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Research Report

Groundwater sustainability in India through nonrice-dominated cropping pattern

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Abstract

Over-exploitation of groundwater for irrigation caused rapid groundwater depletion in north India, leading to food and water security challenges. However, the crucial role of changing cropping patterns on groundwater savings under the observed and projected warming climate remains unexplored. Here, we show that altering the existing rice-dominated cropping systems in India can be a potential solution for groundwater sustainability under the current and future climate. Satellite and model-based estimates show that north India lost ~336 and 297 km^3 of groundwater, respectively during 2002–2022. We developed optimized crop switching scenarios for groundwater savings considering nutritional requirements, farmers' profit, and crop production. Crop switching considering all the three targets (crop switch one: CSI) and allowing rice replacement with alternate crops (crop switch two: CSII) could save 45 and 91 km^3 groundwater, respectively in north India during the observed climate (2002–2022) compared with the current cropping pattern. Altering the current cropping pattern can lead to substantial groundwater savings under the projected future climate without comprising nutritional targets and farmers' profit at the state level. Replacing 37% area of rice with other crops (CSII) can recover 61 to 108 km^3 groundwater compared with −13 to 43 km^3 with current cropping pattern under the 1.5–3 °C global warming levels. Similarly, under the CSI scenario, 36 to 86 km^3 groundwater can be recovered in the future warming world. Moreover, the benefits of crop switching in groundwater saving are higher during the prolonged dry periods compared with the baseline under the warming climate. Therefore, crop switching offers substantial benefits for groundwater sustainability under the current and projected future climate in India.

Keywords: climate change, groundwater depletion, water sustainability, crop switching, irrigation

Significance Statement

Groundwater is essential for irrigation to sustain food production in India. However, the extensive groundwater depletion due to irrigation in the rice-dominated cropping system necessitates assessing alternative cropping patterns. Using observations, crop switching optimization, and hydrological modeling, we quantify the potential groundwater savings by crop redistribution (crop switch one, CSI) and considering 37% rice replacement with alternate crops (crop switch two, CSII) in North India. We show that CSI and CSII scenarios could save 45 and 91 km^3 groundwater, respectively during the observed climate. The CSI and CSII scenarios can lead to additional savings of 42–50 and 65–81 km^3 under the 1.5–3.0 °C global warming levels. An altering cropping pattern reduces over-exploitation of groundwater, which is crucial to ensure food and freshwater security under the warming climate.

Introduction

Agriculture is the largest (85–90%) global water consumption sector (1). Global food production has tripled to meet the food demands of growing population with a substantial contribution of irrigation (2, 3). The green revolution has increased agricultural and food production in India since 1970s to mitigate the food shortage (4). India has tripled its cereal production in the past 50 years (4). In addition, India has the second largest equipped area for irrigation of 73 Mha with a 12 Mha increase in the last two decades (5). India uses 57% land area for food production, which consumes about 87% of the total freshwater (6). India has become self-sufficient in food production in last 30 years by growing wheat as a major Rabi crop and rice as a major Kharif crop. Rice growing season coincides with the Indian summer monsoon (June–September). Rice accounts for 75% of net cropped area in Northwestern India and Indo Gangetic Plains (7). Northern and northwestern regions of India are among the global groundwater hotspots (8, 9) and excessive pumping threatens food and water security (10, 11). Therefore, one of the negative consequences of food security is groundwater pumping for irrigation, which has increased globally, with India being no exception.

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North India remains a dominating contributor among the groundwater depleting regions in India (12). Moreover, north India has become a poster child of unsustainable use of groundwater, and parts of Punjab and the Ganga basin have experienced the most rapid groundwater depletion in the world (13–18), which is mainly attributable to pumping for irrigation (7, 17) as north India has ~58% of area equipped with irrigation from groundwater. Subsidized electricity further increased reliance on groundwater for irrigation (15). While the groundwater depletion in north India has posed challenges for water availability, water quality, and food security, technological interventions to reduce groundwater pumping have contributed little to solve the problem (19).

Agricultural policies aim to meet the food demands while curbing groundwater depletion receives a lower priority (15, 18). Groundwater storage is declining at rates of more than 1 cm/year in north India (16, 18), which leads to deepening of tube wells at increased pumping costs (20). Therefore, increased food production's environmental aspects and associated economic consequences should be addressed (18). One of the classic examples of unsustainable groundwater extraction is Punjab that lost massive groundwater as the current irrigation requirements exceed the renewable groundwater available (13, 16). Groundwater is a reliable source of irrigation and can provide buffer during heat stress and is vital for food production under climate change (21). However, excessive groundwater pumping limits the benefit of groundwater recovery under climate change (12). Therefore, the sustainability of groundwater resources can rely on reducing the groundwater pumping for irrigation.

Groundwater extraction can be reduced by improving irrigation efficiency, enhancing surface water storage, and altering cropping patterns (22). All these three primary drivers of reducing the dependence of irrigation on groundwater storage have limitations. For instance, implementing the improved irrigation efficiency measures at a regional scale remains a challenge along with the constraints related to adapting the capacity of recent technologies by the farmers (19). Enhancing reservoir storage with a canal network may not be possible due to topographical and land availability constraints. Altering cropping patterns and moving toward less irrigation-intensive crops in the regions facing rapid groundwater depletion may have relatively greater feasibility. However, crop switching needs to consider nutritional targets, farmers' profit, and food security concerns associated with reducing rice cultivation (6, 7, 23, 24). Current cropping patterns could be more optimal and can reduce irrigation water withdrawal while maintaining food security (23, 25–28). Moreover, the redistribution of crops to different regions can help in balancing nutrient supply, crop yields, farmers' income, greenhouse gas emissions, and environmental sustainability (7, 24, 26, 27, 29–34). However, several of the proposed optimized cropping patterns have not been critically examined for their effectiveness under the warming climate.

Rice-grown areas in India are expanding (35). For instance, India's rice harvested area during the summer monsoon has increased from 52 to 67% (5). The rice expansion has occurred in regions where water availability for rice cultivation could be better (35). For instance, Punjab, which falls in semi-arid climate, has rapidly expanded rice cultivation in the last 50 years (36). The irrigation water requirement to cultivate rice in Punjab is higher than the mean annual rainfall, which led to unsustainable groundwater extraction. However, changing the current crop distribution is problematic on a national scale as it is associated with food production stability. Drought under the warming climate can further enhance groundwater abstraction (37) and changing the existing cropping pattern is necessary for the rapid depletion of groundwater to be constrained (12). Therefore, policy framing to alter the current cropping patterns is needed to ensure farmers' profitability and income (7, 23). Crop switching can have a high impact on most groundwater stressed regions. Therefore, crop diversification policy must be implemented to ensure groundwater sustainability (30, 36).

Considering the future challenges of climate change and food security of the growing population, it remains to be seen if the existing cropping patterns and irrigation of intensive crops can sustain under the warming climate. Moreover, considering economic, food and water sustainability goals, it is imperative to adopt a multiobjective framework to identify optimal cropping patterns with potential co-benefits in context of groundwater sustainability in the irrigated regions of north India under the current and future climate. Therefore, we address the critical question of to what extent crop switching can help groundwater recovery in the current and projected future climate in north India. Climate warming and enhanced variability in the summer monsoon in the future can further worsen the existing groundwater depletion and overall food and water security in India (12). Examining the role of altering the cropping patterns in groundwater sustainability remains critical. We integrate the current satellite and well observations, and crop switching optimization framework with hydrological modeling to estimate the role of crop switching scenarios on groundwater depletion in north India (Fig. S1). We further advance the knowledge gained from the previous studies (7, 23, 24) through the empirical and statistical methods for the current climate (Table S1). Our findings are based on the combined framework that integrate optimized crop switch scenarios with hydrological modeling to estimate the benefits of crop switching for groundwater savings in current and future climate.

Results

Groundwater loss from the north India

First, we examine the current cropping pattern in the regions that experienced considerable groundwater depletion. Rice is the prevalent crop grown in north India with 80% crop area while cereals account for 15% area. Pulses and oilseeds in the Kharif season are grown in 5% area in the region (Fig. S2). The rice–wheat cropping system has improved food security while depleting the groundwater resources with rates of 31.3 $km^3 year^{-1}$ for wheat and 21.3 $km^3 year^{-1}$ for rice (11). Rice growing regions of India possess over one-third cropland fraction across 79% of its total cropland, with 89% prevalence in North India rice districts (Fig. 1A, E and F). Widespread groundwater and well-sourced irrigation cover over half of the Indian rice region, while 80% of its land area in the northern rice growing region (Fig. 1B, C, E and F). In rice growing regions of India, irrigation from tube wells accounts for 59% (Fig. 1D to F). Notably, irrigation from shallow tube wells is also considerable in parts of North India (Uttar Pradesh).

Next, we identify the regions that have witnessed substantial groundwater depletion in the last few decades. We used groundwater well and satellite observations integrated with a hydrological modeling framework to quantify the groundwater depletion in India during 2002–2022 (Fig. 2A, B). In situ, satellite observations, and model simulations confirm North India as a groundwater depletion hotspot (13, 16). Our hydrological modeling framework based on the H08 model performs well in simulating the groundwater storage anomaly (GWSA) estimated from the GRACE satellites (Fig. 2C). For instance, the inter-annual variability in the satellite-based GWSA is well captured by the H08 model with Nash Sutcliffe Efficiency (NSE) of 0.93 and correlation coefficient

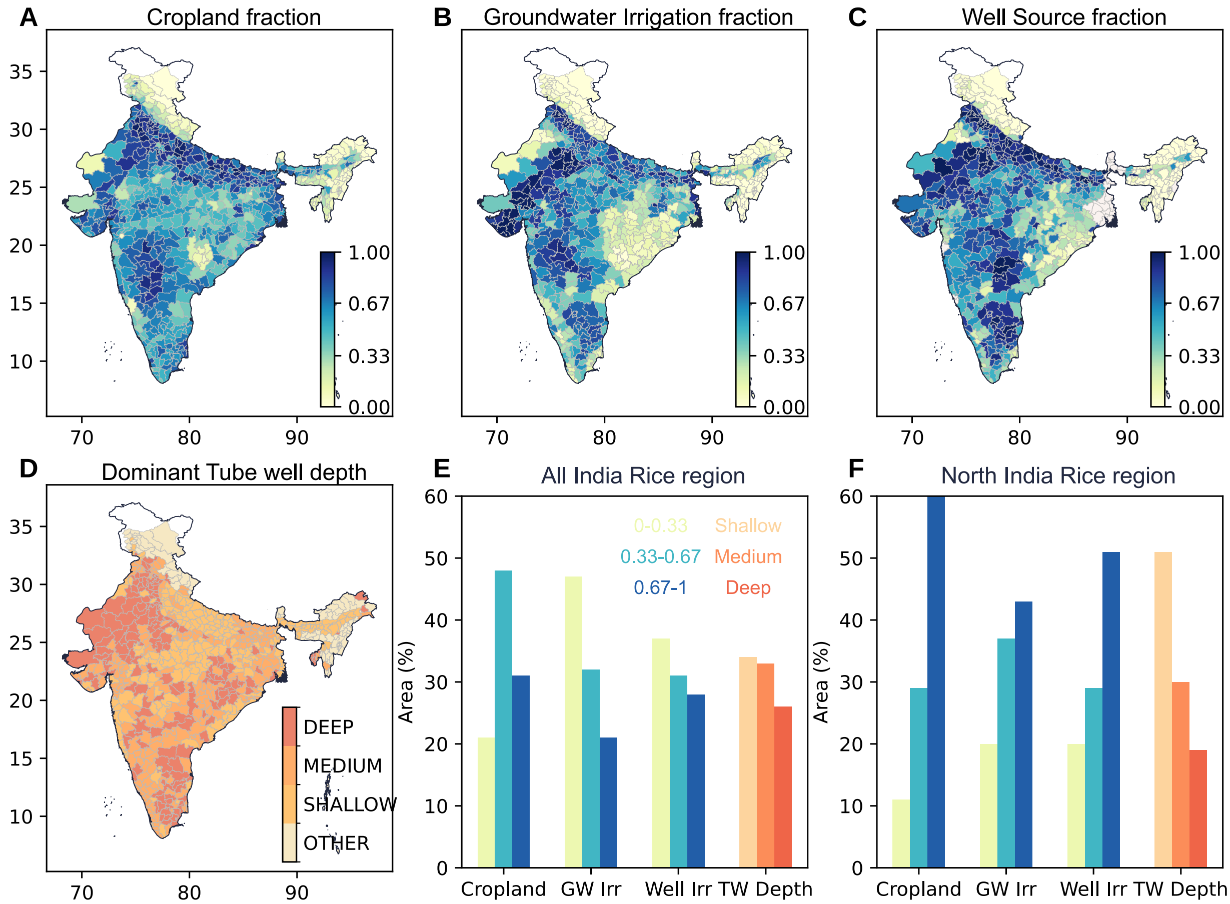

Fig. 1. District-scale indicators for groundwater-based irrigation. A) Cropland fraction of land area, B) Groundwater irrigation fraction, C) Well source irrigation fraction, D) Tube Well depth classification highlighting irrigation dominance. Percentage of area corresponding to the three classes for indicators in rice-grown regions of India E) and North India F). Classes are categorized as follows: 0–0.33 (low), 0.33–0.67 (medium), and 0.67–1 (high) for cropland, groundwater irrigation (GW Irr), and well source irrigation (Well Irr). The dominant depth of tube wells is classified as shallow, medium, and deep. Cropland and groundwater irrigation fractions are obtained from FAO, the well source is acquired from land use statistics, and the depth of tube wells is gathered from minor irrigation census reports.

(r) of 0.97. The H08 model estimates show a good agreement with the total groundwater lost from India and the north Indian region based on the satellite observations during the 2002–2022 period (Fig. 2D). For instance, India has lost ~508 km^3 of groundwater as calculated using the GRACE satellite-based observations. The estimates based on the H08 model show a loss of ~495 km^3 during the same period (2002–2022). Moreover, groundwater loss estimates from the H08 model at a regional scale also agree well with satellite-based observations. For instance, satellite-based estimates show a decline of groundwater storage of ~336 km^3 in north India, while the H08 model-based estimates show a loss of ~297 km^3. The differences in the model-based estimates and observations can be attributed to the model parametrizations and coarse native resolution of the GRACE RL06 mascon product (38, 39).

Crop switching benefits in limiting groundwater depletion during the observed period

We identified the north Indian region to examine the effect of crop switching as it has significantly lost groundwater and intensively irrigated (Figs. S1 and 2). Several districts of Punjab that primarily grow rice experienced a massive groundwater depletion. Punjab experienced the highest groundwater depletion rate of ~5 cm/year, while Haryana, Uttar Pradesh, and West Bengal also witnessed a considerable depletion rate ranging from 2 to 4 cm/year (Fig. S3B).

We considered the current cropping pattern as a baseline scenario to examine the role of crop switching. We have set constraints on the nutritional target, farmers' profit, and crop production to minimize the groundwater withdrawal for irrigation (Fig. S1). We used the optimization model (see Methods for more details) with crop area fraction as decision variable for North India region. We evaluated the two crop switching scenarios, first, where crop-growing areas are redistributed as per the crop switching optimization framework while meeting all the three objectives (Crop Switch I, CSI). In the second scenarios, rice production was compromised along with redistribution of crops as per the optimized crop fraction in each district (Crop Switch II, CSII, see Methods for more details) (Fig. 3). Since rice has the largest crop water requirement, reducing the rice-grown area with another less water-intensive crop can help in groundwater use for irrigation. In addition, the already lost groundwater can also be recovered in the long term, given that the pumping is substantially reduced with crop redistribution.

The CSI scenario maintains a cropping area percentage like the current cropping pattern but decreases rice cropped area by 5%. Conversely in the CSII scenario, the rice-grown area in north India is reduced by 37% and replaced with cereals (27%) as well as pulses and oilseeds (5%) alongside a 5% reduction in cropped area (Fig. 3I). The CSI scenario exhibits a marginal increase in nutritional value, with a 1% rise in calorie content, 2.0% increase in protein, and a 13.5% boost in overall farmers' profit in north

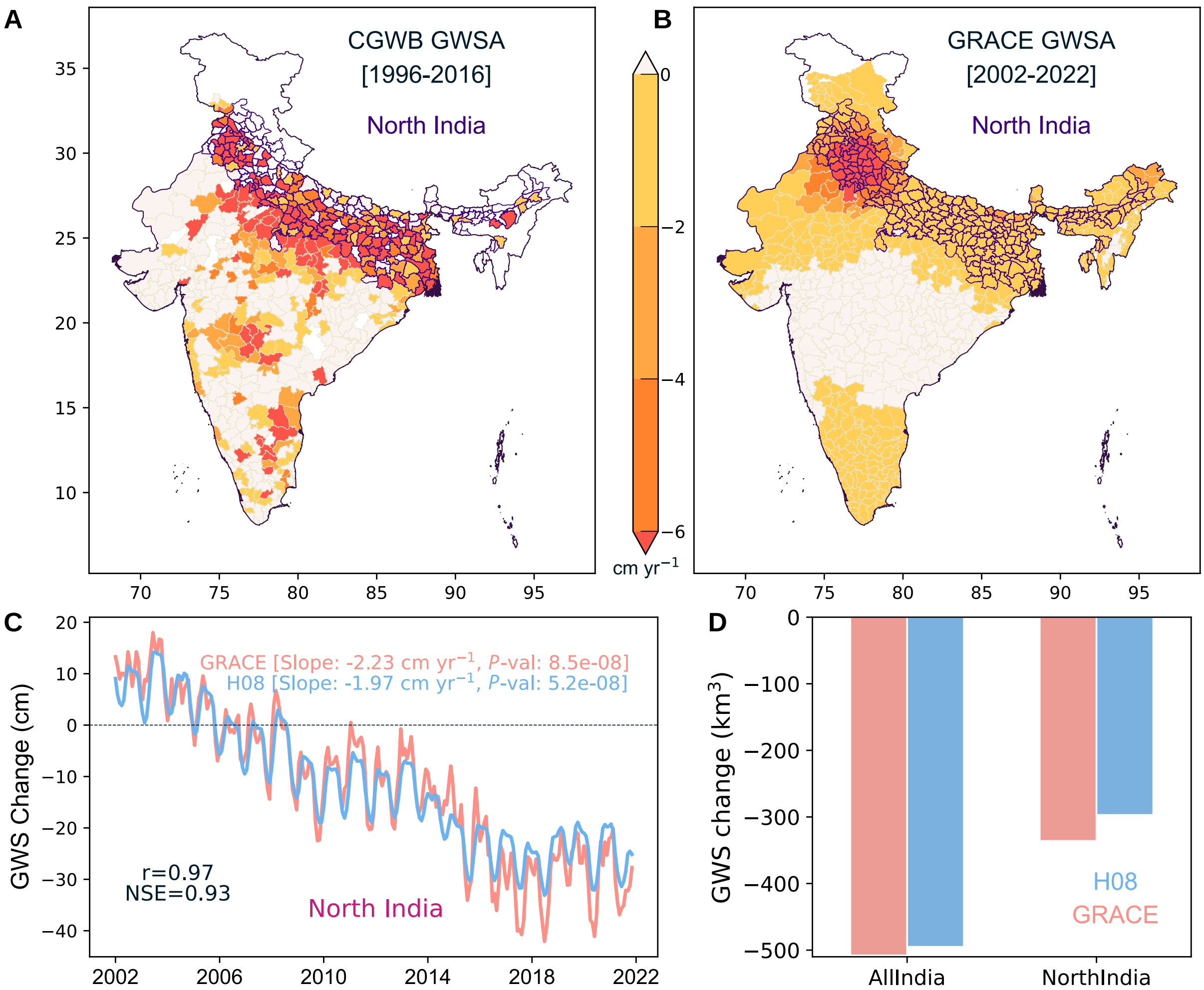

Fig. 2. Variability in observed groundwater storage using wells, satellites, and hydrological model. A) Trend in GWSA on a district scale using CGWB data. Quarterly well level observations accessible from 1996 to 2016 collected from approximately 5,000 wells. B) District-scale trend in GWSA using monthly GRACE data from 2002 to 2022 at 0.25° spatial resolution. C) Time series of GRACE-derived GWSA and H08 model-predicted GWSA for the northern region of India. Sen slope and P-value, along with correlation and NSE values are shown. D) Bar plots showing the total groundwater loss during 2002–2022 for India as a whole and the northern region. The regions of interest selection are detailed in the Methods section.

India while maintaining almost the same rice production (Fig. 3G). On the other hand, the CSII scenario demonstrates a 1% increase in calorie content, 16.6% rise in protein values, and 86% rise in farmers' profits. However, this comes at the expense of a notable (45%) decrease in rice production (Fig. 3G).

The current cropping pattern shows groundwater depletion at ~2 cm/year with a total groundwater loss of about ~300 km^3 during 2002–2022. The crop switching scenarios can substantially reduce groundwater depletion (Fig. 4B to D). For instance, under the CSI and CSII scenarios, groundwater loss could have been reduced by about 45 and 91 km^3, respectively, in northern India during 2002–2022 (Fig. 4E). The CSI scenario can lead to groundwater savings of 13 and 22 km^3 in Punjab and Uttar Pradesh, respectively (Fig. S3A). On the other hand, CSII can lead to groundwater savings of 21 and 53 km^3 in Punjab and Uttar Pradesh, respectively during the same period (Fig. S3A). The groundwater saved in each state in the last two decades is equivalent to one to four times the maximum reservoir capacity of the largest dam in India, Indira Sagar. In Punjab, rice-grown area is reduced by ~17% under CSI and 42% under CSII (Fig. S4). In Uttar Pradesh, cereals are major alternative crops of rice, while in West Bengal, oilseeds are major rice alternatives. Crop switch does not contribute to substantial groundwater recovery or depletion where depletion rates are low as in Himachal Pradesh, Uttarakhand, and Jharkhand. Therefore, optimizing crop switch of rice crop to only districts with extensive groundwater pumping for irrigation can help limit groundwater withdrawal without substantially hampering rice production. Factors like crop yield and cost of production is also considered while redistribution of crops. The CSII scenario can benefit groundwater in the states of Punjab and Uttar Pradesh by rice replacement without decreasing farmers' profitability at a state level. Therefore, both the crop switching scenarios can be a feasible option for groundwater sustainability in major groundwater depletion hotspots especially where rice is grown.

Crop switching contribution to groundwater recovery in the projected future climate

Precipitation is projected to increase in India (Fig. S5A) as the global warming level is likely to cross 1.5 °C by 2030 and can reach 3 °C by 2100 (40). Despite the projected rise in precipitation that will contribute to groundwater recharge, groundwater recovery is limited primarily due to increased potential evapotranspiration (PET) due to warming (Fig. S5B). A projected rise in PET implies

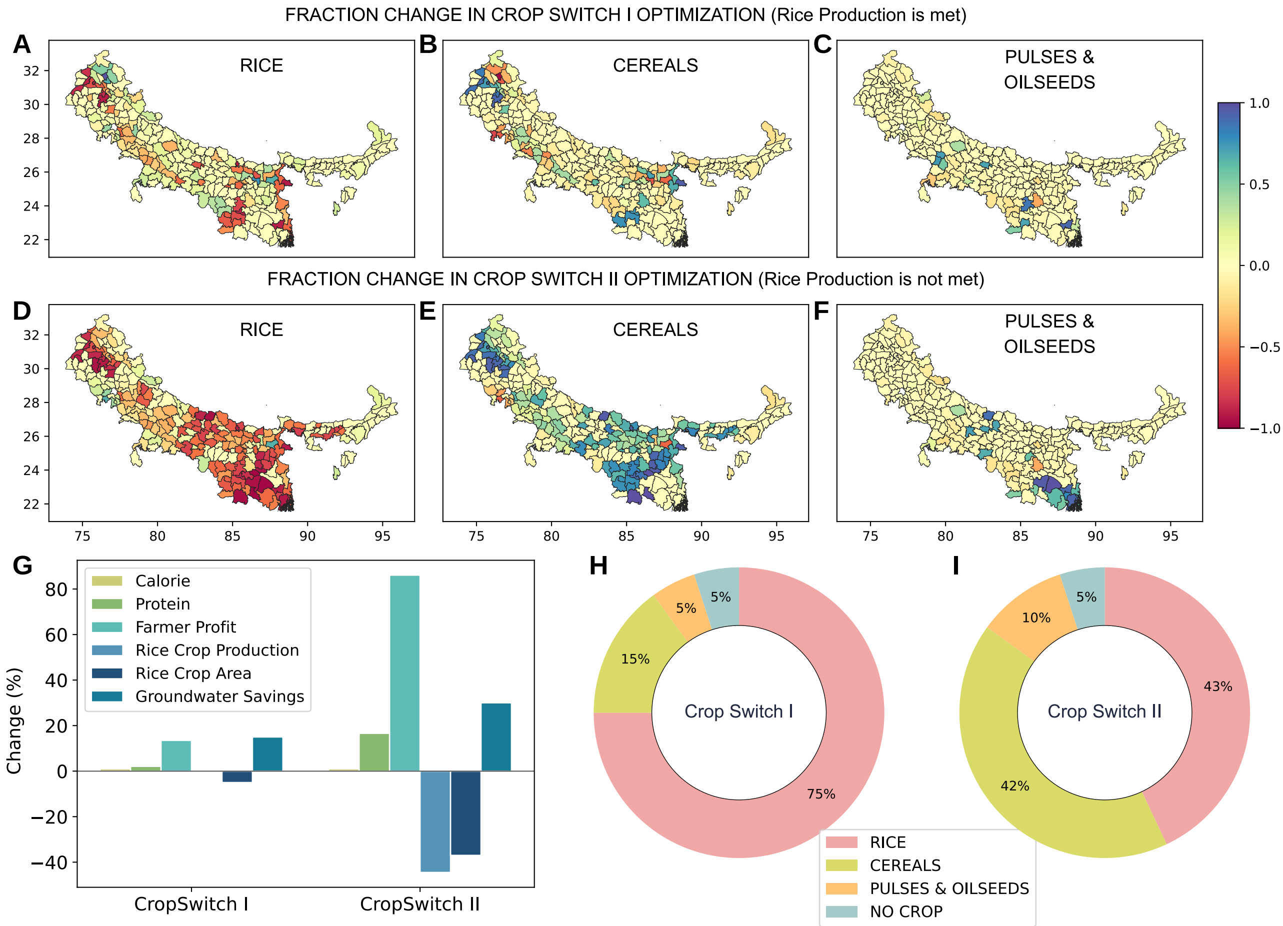

Fig. 3. Optimized scenarios in cropping pattern relative to baseline in Kharif season. Spatial distribution of changes in cropping area fraction in Kharif season under CSI scenario for A) Rice, B) Cereals, and C) Pulses and Oilseeds. Spatial distribution of fractional changes relative to baseline scenario under CSII scenario for D) Rice, E) Cereals, and F) Pulses and Oilseeds. G) Optimized changes in calorie and protein targets, farmers profit, rice crop production, rice cropped area and groundwater savings over the selected North Indian region under the proposed crop switch scenarios. % Crop distribution over the study region for H) CSI and I) CSII scenarios in Kharif season.

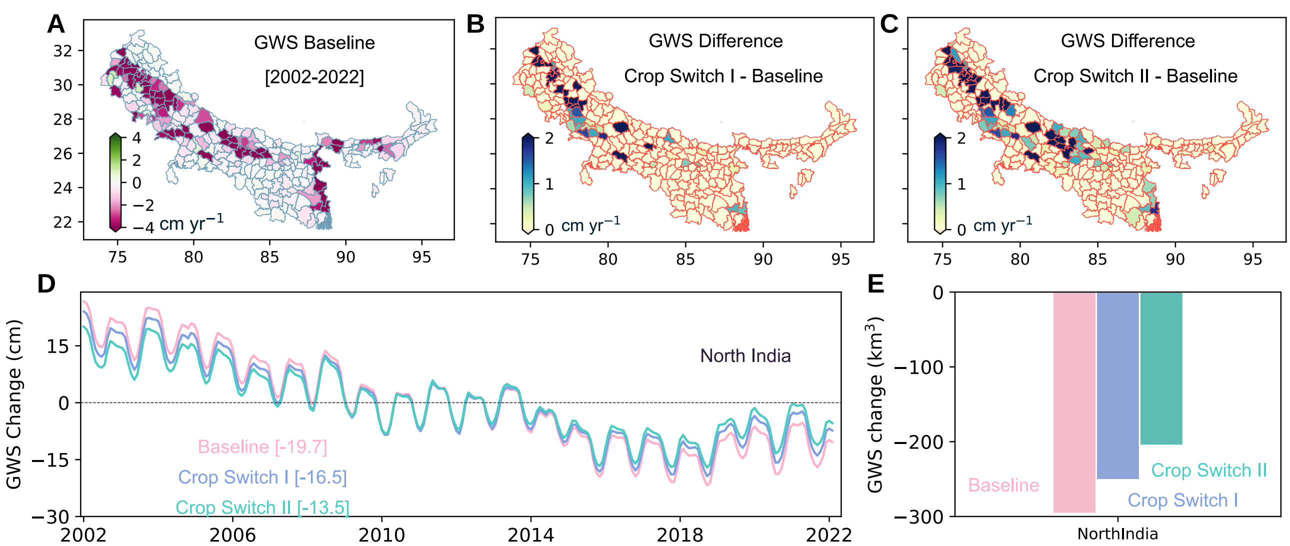

Fig. 4. Observed groundwater storage changes in baseline and crop switching scenarios. A) H08 modeled groundwater storage change trend for North India during 2002–2022 with current (baseline) cropping pattern. Difference in groundwater storage change trend relative to baseline scenario resulting from B) CSI and C) CSII scenarios in North India. D) H08 modeled GWSA time series for the northern region of India in baseline, CSI and CSII scenarios. The Sen slope (in millimeter per year) is shown in brackets. E) Bar plot shows the total groundwater lost in 2002–2022 period for northern region in the baseline and CSI and CSII crop switching scenarios. Specifics of the crop switching scenarios are outlined in the Methods section.

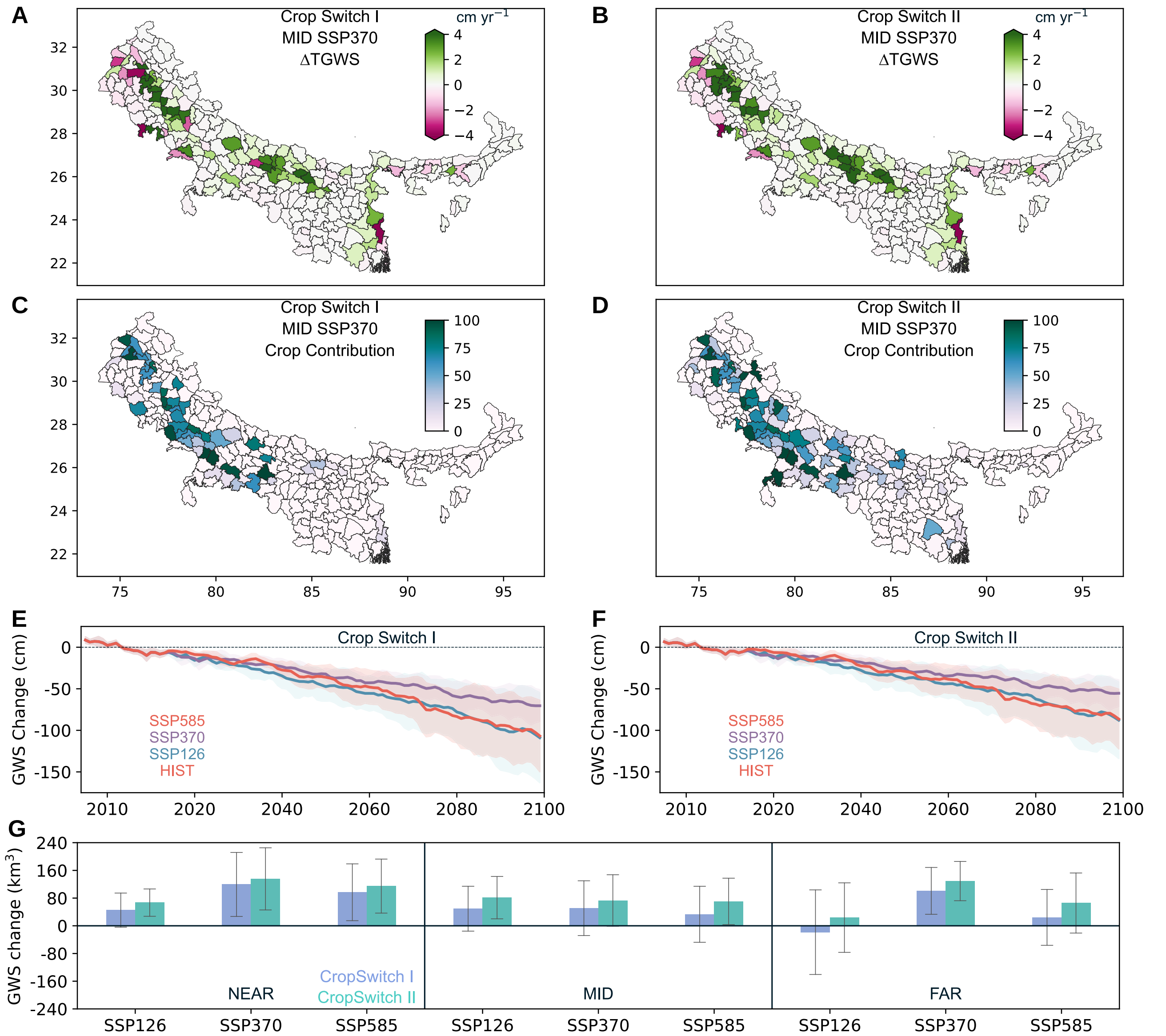

Fig. 5. Future groundwater storage changes in crop switching scenarios. H08 modeled groundwater storage change trend for north India during the mid-period (2041–2060) under SSP370 scenario A) CSI scenario, B) CSII scenario. Contribution of C) CSI and D) CSII scenarios to groundwater recovery relative to the baseline scenario. Time series for groundwater storage changes under different SSP scenarios in E) CSI and F) CSII scenarios. The bold line represents the ensemble mean, and the shading indicates 1 SD across five climate models. G) Bar plots showing the mean groundwater storage changes for CSI and CSII scenarios in the near (2021–2040), mid (2041–2060), and far (2081–2100) periods relative to historical (1995–2014) baseline scenario. Error bars represent 1 SD under different SSP scenarios.

that irrigation water demand will increase in the future, possibly leading to increased groundwater withdrawal, assuming no major change in irrigation efficiency. As the projected increase in precipitation alone is insufficient for the recovery of the lost groundwater (12). We examine the role of crop switching scenarios (CSI and CSII) in groundwater recovery under the warming climate in the states that lead groundwater abstraction for irrigation (Fig. 5).

Punjab, Haryana, and Uttar Pradesh are projected to witness substantial changes in groundwater recovery due to crop switching compared with the existing cropping pattern, which is dominated by rice under the warming climate (Fig. 5A to D). For instance, the crop switch can reduce groundwater depletion compared with the current cropping pattern in the future climate. In addition, crop switch is more effective in the regions that are extensively irrigated, dominated by rice, and groundwater pumping happens through deep tube wells (Figs. 1C and 5C, D). The crop switch can lead to lesser groundwater depletion in the projected future climate compared with the historical period (1995–2014) (Figs. 5E to G and S6). The additional mean groundwater storage saved from CSI is 38–45 km^3 in the near (2021–2040), 44–53 km^3 in mid (2041–2060) and 49–54 km^3 in far (2081–2100) periods depending on the emission scenario. In the CSII scenario, the additional mean groundwater savings are 53–68 km^3 in the near, 66–85 km^3 in the mid and 77–96 km^3 in the far periods, indicating that crop switching will have a positive impact on groundwater storage (Fig. 5G). While increased rainfall cannot fully recover the lost groundwater under the current cropping pattern (Fig. S6), crop switching can be valuable for groundwater sustainability under the warming climate. Despite the benefits of crop switching, groundwater lost from nonrenewable storage cannot be recovered in the centennial timescale.

Under the warming climate, mean precipitation is projected to increase up to $5 \pm 6\%$ in the near and $14 \pm 11\%$ in far periods, while mean PET is projected to rise by $-1 \pm 3\%$ in the near to $12 \pm 7\%$ in the far periods (Fig. S5). In the current cropping (baseline) scenario, the renewable groundwater storage is projected to decline in the mid and far periods, while crop switch scenario CSII show an increase in all the periods (Fig. S7B). The warming climate increases the rate of groundwater abstraction in all the periods under the baseline scenario (Fig. S7A). Crop switch reduces the groundwater abstraction in the projected future climate compared with the historical period (1995–2014) under the baseline scenario. Crop switch has resulted in a decline in renewable abstraction; however, the nonrenewable abstraction still slightly increases in the mid and far periods, leading to less groundwater recovery (Fig. S7C and D). The cumulative effect of the nonrenewable groundwater abstraction over the decades resulted in considerable depletion and full recovery is not possible. Therefore, it is essential to restrict unsustainable groundwater withdrawal to recover groundwater.

The CSI and CSII scenarios can recover 36 to 86 km^3 and 61 to 108 km^3 groundwater respectively, compared with −13 to 43 km^3 with current cropping pattern under the 1.5–3 °C global warming levels (Fig. S8, Table S2). The crop switching can lead to an additional groundwater recovery of 42 to 50 km^3 in the CSI and 65 to 81 km^3 in CSII in the 1.5–3 °C global warming levels (Fig. S8, Table S2). The renewable groundwater storage also increases due to the reduction in groundwater abstraction. The additional mean groundwater saved with crop switching during the dry (CSI: 52 km^3 and CSII: 85 km^3) and wet (CSI: 51 km^3 and CSII: 82 km^3) periods is similar, indicating that there is no substantial difference in groundwater abstraction for irrigation of alternate crops during the dry and wet periods (Fig. S9). Therefore, crop switching now can also sustain groundwater storage during the prolonged dry periods under the warming climate. The wet periods support a greater reduction in nonrenewable withdrawal compared with the dry periods. The renewable groundwater abstraction has a slight difference in dry and wet periods or with warming levels, implying the significant impact of nonrenewable pumping on the abstraction and groundwater storage. The mean changes in nonrenewable groundwater abstraction differs in both crop switch scenarios and is less than the current cropping pattern, indicating that nonrenewable abstraction takes place in the rice growing regions where groundwater irrigation is extensive. Thereby, both CSI and CSII can substantially reduce the nonrenewable groundwater abstraction. Overall, both crop switching scenarios can be beneficial in managing groundwater resources and ensuring sustainable future food production while meeting farmers profit and nutritional requirements.

Discussion

Our analysis showed that crop switch could be an essential measure to enhance groundwater recovery in north India. Groundwater depletion persists in north India, and crop switching can help slow down the groundwater depletion rates. Crop switch can enhance groundwater recovery in stressed aquifers, particularly in Punjab. The crop switch also has more potential for groundwater recovery in regions with substantial groundwater depletion, driven by the reduction in unsustainable pumping from deep tube wells. Therefore, if we can compromise the rice production by 45% (CSII scenario), the benefits to groundwater savings can increase by additional 46 km^3 in the observed and 16–42 km^3 in future climate compared with the CSI scenario. This difference of CSI and CSII crop contribution for groundwater savings increases with the global warming levels. The crop switch contribution to groundwater recovery also increases when climate change does not support groundwater recovery. For instance, in dry periods, though CSI cannot recover groundwater, it helps in reducing the groundwater loss by 52 km^3, while CSII helps in recovering additional groundwater of 85 km^3. Therefore, reducing the dependence of rice cultivation on groundwater is crucial for water sustainability in the future, especially at higher global warming levels where the groundwater recovery becomes significant with crop switching. Crop switching will also limit the nonrenewable pumping (CSI: −10%, CSII: −28%) from deep aquifers, thereby reducing the depletion trend, which is essential for long-term water and food security in India.

Meeting the food demand domestically and achieving sustainability of water resources will be one of the challenges in the coming decades (41). Our simulations have shown potential benefits that can be implemented in policies while taking into considerations regarding farmers' income and readiness, consumer demands, and agricultural markets. Although increased profitability of alternate crops may negate the necessity for subsidies, farmers can still encounter obstacles in adopting crop changes, like alternate crop markets (28). In addition, encouraging farmers and making them realize the benefits of adopting alternative crops can be a challenge on a district scale, which is critical for implementing crop switching. However, these changes are achievable by incentivizing district-level farmers to choose optimal crops that help reduce groundwater depletion (42). Proper strategies should be implemented to overcome the difference in cost and support markets for alternative crops. Cereals like millet and sorghum have other advantages over rice regarding nutrition, water, and reduction of greenhouse gas emissions (23, 43).

Transitioning from the rice to cereals not only enhances irrigation water savings but also offers greater more protein content compared with rice. The government of India has promoted 2023 as the year of millets, as declared by the United Nations (UN). Political and socioeconomic barriers must be overcome to achieve both national food security and groundwater sustainability (7). Our proposed cropping pattern changes to alternate crops aligns with the Sustainable development Goal (SDG2) to achieve food and nutritional security with sustainable irrigation. However, the implementation of crop switching policies relies on mindset toward alternative cereals, which will be possible over time. Identifying districts with the highest potential benefits from optimized cropping patterns should be prioritized, thereby incentivizing farmers. Subsidized distribution of alternate crops like cereals can also stimulate consumer demand (23). Overcoming these challenges and incentivizing crop shifting requires both financial incentives and the expansion of market potential for substitution crops, crucial for transforming agricultural landscapes in water-stressed regions (7, 23).

We adhere to limit groundwater pumping while meeting rice production in CSI scenario and do not aim to reach the predefined rice target production in CSII scenario. Importing water-intensive crops from other states not facing rapid depletion can reduce groundwater stress, while exporting water-intensive crops from the states that are facing rapid groundwater depletion (e.g. Punjab) exacerbates the groundwater depletion problem nationally. India's food production is mainly used for domestic purposes. However, India exports rice (25%) mainly to China (11). Therefore, the food trade will be crucial for mitigating water stress. Policies must be designed across the whole food system to ensure food supply, including interstate trade and international trade, without further depleting the groundwater resources, especially from nonrenewable sources (41). However, international trade should only be considered a buffer to domestic markets, as importing rice might increase dependency, which can lead to food insecurity in extreme cases (44, 45).

The virtual water trade provides a win–win solution where the food system and groundwater will be resilient, though at an economical cost (11, 46). The environmental impacts of groundwater pumping should be assessed while formulating national policies to ensure food security.

Excessive groundwater pumping for irrigation has resulted in alarming groundwater depletion (12, 13, 16). Moreover, declining groundwater caused a reduction in crop yields and cropped area (47). Considering the profound implications of unsustainable groundwater use for irrigation in north India, the need for potential solutions is underscored. Creating more surface water storage and canal networks may not be economically feasible, considering the land requirement and displacement of people. In addition, surface water bodies witnessed a decline in water storage across the globe, which can be partly associated with climate warming (48). Another potential solution is to improve water use efficiency to reduce groundwater pumping. Widespread use of proven adaptation technologies (drip and sprinkler irrigation) can reduce groundwater use for irrigation. However, the potential benefit of using improved technology is compromised by expanding irrigated areas and farmers' choice of irrigation methods (19). Reducing evapotranspiration from crops is essential to reduce the dependence on the groundwater in north India, which can be potentially achieved by short-duration crop varieties and shifting the planting dates (49).

Crop switching can help save groundwater without hampering food production, farmers' profit, and nutrition values, as demonstrated by our analysis under both observed and projected future climate. The benefits of crop switching on environmental sustainability and farmers' income have been highlighted in China (26, 33), the USA (28, 34), and India (7, 23). Implementing crop switch strategies and incentives is needed at various scales (government, market, and farmers) to make it effective (26) in groundwater savings. For instance, subsidies and appropriate markets must be provided to the farmers and the minimum support price (MSP) of the alternative crops. We offered two crop-switching scenarios based on the optimization model. The first scenario does not compromise food production, farmers' income, and nutrition value, yet it can substantially benefit groundwater savings in the current and projected future climate. The challenge remains to encourage farmers to use alternate crops that are beneficial in reducing groundwater pumping without reducing their profits. Implementing crop-switching strategies can be done at a more minor scale, and if farmers see the value, they can be encouraged to implement it in other areas. There are success stories of incentivizing farmers to adopt crop switching in China at the province and county levels (26). The second crop-switching scenario can compromise rice production in north India but with the more significant benefits of groundwater savings. The second crop switch scenario can be considered in extreme conditions if groundwater pumping becomes overly expensive or groundwater availability is a limiting factor for rice production. Therefore, our proposed crop-switching scenarios have a scientific basis, as explained in the previous studies (7, 23, 26, 28). However, the feasibility and success of the crop-switching solutions depend on several factors, including governance, economy, and water availability, that we have not examined in the present work.

Groundwater stress can be the limiting factor for food production in the future (50). As a result, the food system itself is on the verge of becoming unsustainable (51). Therefore, to meet future food production, the pressure on groundwater resources needs to be reduced with sustainable irrigation (52). Crop switching to reduce cropland vulnerability to groundwater loss is a sound national policy amidst depleting groundwater trends in warming climate as it has scope to improve farmer incomes and maintain net production. By redistributing rice production to regions with high yields and available sustainable groundwater resources, crop switching helps use the water resources more efficiently. Our findings highlight significant potential in crop switching scenarios to mitigate the impacts of climate change and is crucial for irrigation in water-stressed regions. The government can strengthen these measures to enhance the alternate crops production to facilitate a transition toward a sustainable water-food future. Yield gaps are also closing for rice in North India (53), and calls for crop diversification. Therefore, future research on optimized crop distributions including yield change, trading and market changes could enhance understanding of adaptation strategies for achieving crop production resilience and ensuring water sustainability under climate change.

Data and methods

Data

We used the cropped area and source irrigated area available for each district from the five-year (2015–2020) land use statistics reports (https://aps.dac.gov.in/LUS/Index.htm). We combined crop-specific data and cropped area to identify the crops grown in the districts. Well and canal sources irrigated areas were aggregated to identify the area irrigated with groundwater (Fig. 1C). The area irrigated through tube wells is classified based on depth, i.e. shallow (0–35 m), medium (35–70 m), and deep (more than 70 m), which was obtained from the minor irrigation census (https://micensus.gov.in/) for the year 2017–2018 (Fig. 1D). The mentioned district-level datasets are used to identify the dominant groundwater-based irrigated regions.

Gridded cropland and irrigated areas are required for input to the hydrological model. Therefore, we used the static (year 2005) cropland area (Fig. 1A), and the area irrigated with groundwater (Fig. 1B) from the Food and Agricultural Organization (FAO). We also obtained the area equipped for irrigation for 2000, 2005, 2010, and 2015 from Mehta et al (54, 55). We considered irrigated area for 2015 for future simulations as the irrigated area projections are unavailable. In our analysis, we considered major Kharif crops of rice, maize, sorghum, millet, pulses, soybean, groundnut, and rapeseed for crop switching that are primarily cultivated in the selected region of nine states in north India (Figs. S1 and 2). Maize, sorghum, and millets are broadly classified as cereals, while soybean, groundnut, and rapeseed are considered under oilseeds.

Seasonal crop-specific water consumption data considering flood irrigation are obtained from Fishman et al. (19). Farmers' profit is estimated as net profit, calculated as the difference between the MSP and the cost of cultivation. Calorie and protein requirement information is obtained from Indian food composition tables (56). Crop-specific inputs such as MSP, nutritional value, and irrigation water requirements remain constant for our simulations. To determine farmers' profits, we utilized state-level cost of production (57), district-level crop yield and crop-specific MSP. In states where cost data were unavailable, we assumed costs to be consistent with nearby states. Additionally, we assumed (due of lack of district-level data) that costs in each district were equivalent to the state-level average cost. Information detailing the datasets and their sources is provided in Table S3.

We obtained gridded precipitation and temperature from India Meteorological Department (IMD), available at 0.25° resolution (58, 59). We obtained well-level observations from the central groundwater board (CGWB) for 1996–2016. Well level is measured four (January, May, August, and November) times a year. Quality-controlled long-term data are available for about 5,000 wells (16, 60). In addition to well observations, we used satellite-based observations of Terrestrial Water Storage Anomaly (TWSA) from the Gravity Recovery and Climate Experiment (GRACE). We used the Center for Space Research (CSR) RL06 mascons solutions v02 for 2002–2022, which is available monthly at 0.25° resolution (38). We filled in the missing data in GRACE and GRACE-FO mission with singular spectrum analysis (61).

Crop switching optimization model

The crop switching model employs linear programming to identify feasible crop-growing regions and changes in the Kharif season crop choices across north India while satisfying baseline constraints. We developed an optimization model to estimate the crop area fraction in each district considering the calorie production, protein value, farmers' profit, and crop production with an overall objective of minimizing groundwater use in irrigation (Fig. S1). The constraints, objective function, and decision variable used in the optimization model are as follows:

Objective function

The goal is to minimize groundwater irrigation requirements during the Kharif season, which is defined as:

$$GI = \sum_{j=1}^{n_d}\sum_{i=1}^{n_c}\left\{(f_{\mathrm{aeig}})_j \times (a_{\mathrm{crp}})_{ij} \times \delta_{ij} \times \frac{(\mathrm{IWR})_i}{\mathrm{Pr}_j}\right\}, \quad (1)$$

where GI is groundwater irrigation, f_{aeig} is fraction of area equipped with irrigation from groundwater, a_{crp} is cropped area, IWR is seasonal (Kharif) irrigation water requirements (mm) by crops. We used the mean summer monsoon (June–September) rainfall from the IMD for 1951–2022 to estimate the district-level rainfall (Pr_j). Here Pr is used to denote the water availability and role of climate in crop switching. Indices i and j denote the crops and districts, respectively. n_c is the total number of crops (6) and n_d is total number of districts (247). δ_{ij} is the crop suitability with value 0 if that crop is not grown in that district and 1 if crop is grown in at least 1% of cropped area of a district. Here, we assume that if crop is previously grown, it is suitable for that district.

The decision variable is the cropped area $(a_{\mathrm{crp}})_{ij}$ denoting area of ith crop in jth district.

CSI constraints

1. **Nutritional constraint:** The nutritional requirements, in terms of calorie and protein, meet the target for the population of the North Indian region.

$$\sum_{j=1}^{n_d}\sum_{i=1}^{n_c}\{C_i \times Y_{ij} \times \delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \geq N_k \qquad \forall\, k, \quad (2)$$

where C_i can be calorie or protein content value and N_k is the nutritional requirements under current cropping pattern in terms of calorie or protein. Y_{ij} is the yield for ith crop in jth district. n_d and n_c are number of districts and crops, respectively.

2. **Profitability constraint:** The farmers' profit does not decrease for each state and results in a net profit increase for North India.

$$\sum_{j=1}^{n_{sd}}\sum_{i=1}^{n_c}\{(\mathrm{MSP}-\mathrm{CC})_i \times Y_{ij} \times \delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \geq \mathrm{FP}_s \qquad \forall\, s, \quad (3)$$

where MSP is minimum support price of crops, CC is cost of cultivation of crops and n_{sd} is the number of districts in each state (s), while FP_s is the farmers profit with baseline cropping pattern for s state.

3. **Food security constraint:** The total crop production of each crop is at least equal to the baseline production for each crop in North India.

$$\sum_{j=1}^{n_d}\{Y_{ij} \times \delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \geq \mathrm{CP}_i \qquad \forall\, i, \quad (4)$$

where CP_i denotes the net aggregate crop production of ith crop in the baseline scenario.

4. The net crop production from all the crops is also ensured at state level and for North India.

$$\sum_{j=1}^{n_{sd}}\sum_{i=1}^{n_c}\{Y_{ij} \times \delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \geq \mathrm{CP}_s \qquad \forall\, s, \quad (5)$$

where CP_s denotes the state level crop production from all crops.

5. **Area constraint:** The cropped area in each district remains within the baseline limit with no expansion.

$$\sum_{i=1}^{n_c}\{\delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \leq \mathrm{CA}_j \qquad \forall\, j, \quad (6)$$

where CA_j is the aggregate crop area of n_c crops in each district.

6. The rice cropped area does not exceed the current rice growing area, while the area of other crops is at least equivalent to current cropping area.

$$\sum_{j=1}^{n_d}\{\delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \leq \mathrm{CA}_i \qquad \forall i,\ i = \text{rice}. \quad (7)$$

$$\sum_{j=1}^{n_d}\{\delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \geq \mathrm{CA}_i \qquad \forall i,\ i \neq \text{rice}. \quad (8)$$

Change in CSII constraints with respect to CSI

The rice crop production can be less than the target current baseline production without compromising net aggregate crop production or other above-mentioned constraints. It is ensured that the total production from all crops meets the current production level (Eq. 5).

$$\sum_{j=1}^{n_d}\{Y_{ij} \times \delta_{ij} \times (a_{\mathrm{crp}})_{ij}\} \leq \mathrm{CP}_i \qquad \forall\, i,\ i \in \text{rice}. \quad (9)$$

The optimization model comprises a total of 281 constraint equations for 247 districts and 6 crops across 9 states, solving for 1,482 (247 × 6) variables. Specifically, there are 2 constraints from Eqs. 1 and 10 from Eqs. 2, 4 and 6 from Eqs. 3 and 6, and 247 from Eq. 5. This model is solved using linear programming methods such as the simplex algorithm, facilitated by the R package lpSolve (62).

Experiment design and future projections

We used bias-corrected climate projections from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) that are based on the global climate models (GCMs) that participated in the Coupled Model Intercomparison Project Phase 6 (CMIP6). Among the available GCMs, we selected the climate models based on their performance to simulate observed precipitation, temperature, and seasonal cycle and trend in TWSA, which is described in detail in Dangar and

Mishra (12). Based on the overall performance, the GCMs that were selected are CNRM-ESM2-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0 (Table S4). In addition, to precipitation and temperature, the hydrological model requires air pressure, specific humidity, surface wind, and shortwave and longwave radiation as input. The bias-corrected data from all the input variables were obtained for the historical and projected future climate from the GCMs from ISIMIP. The bias correction was done using the trend-preserving method (63). Hydrological model simulations were conducted for the historical period (1995–2014) and future period (2015–2100) with three Shared Socioeconomic Pathways (SSP)—Representative Concentration Pathway (RCP) combinations: SSP1-2.6, SSP3-7.0, and SSP5-8.5. SSP1-2.6 represents the least emission scenario, while SSP5-8.5 represents the highest emission scenario leading to radiative forcing of 2.6 and 8.5 W/m^2 by the end of the 21st century.

Using the global mean temperature from the CMIP6-GCMs, we estimated the global warming levels relative to the global mean temperature considering the preindustrial period (1850–1900) as a reference. We estimated the warming level for each GCM-SSP combination for the center of the 20-year moving mean when the respective global warming level (1.5, 2, 2.5, and 3 °C) is first reached (Table S4). As 1.5 °C is likely to reach in the present decade (40) and the sample size drops to half for global warming levels more than 3 °C, we considered a range of 1.5–3 °C global warming levels for our analysis. In addition, to examine the sensitivity of changing the cropping patterns on groundwater depletion, we estimated the wettest and driest periods based on the precipitation changes in the model projections for each SSP-RCP scenario. We estimated GWSA using TWSA from the GRACE and surface water storage anomaly (SWSA) simulated from the H08 model as:

$$\text{GRACE GWSA} = \text{GRACE TWSA–H08 SWSA} \tag{10}$$

We selected the two-decade period in 2015–2100 and estimated anomaly considering 1995–2014 as the reference period. We assessed the changes in GWSA using the nonparametric Mann–Kendall test and Sen slope estimator as:

$$\Delta\text{GWSA} = (\text{Sen slope}) \times (\text{Duration}) \times (\text{Land area}). \tag{11}$$

We conducted our analysis at a district level using the hydrological model grids falling in a given district. Moreover, we selected north India for our analysis primarily for two reasons: the region shows a considerable groundwater depletion of more than −1 mm year^{-1} based on the GRACE-GWSA (Fig. 2B); the region is dominated by groundwater-based irrigation for rice crop (Figs. 1 and S2). Rice is a major crop in North India during the main crop-growing season (Kharif), which was considered for crop switching experiments: CSI: optimal crop redistribution as per crop switching model and CSII: crop switching scenario where rice production can be compromised (Fig. S1). As cropland and irrigation expansion are not considered, we kept the crop and irrigated areas in district the same as the baseline scenario. To limit crop diversification, we switch alternate crops already sown in at least 1% of the net cropped area in the past five years (2015–2020), a proxy for identifying agroecological suitable crops. The cropping pattern at the district level offers a way of assessing groundwater recovery in states and North India to limit groundwater depletion. We estimate crop contribution as the ratio of additional groundwater gained from crop switching scenarios to groundwater lost in the current cropping pattern (baseline) (Fig. S10).

The same crop-switching scenarios (CSI and CSII) are used for the observed, historical, and future climate due to the unavailability of projected data on the required variables (e.g. cropped area, irrigated area, crop production, nutrition, and farmers' profit) in the optimization model (Table S5). Therefore, the difference between the crop switch scenario and the baseline cropping pattern (or existing cropping patterns) shows the impact of crop switching on groundwater savings as the observed climate remains the same in both (baseline and crop switching) scenarios. Similarly, we kept the crop-switching scenarios (CSI and CSII) constant for the historical and projected future climate simulations. Therefore, the difference between the historical and projected future climate enables us to estimate the role of projected climate change on groundwater storage (Table S5). Moreover, we conducted simulations under the projected future climate with the baseline and crop switch scenarios (CSI and CSII). The difference between these (with baseline and crop switch) scenarios helped us to examine the role of crop switching on groundwater savings during the historical and projected future climate.

Hydrological modeling

We used the H08 model to conduct hydrological simulations. The model has a land surface, river routing, crop growth, and water abstraction modules (64), and human interventions (irrigation and groundwater pumping) are well represented in the model. The H08 model solves both water and energy balance by incorporating anthropogenic water fluxes, which enables us to estimate the irrigation water requirements from the groundwater resources. We conducted the model simulations at 0.25° spatial and daily temporal resolutions. The land surface module simulates the evapotranspiration and PET components, which serve as an input to the crop module. Crop types, cropland area, irrigated area, and cropping intensity were considered as inputs to the crop module of the H08 model. The crop growth module is based on the cumulative heat unit threshold required to determine crop maturity, specifying the cropping duration. The planting and harvesting dates are then estimated to maximize crop yield in a year, determining the irrigation water demand during cropping. A minimum of 15 days gap is provided between harvesting the first crop and planting the second crop. In H08, each cell is mosaiced into four categories: single irrigated, double-irrigated, rainfed, and nonagricultural land uses. Irrigation water supply is required to sustain soil moisture above 75% of field capacity during the cropping period.

The water abstraction is taken from surface water sources such as reservoirs or river streamflow, while subsurface water abstraction is from groundwater reservoirs. Groundwater abstraction is divided into renewable components, which can be recharged with monsoonal rainfall, and a nonrenewable deep groundwater component. Nonrenewable groundwater is not recharged in the centennial time scale of our analysis and meets the additional water requirement after renewable groundwater storage is depleted. Nonrenewable groundwater is storage that indicates overexploitation of groundwater. The renewable groundwater storage change (ΔRGWS) can be expressed in terms of water balance as

$$\Delta\text{RGWS} = \text{GW}_{\text{Recharge}} - \text{Baseflow} - \text{RGW}_{\text{abs}} \tag{12}$$

The total groundwater abstraction can be summed as withdrawal from renewable storage (RGW_{abs}) and nonrenewable abstraction (NRGW_{abs}) and can be expressed as:

$$\text{RGW}_{\text{abs}} = \min(f_{\text{gw}} \times \text{W}_{\text{req}},\ \text{RGWS}) \tag{13}$$

$$\text{NRGW}_{\text{abs}} = (f_{\text{gw}} \times \text{W}_{\text{req}}) - \text{RGWS}_{\text{abs}} \tag{14}$$

where W_{req} is the water requirement, and f_{gw} is a fraction of W_{req} withdrawn from the groundwater source, a fraction of the area equipped with groundwater irrigation (Fig. 1B). The H08 model is calibrated against GRACE TWSA at a river basin scale. We obtained the district-level groundwater depth from the CGWB reports as maximum depth during the premonsoon season of 2018 and 2019. Model calibration (65) and a detailed description of groundwater components (64) are presented in Dangar and Mishra (12, 17).

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

Conceptualization, Methodology, and Writing—review and editing: S.D. and V.M. Formal Analysis, Data curation, Investigation, Software, Visualization, and writing—original draft: S.D. Supervision, Project administration, Resources, and Funding acquisition: V.M.

Data Availability

The IMD rainfall and temperature data are obtained from https://www.imdpune.gov.in/. GRACE and GRACE-FO datasets are publicly available from https://www2.csr.utexas.edu/grace/RL06_mascons.html. The CMIP6 data is obtained from the ISIMIP repository and available at https://data.isimip.org/search/tree/ISIMIP3b/. The H08 hydrological model source code is available at https://github.com/h08model/H08. The crop-relevant data are available from the Directorate of Economics and Statistics (DACNET) https://www.aps.dac.gov.in/LUS/Public/Reports.aspx and tube well irrigated area based on depth from minor irrigation census https://micensus.gov.in/state-wise-reports. The data used for crop optimization model can be obtained from sources listed in Supplementary Table S3. The datasets and model simulation results used in figures are archived in figshare data repository (66) https://doi.org/10.6084/m9.figshare.26561161. Depth to groundwater well levels available from the CGWB is uploaded in the data repository (66).

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