLD is yield (kg ha^{-1}), the subscripts irr and ra represent irrigated and rainfed cropping system, respectively; i represents the grids ($i = 1, 2, \cdots, 72000$) and z is crops. The national combined irrigated and rainfed production of each crop agrees well with that reported in FAOSTAT[1] (Table S1, Table 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 (GW) refers to the effective precipitation consumed during the growing period of a crop. Blue water (BW) 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 FAO[37]. This method is widely used for calculating crop water requirements (Equation 2-4). We then calculated crop-specific and grid-level GW and BW demand (Equation 5-8). We used a long-term climatic dataset (1987-2016) from over 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

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

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

$$ET_0 = \frac{0.498\Delta(R_n - G) + \gamma\frac{900}{T_{mean}+273}u_2(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \quad (2)$$

where R_n is the net radiation at the crop surface (MJ·m^{-2}·d^{-1}); G is the soil heat flux density (MJ·m^{-2}·d^{-1}); T_{mean} is the daily average temperature (°C); u_2 is the wind speed at 2 meters height (m·s^{-1}); e_s is the saturation vapor pressure (kPa); e_a is the actual vapour pressure (kPa); Δ is the slope of the vapor 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):

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

where $K_{z(tab)}$ 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 (%); u_2 is the wind speed at 2 meters height (m·s^{-1}); 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.

$$ET_z = K_z ET_0 \tag{4}$$

where ET_z is the crop water requirement (mm), ET_0 is the potential evapotranspiration (mm), and K_z is the calibrated crop coefficient for China.

Step 3: Calculation of crop-specific green and blue water demand

Crop-specific green and blue water demands were calculated as:

$$GW_z = 10 * \sum \min\left(0, ET_{z,t}, P_{eff,t}\right) \tag{5}$$

$$BW_z = 10 * \sum \max\left(0, ET_{z,t} - P_{eff,t}\right) \tag{6}$$

where GW_z is the green water use of a crop z; BW_z is the blue water demand of a crop z; $ET_{z,t}$ refers to the water requirement in the t^{th} growth period of the crop; $P_{eff,t}$ is the effective precipitation in the t^{th} growth stage of the crop calculated following *Yin et al.*[39]. In order 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 get the data for green water demand (GW_z). On irrigated cropland, however, we can get 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

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

GW_z and BW_z values into grid-cell (5-arcminute) data as $GW_{i,z}$ and $BW_{i,z}$,using the 'inverse distance weighted (IDW)' tool in ArcGIS 10.2 software.

Step 4: Current green and blue water demand at the grid-level

Current total green water demand ($TGW_{irr/ra,i}$) and blue water demand ($TBW_{BW,irr,i}$) of each grid was calculated as:

$$TGW_{irr/ra,i} = \sum_z HA_{irr/ra,i,z} * GW_{i,z} \quad (7)$$

$$TBW_{BW,irr,i} = \sum_z HA_{irr,i,z} * BW_{i,z} \quad (8)$$

Current state of sustainability outcomes

Unlike the process-based modeling required to estimate crop water demand above, fertilizer use, pesticide use, and farmer incomes are assessed directly based on official statistical data, while the GHGs intensity data is from the previous literature[20].

Current fertilizer use

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

$$TFN_{irr/ra,i} = \sum_i HA_{irr/ra,i,z} * FN_{i,z} \quad (9)$$

where $FN_{i,z}$ is nitrogen fertilizer use intensity of different crops ($kg \cdot ha^{-1}$). 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. Due 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

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

analysis, we also improved the resolution of fertilizer use data, where 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] (Figure S17). It is noted that the fertilizer data from NDRC cover four parts, i.e., 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 ($(NH_4)_2H\ \ PO_4$), we divide it into N and P_2O_5 according to the ratio of 1:2.56; for the other compound fertilizers, we divide it into N, P_2O_5 and K_2O according to the ratio of 1:1:1.

Current pesticide use

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

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

where $PT_{i,z} = PTC_{i,z}/pc$, $PTC_{i,z}$ is crop-specific pesticide cost per hectare (US$·ha^{-1}) in grid *i*, which was taken in the same way as fertilizer use intensity. pc (US$ 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 grid-level ($TFI_{irr/ra,i}$) was calculated as:

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

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

Current GHG emissions

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

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

where $GHG_{i,z}$ is crop-specific GHGs intensity (Mg CO_2 eq·ha^{-1}) in grid i, taken from Carlson *et al.* [20]. Because the crop-specific GHGs intensities from Carlson *et al.* are for the year 2000, we used FAO's crop emissions data[1] to estimate percent changes in China's GHG emissions from 2000 to 2010 and update grid-level crop-specific GHGs intensities for 2010.

The crop switching model

To evaluate different degrees of coordination in government management, we developed three groups of crop optimization scenarios (Table 1; Table S5) and solved them using the software GAMS (Version 22.8). 1) The first group, G1 (No coordination), simulates the potential behavior of different independent government departments with a narrow focus on their own political responsibility. Specifically, the first group contains eight optimization scenarios that prioritize 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 prioritizing 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 prioritizing a single sustainability objective each time

Min/Max SDG_{Dim} (minimize national use of blue water or other 6 sustainable dimensions, or maximize national farmer incomes)

s.t.

$$\sum_{\{irr,ra\},i,j} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \geq \sum_{\{irr,ra\}} Production_{Cur,irr/ra,z} \quad \text{(13) Production (national level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\}} TFI_{irr/ra,i} \quad \text{(14) Farmer incomes (grid level)}$$

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z} \geq \sum_{\{irr,ra\},i} CURRENT_{Dim,irr/ra,i} \quad \text{(15) SDG (national level)}$$

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

$$\sum_j x_{irr/ra,i,j} \leq 1 \quad \text{(17) Cultivated Area (grid level)}$$

$$\sum_{j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} = \sum_z HA_{irr/ra,i,z} \quad \text{(18) Harvested Area (grid level)}$$

$$SDG_{Dim} = \sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z} \quad \text{(19) Optimization Object}$$

where Dim represents 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 ($j = s1, s2, \cdots, s153$) (Table S4 and Table 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 Section 1.2.2) according to the crop-specific growth stage information in each region of China (Table S2 and Table S3; Figure S3). $UI_{Dim,i,z}$ is the use (or emissions) intensity of a specific sustainability dimension (Dim) in grid i of crop z, and $CURRENT_{Dim,irr/ra,i}$ represents the current use (or emissions) of a specific sustainability dimension (Dim) across all crops in grid i. $UPBOUND_{Dim,i}$ represents the upper boundary of the total use (or emissions) across all crops in grid i, which is great than $\sum_{\{irr,ra\}} CURRENT_{Dim,irr/ra,i}$ when $Ind_{Dim,i} \leq BD_{Dim,i}$. $Ind_{Dim,i}$ represents an indicator to evaluate the scarcity or stress of a sustainability dimension (Dim) in grid i, and $BD_{Dim,i}$ is a scientifically-defined sustainability boundary. Taking blue water as an example, $UPBOUND_{BW,i} = BD_{BW,i}/Ind_{BW,i} \cdot \sum_{\{irr,ra\}} CURRENT_{BW,irr/ra,i}$, where $Ind_{BW,i}$ is blue water scarcity indicator, that is equal to blue water use divided by irrigation water availability, taken from the work of Zhou *et al.*[35] (with boundary =0.2), which is a presumptive standard for environmental flow requirements following Richter *et al.*[41]. For nitrogen and phosphorus fertilizer, $UPBOUND_{N/P,i} = \sum_{\{irr,ra\}} CURRENT_{N/P,irr/ra,i} - Ind_{N/P,i}$, where $Ind_{N/P,i}$ is nutrient balance indicator representing the excess nitrogen and phosphorus nutrients in the soil (kg) – meant to prevent nutrient loading and eutrophication – were taken from West *et al.*[42], and the boundaries $BD_{N/P,i}$ are all 0. For green water and pesticides, we impose the constraint that they cannot degrade at 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 a 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. Equations 15 and 16 represent the constraints of resource use and environmental footprints on the national and grid level, respectively. For the grids currently experiencing unsustainable resource use ($Ind_{Dim,i} \geq BD_{Dim,i}$), we do not allow resource use to increase; for the grids in which resource use is not beyond the sustainability boundary ($Ind_{Dim,i} < BD_{Dim,i}$), 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 since there are no grid level constraints for these two dimensions. Equations 17 and 18 are constraints of cultivated land and harvested land. The harvested area is held constant at the grid level.

(2) G2 (Cross-ministry coordination): prioritizes one sustainability dimension while not degrading outcomes for the other sustainability dimensions.

Min/Max SDG_{Dim} (minimize national use of blue water or other 6 sustainable dimensions, or maximize national farmer incomes)

s.t.

$\sum_{\{irr,ra\},i,j} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \geq \sum_{\{irr,ra\}} Production_{Cur,irr/ra,z}$ (20) Production (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\},i} TFI_{irr/ra,i}$ (21) Farmer incomes (National level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot BW_{i,z} \leq \sum_{\{irr,ra\},i} TBW_{irr/ra,i}$ (22) Blue Water (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GW_{i,z} \leq \sum_{\{irr,ra\},i} TGW_{irr/ra,i}$ (23) Green Water (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GHG_{i,z} \leq \sum_{\{irr,ra\},i} TGHG_{irr/ra,i}$ (24) GHGs (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FN_{i,z} \leq \sum_{\{irr,ra\},i} TFN_{irr/ra,i}$ (25) Nitrogen (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FP_{i,z} \leq \sum_{\{irr,ra\},i} TFP_{irr/ra,i}$ (26) Phosphorus (national level)

$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FK_{i,z} \leq \sum_{\{irr,ra\},i} TFK_{irr/ra,i}$ (27) Potash (national level)

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot PT_{i,z} \leq \sum_{\{irr,ra\},i} TPT_{irr/ra,i}$$ (28) Pesticide (national level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\}} TFI_{irr/ra,i}$$ (29) Farmer incomes (grid level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot BW_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TBW_{irr/ra,i} | (Ind_{BW,i} \geq BD_{BW,i}) \\ UPBOUND_{BW,i} | (Ind_{BW,i} < BD_{BW,i}) \end{cases}$$ (30) Blue Water (grid level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GW_{i,z} \leq \sum_{\{irr,ra\}} TGW_{irr/ra,i}$$ (31) Green Water (grid level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FN_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TFN_{irr/ra,i} | (Ind_{N,i} \geq BD_{N,i}) \\ UPBOUND_{N,i} | (Ind_{N,i} < BD_{N,i}) \end{cases}$$ (32) Nitrogen (grid level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FP_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TFP_{irr/ra,i} | (Ind_{P,i} \geq BD_{P,i}) \\ UPBOUND_{P,i} | (Ind_{P,i} < BD_{P,i}) \end{cases}$$ (33) Phosphorus (grid level)

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot PT_{i,z} \leq \sum_{\{irr,ra\}} TPT_{irr/ra,i}$$ (34) Pesticide (grid level)

$$\sum_{j} x_{irr/ra,i,j} \leq 1$$ (35) Cultivated Area (grid level)

$$\sum_{j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} = \sum_{z} HA_{irr/ra,i,z}$$ (36) Harvested Area (grid level)

$$SDG_{Dim} = \sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z}$$ (37) Optimization Object

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

(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 $Aver(G_{Dim})/Var(G_{Dim})$

s.t.

$$\sum_{\{irr,ra\},i,j} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \geq \sum_{\{irr,ra\}} Production_{Cur,irr/ra,z}$$ (38) Production (national level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\},i} TFI_{irr/ra,i}$$ (39) Farmer incomes (National level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot BW_{i,z} \leq \sum_{\{irr,ra\},i} TBW_{irr/ra,i}$$ (40) Blue Water (national level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GW_{i,z} \leq \sum_{\{irr,ra\},i} TGW_{irr/ra,i}$$ (41) Green Water (national level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GHG_{i,z} \leq \sum_{\{irr,ra\},i} TGHG_{irr/ra,i}$$ (42) GHGs (national level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FN_{i,z} \leq \sum_{\{irr,ra\},i} TFN_{irr/ra,i}$$ (43) Nitrogen (national level)

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FP_{i,z} \leq \sum_{\{irr,ra\},i} TFP_{irr/ra,i}$$ (44) Phosphorus (national level)

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FK_{i,z} \leq \sum_{\{irr,ra\},i} TFK_{irr/ra,i} \quad \text{(45) Potash (national level)}$$

$$\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot PT_{i,z} \leq \sum_{\{irr,ra\},i} TPT_{irr/ra,i} \quad \text{(46) Pesticide (national level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot YLD_{irr/ra,i,z} \cdot NetProfit_{i,z} \geq \sum_{\{irr,ra\}} TFI_{irr/ra,i} \quad \text{(47) Farmer incomes (grid level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot BW_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TBW_{irr/ra,i} | (Ind_{BW,i} \geq BD_{BW,i}) \\ UPBOUND_{BW,i} | (Ind_{BW,i} < BD_{BW,i}) \end{cases} \quad \text{(48) Blue Water (grid level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot GW_{i,z} \leq \sum_{\{irr,ra\}} TGW_{irr/ra,i} \quad \text{(49) Green Water (grid level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FN_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TFN_{irr/ra,i} | (Ind_{N,i} \geq BD_{N,i}) \\ UPBOUND_{N,i} | (Ind_{N,i} < BD_{N,i}) \end{cases} \quad \text{(50) Nitrogen (grid level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot FP_{i,z} \leq \begin{cases} \sum_{\{irr,ra\}} TFP_{irr/ra,i} | (Ind_{P,i} \geq BD_{P,i}) \\ UPBOUND_{P,i} | (Ind_{P,i} < BD_{P,i}) \end{cases} \quad \text{(51) Phosphorus (grid level)}$$

$$\sum_{\{irr,ra\},j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot PT_{i,z} \leq \sum_{\{irr,ra\}} TPT_{irr/ra,i} \quad \text{(52) Pesticide (grid level)}$$

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

$$\sum_{j,z} CAz_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} = \sum_{z} HA_{irr/ra,i,z} \quad \text{(54) Harvested Area (grid level)}$$

$$G_{Dim} = \left(1 - \frac{\sum_{\{irr,ra\},i,j,z} CA_{irr/ra,i} \cdot x_{irr/ra,i,j} \cdot R_{j,z} \cdot UI_{Dim,i,z}}{\sum_{\{irr,ra\},i} CURRENT_{Dim,irr/ra,i}}\right) * 100\% \quad \text{(55) Optimization Object}$$

Where $Aver(G_{Dim})$ and $Var(G_{Dim})$ are the average and variance of the improvement of all sustainable dimensions. Here we perform a limited analysis with weights of 1 or 0 for the seven sustainability indicators to demonstrate our approach's flexibility (See Extended Data Figure 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 weight of 0 and 1 represent whether the planners consider the corresponding indicator least or most important. 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 Figure 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 Figure 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, Figure S16), relaxing the constraint of crop production (Table S6 and Table S7), and testing the sensitivity of our outcomes to the input data (Table S6, Figure 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 Figure 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 (Figure S16). In addition to 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 (e.g., flood plains vs. 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, e.g.,

Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41586-023-05799-x

irrigation change would affect fertilizer use and GHG emissions. While such interconnections are beyond the scope of this present 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 SI sections 2.6 (Table S8) and 2.7 (Figures S18 and S19).

Data availability

The SPAM database (version 1.1, the 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 crop water model and the crop growth stage data for crop rotation model are available at http://data.cma.cn/. The crop coefficients (Kz(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 greenhouse gas emissions data at grid level is from Carlson *et al*.[20]. Crop-specific fertilizer use, pesticides use, and farmer incomes 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

Linear Programming (LP) 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.

37. Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements Irrigation and Drainage Paper 56, FAO (1998) http://www.fao.org/3/X0490E/x0490e00.htm#Contents.

38. Allen, R. G., Smith, M., Pereira, L. S., Raes, D., & Wright, J. L. Revised FAO procedures for calculating evapotranspiration: irrigation and drainage paper no. 56 with testing in Idaho. *Watershed Manage. Oper. Manage.* 1-10 (2000).

39. Yin, X. *et al*. Effects of climatic factors, drought risk and irrigation requirement on maize yield in the Northeast Farming Region of China. *J. Agr. Sci.* **154**, 1171-1189 (2016).

40. Chinese Academy of Agricultural Sciences. County-level Agricultural Database. http://aii.caas.net.cn/ (in Chinese).

41. Richter, B. D., Davis, M. M., Apse, C., & Konrad, C. A presumptive standard for environmental flow protection. *River Res. Appl.* **28**(8), 1312-1321 (2012).

42. West, P. C. *et al*. Leverage points for improving global food security and the environment. *Science* **345**(6194), 325-328 (2014).

Acknowledgments

W.X. and A.Z. thank the National Natural Science Foundation of China (NSFC) (grant nos. 71873009, 71922002, and 72261147472) and China Grain Research and Training Center of National Food and Strategic Reserves Administration for financial support; T.A. was supported by the Jiangxi Agricultural University's research fund; Z.Z. thanks the NSFC (grant no. 42271076) and the Second Tibetan Plateau Scientific Expedition and Research Program (grant no. 2019QZKK0906) for financial support; X.C. thanks the NSFC (grant no. 72061147001) for financial support; F.W. thanks the Strategic Priority Research Program of Chinese Academy of Sciences (grant nos. XDA23100403, XDA23070402), the Third Xinjiang Scientific Expedition and Research(grant no.2021xjkk0903) and NSFC (grant no 41971233) for financial support; J. H. acknowledges the support of the National Natural Science Foundation of China (grant no. 71934003) for financial support; K.F.D. was supported in part by the University of Delaware General University Research fund. We also thank Professors Yongdeng Lei, Mingsheng Fan, and Dr. Li Zhang from China Agriculture University for the discussions on the method framework of this study and Qinyu Deng from Beijing Normal University, Maoran Zhu and Jian Zong from Peking University for their assistance in this paper.

Author information

Authors and Affiliations

These authors contributed equally to this work: Wei Xie, Anfeng Zhu, Tariq Ali

China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China

Wei Xie, Anfeng Zhu, & Jikun Huang

School of Economics and Management, Jiangxi Agricultural University, Nanchang, China

Tariq Ali

School of National Safety and Emergency Management, Beijing Normal University, Beijing, China

Zhengtao Zhang

Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, 610074, China

Xiaoguang Chen

Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China

Feng Wu

Department of Geography and Spatial Sciences, University of Delaware, Newark, Delaware, USA

Kyle Frankel Davis

Department of Plant and Soil Sciences, University of Delaware, Newark, Delaware, USA

Kyle Frankel Davis

Contributions

W.X. led the study. W.X., K.F.D., and T.A. conceived the study and designed all analyses. W.X., Z.Z., X.C., F.W. and A.Z. collected the crop, environment, and farmer income data. W.X. and A.Z. conducted the crop switching model simulations. W.X., A.Z., and T.A. conducted the uncertainty analysis. W.X., K.F.D., A.Z., T.A., F.W., and J.H. interpreted the final results. W.X., T.A., A.Z., and K.F.D. wrote the paper. W.X., A.Z., and Z.Z. produced the graphical representation of the results. All authors contributed to revising the paper.

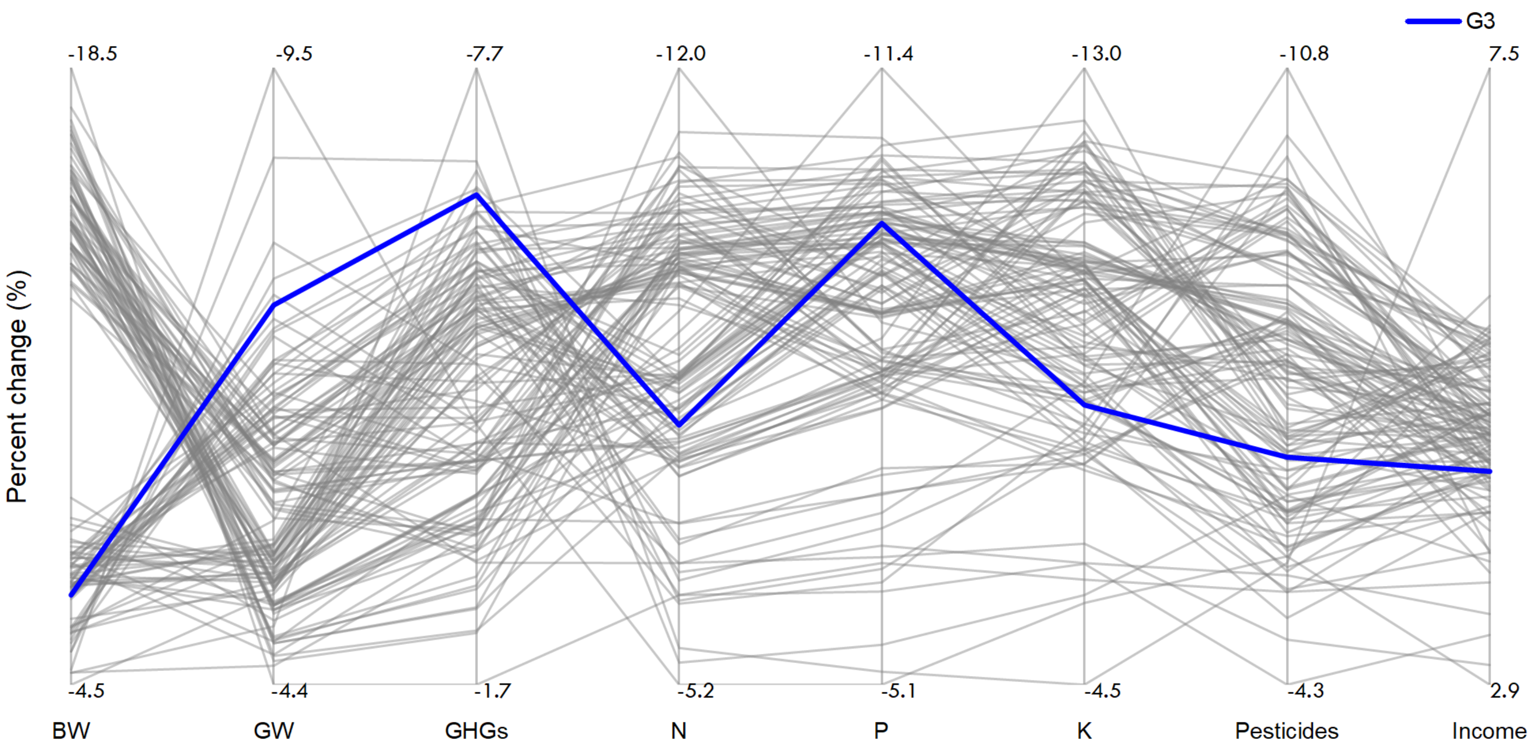
Corresponding authors

Correspondence to Wei Xie, Xiaoguang Chen, Feng Wu or Kyle Frankel Davis.

Ethics declarations

Competing interests

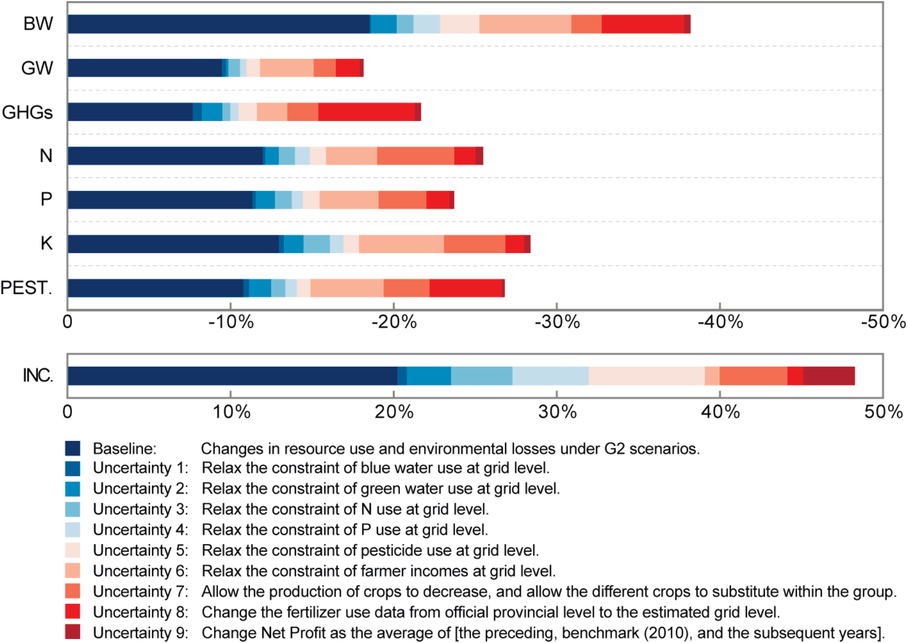
The authors declare no competing interests.



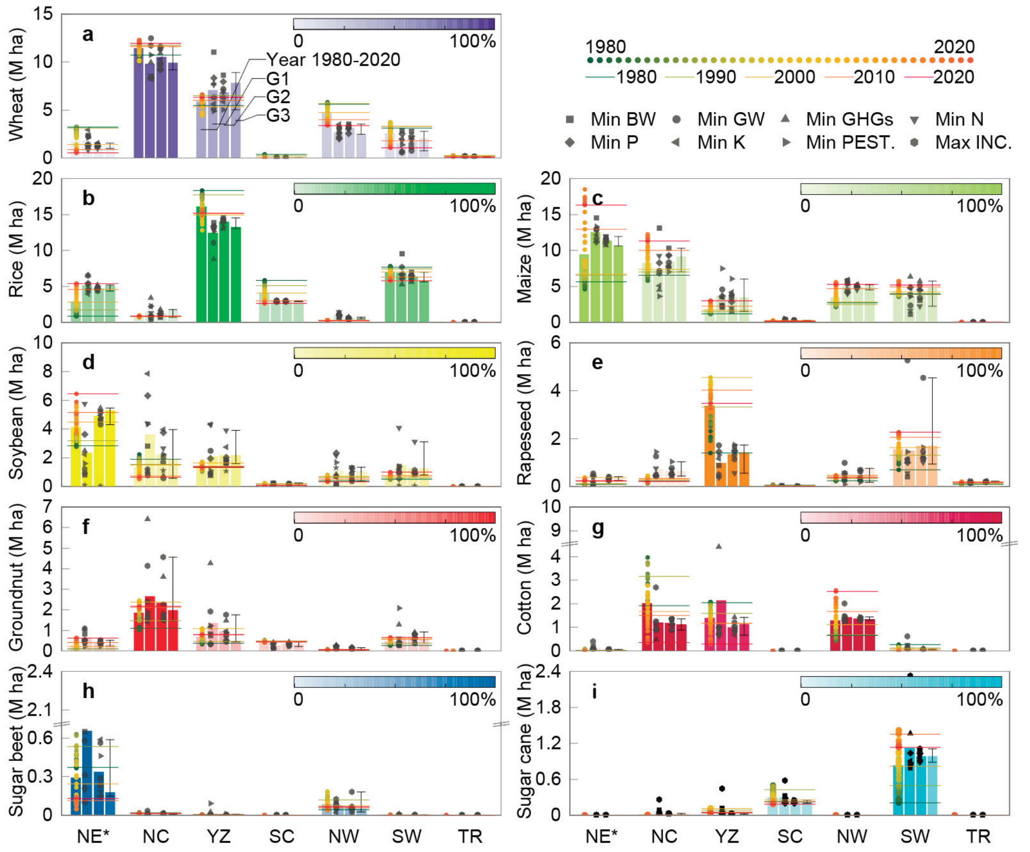
G3
-18.5
-9.5
-7.7
-12.0
-11.4
-13.0
-10.8
7.5
Percent change (%)
-4.5
-4.4
-1.7
-5.2
-5.1
-4.5
-4.3
2.9
BW
GW
GHGs
N
P
K
Pesticides
Income

Extended Data Figures

Extended Data Figure 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, PEST = pesticides.


BW
GW
GHGs
N
P
K
PEST.
0
-10%
-20%
-30%
-40%
-50%
INC.
0
10%
20%
30%
40%
50%
Baseline: Changes in resource use and environmental losses under G2 scenarios.
Uncertainty 1: Relax the constraint of blue water use at grid level.
Uncertainty 2: Relax the constraint of green water use at grid level.
Uncertainty 3: Relax the constraint of N use at grid level.
Uncertainty 4: Relax the constraint of P use at grid level.
Uncertainty 5: Relax the constraint of pesticide use at grid level.
Uncertainty 6: Relax the constraint of farmer incomes at grid level.
Uncertainty 7: Allow the production of crops to decrease, and allow the different crops to substitute within the group.
Uncertainty 8: Change the fertilizer use data from official provincial level to the estimated grid level.
Uncertainty 9: Change Net Profit as the average of [the preceding, benchmark (2010), and the subsequent years].

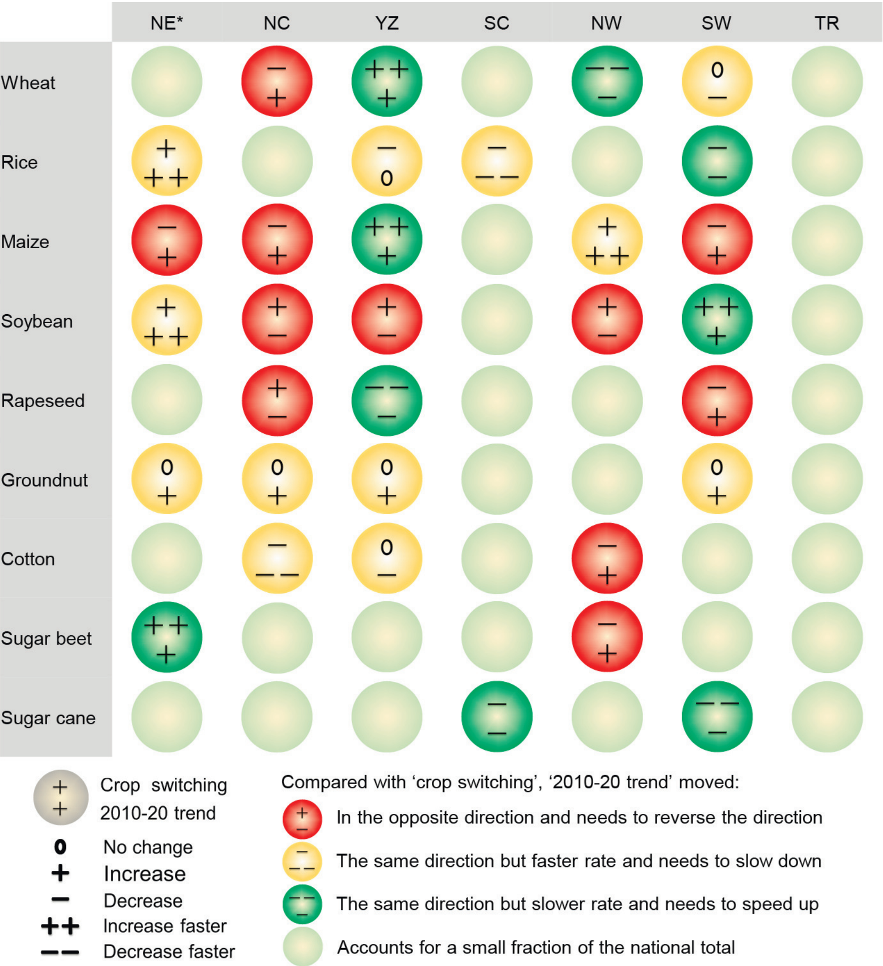
Extended Data Figure 2 | Decomposition of the sources of uncertainty. 'Baseline' (dark blue bar) shows the reduction in resource use, reduction in environmental impacts and increase in farmers' income under G2 scenario. Other colors represent the difference between results of uncertainty scenarios and the baseline scenario (G2 scenario) (see Table S6 and SI Section 2.5 for details on the varying assumptions regarding different uncertainty sources).



Wheat (M ha)
Rice (M ha)
Maize (M ha)
Soybean (M ha)
Rapeseed (M ha)
Groundnut (M ha)
Cotton (M ha)
Sugar beet (M ha)
Sugar cane (M ha)
a
b
c
d
e
f
g
h
i
0
100%
Year 1980-2020
G1
G2
G3
1980
2020
1980
1990
2000
2010
2020
Min BW
Min GW
Min GHGs
Min N
Min P
Min K
Min PEST.
Max INC.
NE*
NC
YZ
SC
NW
SW
TR

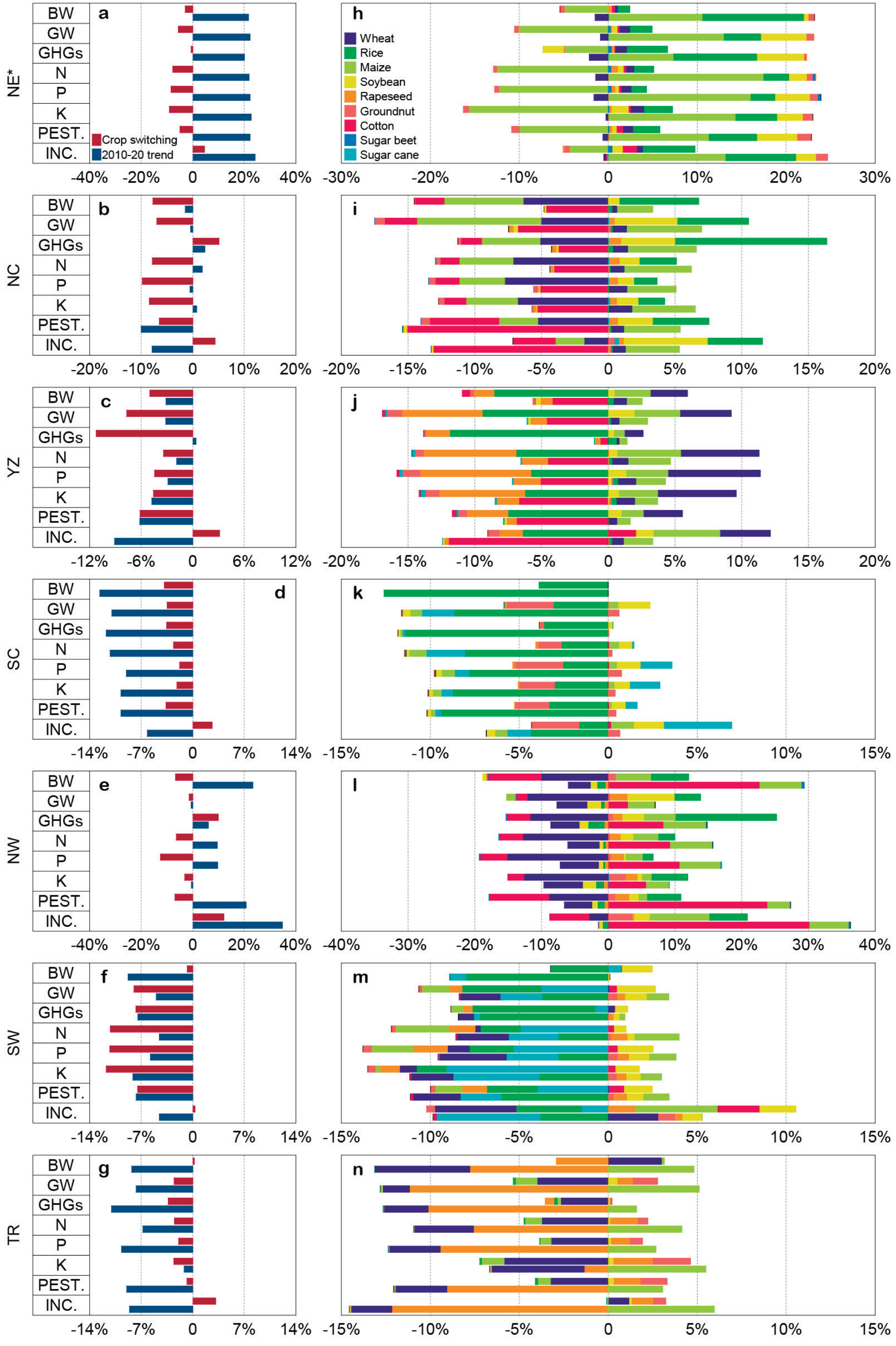
Extended Data Figure 3 | Comparison of proposed crop switching with historical crop distribution. The five horizontal lines within each panel show crop distributions at decadal intervals (i.e., between 1980 – 2020) that can be compared with our proposed crop switching. The color scale of the bars corresponds 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.

*Note that because crop distribution changes during the last ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from the one 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.


NE*
NC
YZ
SC
NW
SW
TR
Wheat
Rice
Maize
Soybean
Rapeseed
Groundnut
Cotton
Sugar beet
Sugar cane
Crop switching
2010-20 trend
0 No change
+ Increase
− Decrease
++ Increase faster
−− Decrease faster
Compared with 'crop switching', '2010-20 trend' moved:
In the opposite direction and needs to reverse the direction
The same direction but faster rate and needs to slow down
The same direction but slower rate and needs to speed up
Accounts for a small fraction of the national total

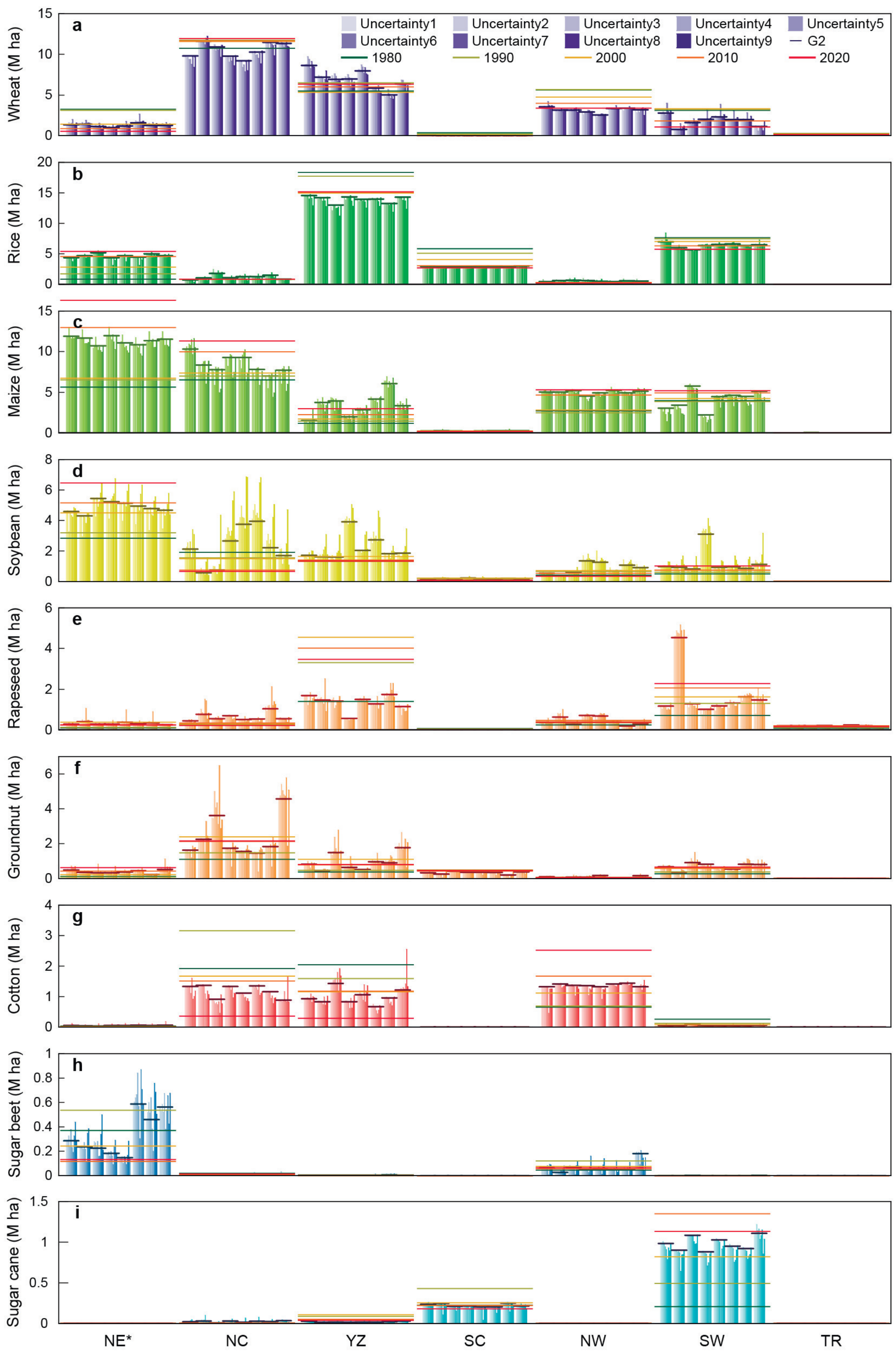
Extended Data Figure 4 | Trend agreement between proposed and recently observed changes in cropping patterns. Circle colors denote whether – compared to our proposed crop switching (G3) – the observed distribution change of the crop in that region during the last ten years has moved in the opposite direction 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, while the bottom signs (+, −, 0) show recent crop distribution changes during 2010-2020. We find that in 68% (21/32) of cases recent cropping pattern changes are moving in the same (green or yellow) direction as our proposed switches.

*Note that because crop distribution changes during the last ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from the one used in our crop switching model, which is based on 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.


NE*
NC
YZ
SC
NW
SW
TR
BW
GW
GHGs
N
P
K
PEST.
INC.
a
b
c
d
e
f
g
h
i
j
k
l
m
n
Crop switching
2010-20 trend
Wheat
Rice
Maize
Soybean
Rapeseed
Groundnut
Cotton
Sugar beet
Sugar cane
-40%
-20%
0
20%
40%
-30%
-20%
-10%
10%
30%
-15%
-5%
5%
15%
-12%
-6%
6%
12%
-14%
-7%
7%
14%

Extended Data Figure 5 | Comparison of sustainability outcomes between proposed crop switching (G2) and observed crop distribution changes during the last 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.

*Note that because crop distribution changes during the last ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from the one used in our crop switching model, which is based on 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.



Uncertainty1
Uncertainty2
Uncertainty3
Uncertainty4
Uncertainty5
Uncertainty6
Uncertainty7
Uncertainty8
Uncertainty9
G2
1980
1990
2000
2010
2020
a
Wheat (M ha)
b
Rice (M ha)
c
Maize (M ha)
d
Soybean (M ha)
e
Rapeseed (M ha)
f
Groundnut (M ha)
g
Cotton (M ha)
h
Sugar beet (M ha)
i
Sugar cane (M ha)
NE*
NC
YZ
SC
NW
SW
TR

Extended Data Figure 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 (8 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 SI Section 2.5 for details on the varying assumptions regarding different uncertainty sources). The five long horizontal lines show crop distributions at decadal intervals (i.e., between 1980 – 2020) that can be compared with our proposed crop switching.
*Note that because crop distribution changes during the last ten years are only available based on the administrative divisions, the regional aggregation used here is slightly different from the one used in our crop switching model, which is based on 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.