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Unraveling the Phenomenon of Supply-Demand Feedback in Agricultural Water Interventions

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Key Points:

- Narrow focus on technological interventions, discarding human behavior, can lead to inequitable and unsustainable outcomes
- Groundwater recharge (supply intervention) in the study areas resulted in an increase in irrigation demand (supply demand feedback)
- Agent-Based Model integrating hydrological and farmer behavior can reveal strategies for mitigating unintended negative outcomes

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract The Agricultural water interventions can trigger human-water feedback, including unintended supply demand feedback—where increased water availability drives greater water use. In the Kamadhiya catchment, India, the introduction of check dams (CDs) led to a shift toward more water-intensive crops like cotton and wheat. This study formulates and tests hypotheses to understand these dynamics using an agent-based model (ABM) that integrates a spatially explicit hydrological model with a farmer behavior module. The ABM simulates 38,447 farmers using the RANAS behavioral framework, based on household surveys and observed data. Model results confirm the hypothesized feedback: increased water from CDs led to an 11.9% rise in cotton and 36.1% in wheat areas, boosting incomes and increasing adoption of drip and borewell irrigation, particularly near CDs. While drip irrigation systems improve water efficiency and post-monsoon groundwater levels, the saved water enables further wheat expansion—triggering a second supply demand feedback loop. These changes are spatially concentrated near CDs, exacerbating within-catchment disparities. Overall, about 54% of the additional recharge is used for irrigation expansion, lowering groundwater levels by 1.0 m and reducing the net benefit of recharge interventions. These findings underscore the need to critically understand human-water feedback and value of ABM as a tool to support more informed planning by offering strategies that mitigate negative externalities.

Plain Language Summary Agricultural water interventions, like building structures to store water or recharge groundwater, can sometimes have unintended effects. For example, when farmers see an increase in water availability, they may use more water, sign of supply demand feedback. This study looks at the case of supply demand feedback in the Kamadhiya catchment of India, where many small check dams (CD) were built to recharge groundwater for irrigation. The study uses an agent-based model that integrates a hydrological model with farmer behavior, derived based on surveys and observed patterns to understand these dynamics. Decisions of over 38,000 farmers are simulated. The study found that farmers near CDs expanded cotton cultivation by 11.9% because of increased water availability. This increased their incomes, allowing them to invest in acquiring drip irrigation and deeper wells. While drip irrigation improved water use efficiency for cotton, the saved water was used to expand wheat area. This unexpected increase in water use reduced the overall benefits of the CDs with about 54% of the water recharged used to irrigate more cotton and wheat, causing groundwater levels to drop by 1 m. These findings highlight how human behavior and water systems interact, sometimes creating challenges for sustainable water use.

1. Introduction

The vulnerability of agricultural sector, heavily dependent on climate, to climatic variability and extreme weather events (FAO, 2015; Holleman et al., 2020) and escalating rate of climate change, impacting agriculture through shifting rainfall patterns and rising temperatures, is detrimental to global food security (IPCC, 2022; United Nations, 2019). Against this backdrop, adapting to climate change becomes imperative, with agricultural water interventions assuming a pivotal role (GCA and WRI, 2019; Sikka et al., 2022). Many successful agricultural water interventions are well-documented and demonstrated to have a positive impact (GCA and WRI, 2019; Sikka et al., 2022).

However, there is a risk that poor and unplanned implementation of the interventions may lead to unintended consequences leading to inequitable and unsustainable outcomes such as groundwater depletion and increased income disparity (Adla et al., 2023; Alam et al., 2022a). Examples of these unintended consequences include an increase in water use as farmers adopt more efficient irrigation methods to intensify production or use subsidies

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aimed at increasing crop yields to intensify use of fertilizers and pesticides (Alam et al., 2022a; Birkenholtz, 2017). Of particular concern in the agricultural water management setting is the phenomenon of supply demand feedback where demand rises following increased water availability or perception thereof (Adla et al., 2023; Di Baldassarre et al., 2013, 2019; Shah et al., 2021). This is because a significant portion of these interventions is narrowly focused towards enhancing water supply through construction of small storage and groundwater recharge interventions (Sikka et al., 2022).

Triggering an increase in demand may potentially nullify the supply benefits, through additional storage and recharge, and increase vulnerability (Alam et al., 2022b; Shah et al., 2021). Additionally, the distribution of benefits (or losses from unintended consequences) may not be equitable (Alam et al., 2022a) with benefits of water harvesting, and groundwater recharge concentrated in nearby farms in low-lying areas (Shah et al., 2021) and among the influential, wealthier farmers who have the financial capacity to invest in irrigation infrastructure (Alam et al., 2022a; Calder et al., 2008).

These Unintended consequences emerge from the complex bidirectional feedback and dynamics between human and water systems (Adla et al., 2023; Sivapalan et al., 2012). Human behavior and responses are often overlooked during the planning phase, which tends to prioritize narrow technological solutions to resource management challenges. Similarly, these human-water interactions are frequently underrepresented in hydrological models designed to support planning. Such models, typically used to simulate and assess the impacts of agricultural water interventions, seldom account for the intricacies of human responses (Adla et al., 2023; Alam et al., 2022a; Sivapalan et al., 2012). Often elements of human systems (e.g., crops, adoption of interventions) are prescribed as boundary conditions. To incorporate human-water feedback, sociohydrology which emphasizes the consideration of bidirectional feedback between human and water systems to interpret unintended consequences (Sivapalan et al., 2012) is increasingly being used in the agricultural water sector to unpack unintended consequences such as the phenomenon of supply demand feedback (Adla et al., 2023; Alam et al., 2022a).

To model the emerging dynamics of supply and demand—driven by individual behavioral responses to changes or perceptions of water availability, which itself is spatially and temporally variable— it is essential to explicitly represent individual farmers and associated heterogeneities in social, economic and biophysical capital. In this context, sociohydrology-informed Agent-Based Models (ABMs) are particularly valuable. They can uniquely capture human–water feedback while accounting for farmer heterogeneity, which is critical for understanding the uneven, often inequitable impacts of agricultural water interventions across space and time (Alam et al., 2022a). In contrast, system dynamics models primarily simulate aggregate system behavior, making them less effective in capturing the spatial variability in farmer responses or the distribution of benefits and losses at local scales (Alam et al., 2022a).

However, despite their potential, ABMs applied to agricultural water systems face key limitations. These include the lack of integration with spatially explicit hydrological models, reliance on aggregated rather than individual agents (Farhadi et al., 2016; Hu & Beattie, 2019), and most critically, the absence of empirically grounded behavioral rules. Many ABMs assume overly simplistic rational decision-making (Schreinemachers & Berger, 2011) or use heuristics that are not sufficiently rooted in observed behavior (Castilla-Rho et al., 2015). This highlights the need for further advancements of ABMs for integration of human and hydrological dynamics to critically understand the human-water feedback related to agricultural water interventions.

This paper examines the supply demand feedback observed in the Kamadhiya catchment, India (Section 2), to demonstrate how an agent-based model for agricultural water management (ABM-AWM) can be used to unpack emergent human-water feedback. Specifically, it shows that by integrating human behavior into hydrological models, ABMs help reveal unintended consequences of water interventions and identify strategies to mitigate them. The study formulates hypotheses based on observed dynamics (Section 2) and tests them through the development and application of the ABM-AWM (Sections 3 and 4), ultimately generating policy-relevant recommendations (Section 5).

2. Case Study Catchment

The ABM-AWM is developed to study, understand and explore the case of observed supply demand phenomenon in Kamadhiya catchment ($\sim$1,100 km^2) located in the western state of Gujarat in India (Figure 1). The catchment has a semi–arid climate, characterized by low average annual rainfall of 438 mm per year (1983–2015) with more

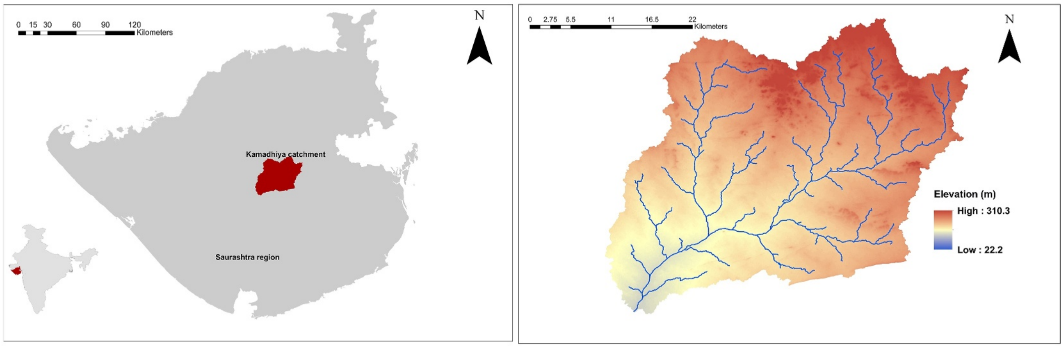

Figure 1. Location of the case study area showing Saurashtra region in Western India and Kamadhiya catchment in the Saurashtra region.

than 90% of the annual rainfall occurring during the monsoon months, spanning from June to September (Pai et al., 2014). Agriculture dominates the catchment but is highly vulnerable due to high variation in rainfall both within and between years (Alam et al., 2022b). Groundwater is the main source of irrigation with farmers accessing groundwater through large-diameter dugwells (∼3–4 m) (Figure 2a, Alam et al., 2022b; Mohapatra, 2013). These wells are drilled into the area's hard rock aquifers, mainly comprising of deccan trap basalt, with low porosity and hydraulic conductivity (Alam et al., 2022b), and are confined to water-bearing zones in the upper 15–30 m of weathered and fractured rock (Alam, Pavelic et al., 2022; Kulkarni et al., 2000). The low storage aquifer in the catchment area is typically depleted by the end of the hydrological year (May month), leaving little carryover storage and gets replenished during the next monsoon season (Alam et al., 2022b, Alam, Pavelic et al., 2022).

2.1. Construction of Check Dams and Evolution of Supply Demand Feedback

To manage water variability and enhance groundwater recharge, the Kamadhiya catchment has seen intensive construction of check dams (CDs) which gained momentum in response to a severe drought from 1999 to 2001 (Alam et al., 2022b; Shah et al., 2009). In the catchment, the CDs count reached 575 by 2006, contributing to a

Figure 2. (a) Open dugwell commonly used for irrigation in the study area; (b) and (c) check dam in the area in dry and wet season, respectively (images taken from downstream side).

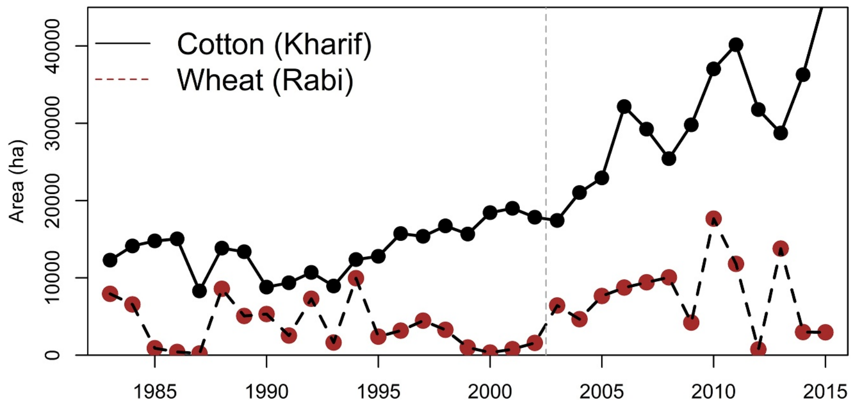

Figure 3. Annual Cultivated area (ha) of cotton (kharif crop) and wheat (rabi crop) for the time period 1983–2015.

density of approximately one CD per 2 km^2 (Patel, 2007). These CDs are in-channel modifications constructed as physical barrier within the bed of an ephemeral stream or river (Mozzi et al., 2021, Figures 2b and 2c). They capture seasonal monsoon surface runoff, with water storage lasting in the CDs from 3 months in dry years to upto 8 months in high rainfall years (Alam et al., 2022b). The size of CDs vary based on the stream order they are built with storage ranging from >400,000 m^3 to <1,000 m^3 (Patel, 2007). The farmers do not directly use (lift) water from CDs, but indirectly with additional recharge from CDs feeding their large diameter dugwells (Figure 2a, Alam et al., 2022b; Mohapatra, 2013). The recharge from CDs to dugwells is affected by multiple factors including distance to CDs, hydrogeology, soil type, water table depth and nearby pumping (Mozzi et al., 2021).

The development of CDs at the catchment scale, intended for groundwater recharge and conservation, has been associated with a notable increase in groundwater irrigation demand, reflecting the evolution of supply demand feedback (Alam et al., 2022b, 2024). Catchment water assessments reveal that post-CD introduction, the water intensive cotton cultivation area has expanded by 124%, and wheat cultivation increased by 112% (Figure 3). This led to a rise in groundwater irrigation demand to 121.8 million cubic meters (MCM), an increase of 67.5 MCM compared to pre-CD levels. Importantly, this increase in demand has outstripped the additional groundwater recharge facilitated by CDs and reduced the intended benefits of CDs, resulting in no significant improvement in groundwater levels (Alam et al., 2022a). Additionally, data from Alam, Pavelic et al. (2022) indicate that the perceived benefits of CDs are unevenly distributed across space, with benefits declining with increasing distance from the CDs. This highlights an inequitable distribution, where farmers located closer to streams—where the CDs are constructed—tend to gain disproportionately more.

2.2. Hypothesis

Based on the observed supply dynamics in the catchment, we hypothesize that (a) intensification of more water-intensive crops is driven by individual farmer behavior in response to their perception of CDs and the resulting increase in water availability; (b) that this behavior change is not uniform but is spatially heterogeneous, with the changes accruing primarily to farmers situated near the CDs, reinforcing spatial disparities within the catchment; (c) these individual behavioral changes, when aggregated, have led to increased groundwater extraction across the catchment; and (d) changes in cropping patterns influence farmers' incomes and profits, with subsequent impacts on related water related investments—specifically in drip irrigation systems and borewells in which farmers invest individually (Alam et al., 2024). —thereby affecting overall water use dynamics.

We aim to test above hypothesis through the application of the ABM-AWM (Sections 3 and 4), ultimately generating policy-relevant recommendations (Section 5). This would provide a valuable tool to understand unintended consequences and support more informed planning of agricultural water interventions by offering strategies that mitigate negative externalities.

3. Agent-Based Model for Agricultural Water Interventions (ABM-AWM)

To test the hypothesis, an agent-based model for agricultural water interventions (ABM-AWM) is used. The ABM-AWM model consists of:

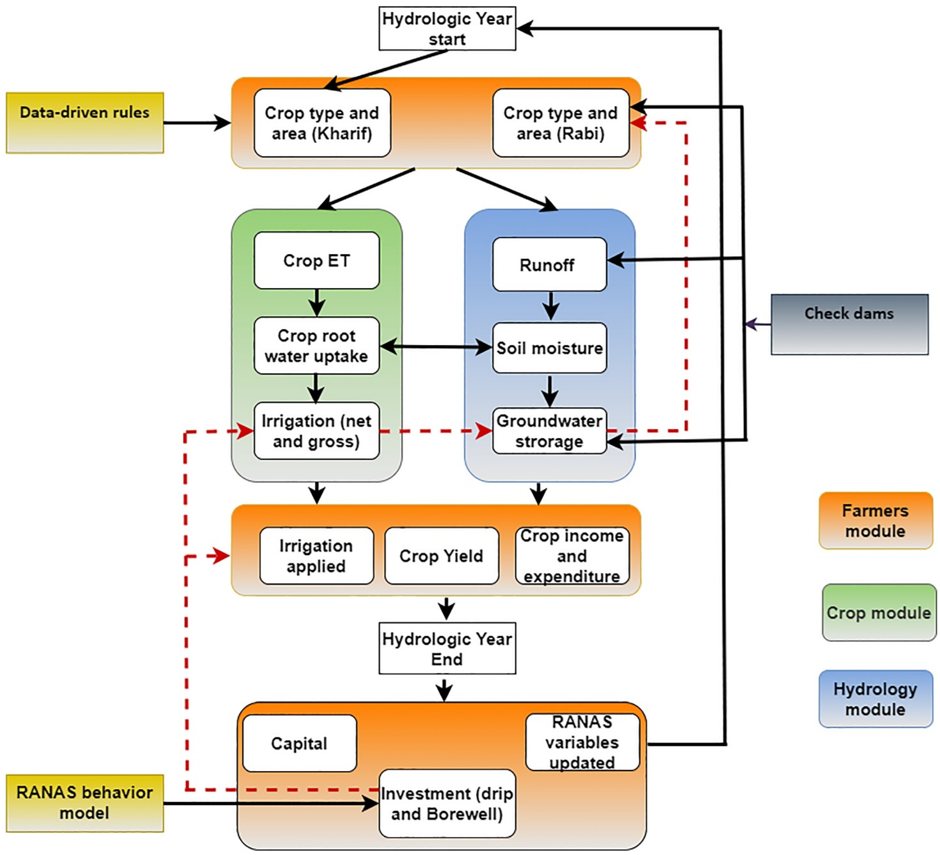

Figure 4. Conceptual workflow of the agent-based model for agricultural water management model. Dotted lines show the feedbacks between the modules.

1. *Individual farmer decision module (Section 3.1)* to capture heterogeneity in farmers behavior on crop choices and water-related investments (drip irrigation and borewell) which vary based on (perceived) water availability, socio-economic status, and social influence. The behavior of 38,447 farmers, number and distribution derived based on population census data, in the catchment is modeled using combination of the RANAS behavior model (Mosler, 2012) and data-driven rules. This is critical to test the main hypothesis that intensification of more water-intensive crops is *driven by individual farmer behavior* in response to their perception of CDs.
2. *Spatially explicit hydrological (Section 3.2)* to capture spatial differences in water availability. A spatial explicit model was necessitated as water availability (which influences farmers' decision) varies significantly across space due to differences in rainfall, runoff, presence of CDs, and most importantly groundwater levels —which is shaped by local cultivation intensity and the number of farmers extracting water. Capturing this spatial variability and resulting heterogeneity in farmers behavior is essential to modeling the feedback between supply and demand, which we hypothesize result from individual behavior in response to change (or perception) of water availability and is spatially heterogeneous.
3. *Crop growth model (Section 3.3)* to capture changes in crop production and the resulting benefits and income, which in turn influence farmers' decisions to invest in drip irrigation and borewells.

Figure 4 gives the overall conceptual workflow of the ABM-AWM model. The ABM-AWM is developed in Python 3.7 (Python Software Foundation, 2018) in a modular structure, allowing to switch on modules and processes and add new modules making the code more scalable while integrating the hydrological, crop, and farmer behavioral models. This expands the previous model (Pande & Savenije, 2016), allowing for adapting model codes and altering model resolution and farmer characteristics.

At the start of the hydrological year, the farmers, based on behavioral rules make decisions on crop choices and cultivation areas. Thereafter, daily crop evapo-transpiration requirement (ET_c), and irrigation needs are calculated for each grid cell, total of 1,319 such grid cells in the catchment, and mapped to the 38,447 farmers distributed across these grid cells. Groundwater storage per grid cell from the hydrological module is also allocated to the farmers. The farmers decide on providing irrigation based on prescribed rules, access to irrigation, and available groundwater storage. After that, each farmer's crop actual ET (AET), which is the sum of root soil water uptake and applied irrigation, is aggregated at the grid level. This reduces soil moisture and groundwater storage. This is repeated daily, with the seasonal aggregates of crop ET_C and AET used for yield calculation using the FAO yield response function. Farmers' capital and profits are updated based on crop prices and production costs, with annual decisions on investments (e.g., investing in drip irrigation, and borewells) influenced by capital and behavioral rules. The feedback generated by the agriculture water interventions are integrated across these modules, affecting water supply (hydrological module), demand (crop module), and farmers behavior (farmers module). The below section gives a brief description of each module with detailed model description given in (Texts S1 to S4 in Supporting Information S1).

3.1. Farmers Decision Module

The *farmers' decision module* models the daily, seasonal, and annual behavior of the farmers captures their responses and feedback amongst them and the environment (*see* Text S3 in Supporting Information S1 *for model details*). There are 38,447 individual farmers distributed across catchment grid cells, derived and allocated based on population census data. Each grid contains a unique set of farmers, though the distribution among different types of farmers (e.g., large vs. marginal) is consistent across all grids, as determined by the agricultural census (Department of AgricultureCooperationand Farmers Welfare, 2019). The behavior of these farmers is based on the combination of RANAS behavior model (Mosler, 2012) and data-driven rules to integrate human decisions. The RANAS (i.e., R-risk, A-attitude, N-norm, A-ability, and S-self-regulation) behavioral model assumes that multiple sociopsychological factors (i.e., risk, attitude, norm, ability, and self-regulation) impact behavioral outcomes (i.e., behavior, intention, use, and habit). The RANAS behavior rules were derived from household surveys (Alam, Pavelic et al., 2022) and data-driven rules based on the analysis of crop and hydrological data in the catchment (Alam et al., 2022b).

While farmers make numerous decisions, the model focuses on a subset of these. These include: (a) allocating crop areas between kharif crops like cotton and groundnut; (b) deciding on the cultivated area for post-monsoon crops, and (c) making investments in drip irrigation and borewells. The behavior on allocation of kharif crop area is linked to the introduction of CDs, starting in year 2002, as given below and applies only to farmers residing in grid cells with CDs. In contrast, behavior related to wheat cultivation and investment in drip and borewell irrigation is universal, affecting all farmers in the area, regardless of CD presence in their grid cell.

3.1.1. Decision Rules for the Distribution of Kharif Crop Areas

All farmers are assumed to cultivate two kharif crops: cotton and groundnut. This is based on a farmer survey data (Alam, Pavelic et al., 2022)˙ which indicates that the majority of farmers cultivate both the crops. The decision rule for the Kharif season area was based on data from farmer survey and its analysis (Alam, Pavelic et al., 2022) which showed that the primary benefits perceived by farmers from CDs include increased availability and reliability of water for irrigation and helps them expand their crop area. In addition, a comparison of farmers' cotton area fraction (cotton area/net cultivated area) based on the survey data showed that the farmers who are near CDs (≤250 m) devote 4.5% more cotton area than the farmers who are away from CDs.

This study further performed a breakpoint analysis employing Bayesian Information Criterion to identify breakpoints using *R* "strucchange" package (Zeileis et al., 2002), on cotton area (3-year moving average) and its proportion to total cultivated area (Figures S4a and S4b in Supporting Information S1). It identified the year 2002 as the breakpoint (Table S7 in Supporting Information S1) which corroborates that enhanced supply in the post-CD period (starting 2002) led to an increase in cotton areas. This analysis, drawing on multiple methods and data sets, supports the argument that improved irrigation supply and reliability contributed to the expansion of cotton, a more water-intensive crop. However, this is just one interpretation of the data, and we cannot discount the influence of other factors not examined in this study (e.g., market prices). Here, we model a specific interpretation of the observed behavior, highlighting the supply demand feedback in response to the construction of CDs.

Based on the identified breakpoint of 2002, the cotton area data set was divided into two segments (pre- and post-CD) and segmented linear regression models were fitted to each segment. The fitted segmented models' coefficients (slope and intercept) and their standard errors were derived. The difference in slopes between the two segments was tested using the two-tailed p-value to test the significance of the difference (Table S7 in Supporting Information S1). The slope (ration of cotton area to net cultivated area) increased in the post-CD period (0.0175 years^{-1}) when compared with pre-CD period (0.0132 years^{-1}) (Figure S4b in Supporting Information S1). This finding was integrated into the model as a rule (Equation 1). For farmers without CDs and irrigation, the slope of the equation was kept the same as in the pre-CD period. In contrast, the farmers with access to CDs and irrigation were modeled to have an increased slope, representing higher cotton area as a proportion of their net cultivated area over the post-CD period (Equation 1). This equation resulted in higher cotton area, by 4%–6% over the period 2002–2015, cultivated by farmers in the grid cells with CDs as compared to those without CDs. The area dedicated to groundnut is calculated as the total area minus the area used for cotton.

$$\text{Area}_{\text{cotton}} = (-26.151 + \text{slope} * \text{year}) * \text{Area}_{\text{farmer}} \tag{1}$$

where slope (cotton area/net cultivated area) before 2002 (pre-CD period) = 0.0132/year; slope after 2002, that is, post-CD period (for farmers with irrigation and in grid cells with check dams) = 0.0175/year; and for farmers in grid cells without check dams = 0.0132/year. $\text{Area}_{\text{farmer}}$ is farmer-owned cultivated land. Thus, the behavior on allocation of kharif crop area is only associated with farmers living in grid cells with CDs.

3.1.2. Decision Rules for the Cultivated Area of Post-Monsoon Crops

The catchment water balance analysis demonstrated that the area cultivated with post-monsoon crops is highly dependent on the groundwater levels after the monsoon (Alam et al., 2022b). This finding indicates that farmers consistently plan their wheat crop areas by taking into account the irrigation demand that can be supported by the post-monsoon groundwater storage.

A relationship ($R^2 \sim 0.87$) was developed between the ratio of the rabi (post-monsoon) area to the net cultivated area and the post-monsoon groundwater level (Figure S4c in Supporting Information S1). This correlation was incorporated into the model for each farmer (Equation 2). According to the model, farmers assess groundwater levels at the onset of the post-monsoon crop sowing period to determine their cultivated area. Only the farmers that have irrigation facilities can cultivate crops in the post-monsoon season.

$$\text{Area}_{\text{wheat}} = (0.2765 - 0.0212 * \text{GWL}_{\text{post-monsoon}}) * \text{Area}_{\text{farmer}} \tag{2}$$

Where, $\text{GWL}_{\text{post- monsoon}}$ is the groundwater level below the surface at the sowing date of wheat and $\text{Area}_{\text{farmer}}$ is the farmer-owned cultivated land. While wheat cultivation behavior is universal, the impact of CDs on wheat area is more pronounced in grid cells with CDs. In these areas, CDs not only improve groundwater recharge but also affect cotton cultivation, which subsequently influences groundwater levels.

3.1.3. Decision Rules of Investments in Drip and Borewell

Farmers' decision on investments was modeled for drip irrigation and borewells based on RANAS model. Drip irrigation is a demand management intervention to increase the efficiency of irrigation water applied supported by a government capital subsidy program (Nair & Thomas, 2022). The government subsidy program (~covering 50%–70% of costs) aims to promote the adoption of micro-irrigation. Research has shown that while subsidies positively influence adoption, they are insufficient on their own to drive widespread uptake of drip irrigation system adoption rates which remains low at around 16% in the study area (Alam et al., 2024). On the other hand, farmers drill borewells, not subsidized, to hedge against the production risks associated with low rainfall years, particularly during the dry seasons after the monsoons when the shallow weathered aquifer (15–30 m) in the region dries out (Steinhübel et al., 2020).

To model investment decisions, data on socio-economic and psychological variables were obtained through household surveys of 492 farmers across 24 villages in the catchment in December 2021 (Alam, Pavelic et al., 2022). RANAS psychological factors (R-risk, A-attitude, N-norm, A-ability, and S-self-regulation) were measured using 2–4 questions on five-point Likert scales. The survey analysis showed that psychological factors play a significant role in the adoption of the technologies (Alam et al., 2024).

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The binary logistic regression is used to generate farmer decision rules of the adoption of drip irrigation and borewells. First, based on the earlier results (Alam et al., 2024), a binary logistic regression was carried out for both drip irrigation and borewell adoption using a subset of variables found to be significant and for which data are available for the farmers (Tables S8 and S9 in Supporting Information S1). Using the regression coefficient estimates (α) of the variables, farmer decision-making of the adoption of drip irrigation and borewells was formalized using Equations 3 and 4. The experience factor was found to significantly influence drip adoption (Table S8 in Supporting Information S1) based on the cross-sectional data where farmers have diverse experiences. However, controlling this effect of varying experiences at any point in time was not needed in the current simulation model. This is because all the farmers at any point in simulation time have the same experience (all farmers begin with the same initial conditions), resulting in no variation in experience in a cross section (panel) of farmers at any point in time. Consequently, this factor was excluded from the model (Equation 3).

The probability of adoption was estimated using Equation 5. Similar approaches, that is, using regression equations to define rules, have been employed by others (Kaufmann et al., 2009; Pouladi et al., 2019). The probability thresholds ($\text{Prob}_{\text{drip/BW}}$), above which farmers were classified as adopters, were set based on the analysis of the accuracy, sensitivity, and specificity of the regression models. This was set at 0.35 and 0.25 for drip and borewell adoption at which the accuracies of the model predictions were 85.9% and 65.9%, respectively (Table S8 and S9 in Supporting Information S1).

$$V_{\text{drip}}[t] = c_{\text{drip}} + \alpha_{\text{ability}} * \text{ability}[t] + \alpha_{\text{risk}} * \text{risk(percieved)}[t] + \alpha_{\text{impact}} * \text{risk(severity)}[t] + \alpha_{\text{attitude}} * \text{attitude}[t] + \alpha_{\text{norm}} * \text{norm}[t] \tag{3}$$

$$V_{\text{BW}}[t] = c_{\text{BW}} + \alpha_{\text{SR}} * \text{self\_regulation}[t] + \alpha_{\text{attitude}} * \text{attitude}[t] + \alpha_{\text{norm}} * \text{norm}[t] + \alpha_{\text{livestock}} * \text{livestock}[t] + \alpha_{\text{water}} * \text{water\_proximity}[t] + \alpha_{\text{area}} * \text{area}[t] \tag{4}$$

$$\text{Prob}_{\text{drip/BW}}[\text{t}] = \frac{e^{V[t]_{\text{drip/BW}}}}{(1 + e^{V[t]_{\text{drip/BW}}})} \tag{5}$$

Where c is the regression intercept and α is the regression coefficient, or parameter, of a socio-economic or psychological variable that is significant at $p < 0.05$ significance level (Tables S8 and S9 in Supporting Information S1). The behavior on investment in drip and borewell irrigation is universal that is, applicable to all farmers in the area irrespective of CD presence in the grid cell they reside.

The variables in regression Equations 3 and 4 were linked to model variables that were either constant for the simulation period (e.g., farmer area, proximity to water, livestock ownership) or dynamically simulated in the model (e.g., risk (perceived) to drought occurrence, ability to capital, Figure S3 in Supporting Information S1). This linking involved estimating RANAS variables in Equations 3 and 4 (based on the simulated model variables for each year (*see* Text S4 in Supporting Information S1). Further, household survey data (Alam et al., 2024) showed that ~60% of farmers faced borewell failures, drilling an average of 2.1 failed wells before success. This was modeled using a random function, where only one-third of adopters achieve a functional well (based on Equation 4) despite the utilization of capital, aligning with high failure rates in hard rock areas (Anantha, 2013). This is similar to earlier results in hard rock areas, which showed high failure rates of borewells (Anantha, 2013). For the costs of acquiring drip systems and borewells, which vary based on the introduction of government subsidies and limited access to technology in the early 2,000s *see* Text S4 in Supporting Information S1.

3.2. Hydrological Module

The spatially distributed hydrological module captures the availability and variability of water across space, providing location-specific information to farmers distributed across grid cells. The model is adapted from the open-source Spatial Processes in Hydrology model (Terink et al., 2015). It is a three-layered leaky bucket model, including two soil layers (rootzone and subzone) and a groundwater layer (*see* Text S1 in Supporting Information S1 *for model details*). The spatially distributed hydrological module operates at 1 km^2 resolution with 1,319 such grid grids within the study area. The model captures spatial variability in water availability driven by differences in rainfall, runoff, CD presence, and—most critically—groundwater levels. These factors influence farmers' crop choices (Equations 1 and 2), while the resulting outcomes (income, profit) shape their investment decisions (Equations 3 and 4).

A module on small storage structures (e.g., CDs, and ponds) was developed and integrated into the hydrological module (*see* Text S1 in Supporting Information S1 *for model details*). In total 575 CDs distributed in 453 grid cells (∼34% of total grid cells) with combined storage of 12.9 MCM were incorporated in the model. To allocate CDs storage in each grid cell, data on the number of CDs and their total storage capacity in each village were utilized (Alam et al., 2022b; Mozzi et al., 2021; Patel, 2007). The total CD storage in each village was converted into an average capacity per CD for each village, and grid cells corresponding to each village were assigned this average storage capacity. In cases where a village had more grid cells than CDs, the locations were randomly assigned within the village. The average storage capacity of the CDs was 28,575 m^3, with a minimum of 285 m^3 and a maximum of 353,960 m^3, effectively capturing the spatial heterogeneity of the CDs and their storage capacities.

To simulate runoff capture and recharge from storage structures, each grid cell is assigned the surface storage created from built storage structures (e.g., ponds and CDs). Based on the total storage in each grid cell and if the storage space is available, part of the runoff is captured by storage structures and is lost from the storage through recharge and evaporation. No direct lift from CDs takes place. The recharge from the storage structures was simulated using the recharge empirical equations (Bouwer, 2002), as developed and calibrated for the study region (Mozzi et al., 2021).

The groundwater module in the model does not account for lateral flows across grids. This is due to negligible regional lateral flows in hard rock regions due to low hydraulic conductivities (Kulkarni et al., 2000; Mohapatra, 2013) with studies showing very limited lateral groundwater when grid area exceeds ∼500 m (Dewandel et al., 2012). Restricting lateral flows across grids means that the benefits of additional recharge remain localized within the grid containing the CDs. At the same time, modeling these laternal flows is challenging because hard rock aquifers exhibit high heterogeneity in their properties (Varalakshmi et al., 2014). Without detailed hydrogeological data, the model simplifies by representing each grid with average groundwater properties (e.g., depth, hydraulic conductivity, specific yield). Future research could enhance the model by incorporating more detailed and nuanced representations of groundwater dynamics.

3.3. Crop Module

The *crop module* calculates crop water requirements, irrigation needs, and yields (*see* Text S2 in Supporting Information S1 *for model details*) and resulting changes in crop production, benefits and income. It employs the FAO four-stage crop coefficient approach to estimate crop potential evapotranspiration (ET_c) (Allen et al., 1998), with reference evapotranspiration (ETo) determined via the Hargreaves method (Hargreaves & Samani, 1985). The model simulates the primary crops cultivated in this region including cotton and groundnut during the kharif season (the monsoon season, from June to October) and chickpea and wheat during the rabi season (the post-monsoon season, from November to February/March) (Alam, Pavelic et al., 2022). The kharif crops were modeled separately, whereas the rabi crops were simulated as one crop, that is, wheat, for which long-term time series data are available.

To meet irrigation needs, which is groundwater-dependent, farmers access shallow groundwater through large-diameter open dugwells. Groundwater storage availability for each day, simulated by the hydrological module, is distributed equally among all the irrigated farmers in a grid cell. Farmers can abstract groundwater but are limited by available groundwater storage and pumping and well capacities, to meet the gross irrigation requirement. Also, farmers can access deeper groundwater, if they have invested in borewells, and again daily abstraction is limited by maximum possible abstraction. From the groundwater storage, the model first meets the irrigation needs of cotton and then groundnut in the kharif season. This is because groundnut is a rainfed crop (DoA, 2021). However, survey data (Alam, Pavelic et al., 2022) showed that farmers irrigate groundnut crops when needed and this was also observed during field visits (November and December 2021). This is simulated by applying partial irrigation to groundnut by applying a deficit irrigation coefficient (GN_{Irr}) which ranges from 0 (no irrigation is applied) to 1 (full irrigation is applied). In the model, farmers are assumed to apply full irrigation whenever water is available, disregarding the heterogeneous irrigation behaviors observed among farmers. Surveys (Alam, Pavelic et al., 2022) indicate that most farmers typically do not use soil moisture devices, instead opting to irrigate based on their visual perception and feeling. Future models could incorporate this variability by adopting a random irrigation approach based on field data (O'Keeffe et al., 2018) which would provide a more accurate representation of irrigation behaviors and their impact on the model's outcomes.

At the end of the season, crop water needs met (AET) from root soil moisture uptake and irrigation, as a fraction of potential crop water needs, that is, ET_c, is calculated and is used with crop stage-specific crop yield reduction factor (K_y) (Steduto et al., 2012) and potential yield (Y_p) to estimate each farmer's yield (Equation 6). This is multiplied by crop price (Ministry of Agriculture and Farmers Welfare, 2021) and then the cost of cultivation (DoES, 2015) is subtracted from it to estimate profit that is accumulated as capital over time.

$$\frac{Y}{Y_p} = \prod_{j=1}^{J} \sum_{i \in s_j}^{I_{s_j}} \left[1 - K_Y\left(1 - \frac{AET}{ET_c}\right)\right] \tag{6}$$

Where, K_Y is crop yield reduction factor, AET^i, $ET_c{}^i$ are AET and ET_c for day i in a growth stage s_j with I_{sj} number of days, and there are $(s_1,..,s_j,.s_J)$ growth stages with $J = 4$ stages. Y_p is the potential yield and Y is the actual yield.

3.4. Model Calibration and Uncertainty Analysis

The model was calibrated using PEST, which is a model-independent parameter estimator (Doherty et al., 2010). PEST estimates the optimal values of model parameters by minimizing the sum of squares of the differences between calculated and observed model results with an optimization algorithm based on Gauss-Marguardt-Levenberg search algorithm (Doherty et al., 2010). The model was calibrated for monthly runoff (available for monsoon months from June to October) measured at the catchment outlet and catchment average groundwater levels available for pre-monsoon (month of May) and post-monsoon (month of November) months (Alam et al., 2022b). The catchment average groundwater levels (for pre-monsoon and post-monsoon) are derived by spatially interpolating observed groundwater levels from available monitoring points (Figure S5 in Supporting Information S1) using inverse distance weighting. Since the model assumes uniform groundwater properties (specific yield, depth, hydraulic conductivity) across the entire catchment, only the catchment average groundwater levels are calibrated.

The model was calibrated for the period 1991–2008 and validated for the period 2009–2015. A manually calibrated version of the model served as the baseline model. Thereafter, two versions of the model were calibrated: HB_{on} and HB_{off}. In both the versions, CDs were incorporated starting the year 2002. They differed only in the presence of human behavior rules. HB_{on} integrated all human behavior rules as described above into the model, while HB_{off} excluded them. Both models were calibrated in the same way, allowing for a comparison of how incorporating human-water feedback (in the HB_{on} model) improves model performance. Without human behavior, parameters can still be calibrated, but they may lack realism. This is similar to calibrating simple conceptual hydrological models such as SIXPAR model rather than its more complex model version such as SAC-SMA (Arkesteijn & Pande, 2013). Calibration of simplified models that miss certain processes or other details is always possible, yet it may only unpack limited understanding of corresponding systems. Thus, comparison of calibrated HB_{on} and HB_{off} (simpler model with no behavior) was done in order to assess whether the integration of human-water feedback improves the explanatory capabilities of the ABM-AWM in terms of runoff and groundwater storage, both of which are influenced by human behavior.

The HB_{off} model configuration involved deactivating the investment behavior module (drip and borewell), maintaining the rate of change of cotton (slope in Equation 1) at the pre-CD period value for all farmers, and substituting groundwater-dependent wheat area with a fixed input (as it would be in the absence of CDs). The wheat area input for HB_{off} model was derived from a manually calibrated HB_{on} model run without CDs (representing a counterfactual scenario with no additional recharge), with only the wheat area rule active (Equation 2). This provided the wheat area as a fixed input in the absence of CDs, since it represents the behavior of farmers, unrelated to CDs, of deciding on wheat area based on post-monsoon groundwater levels.

3.5. Uncertainty Analysis

For the uncertainty analysis, the confidence intervals (5%–95%) of the most sensitive model parameters (Table S1 in Supporting Information S1) were estimated based on the computation of the Jacobian matrix in the PEST search algorithm (Doherty et al., 2010). Additionally, the confidence intervals of regression estimates (in

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Equations 1–4) were derived from the corresponding regression models. Thereafter, based on the calibrated parameters and their confidence intervals (Table S16 in Supporting Information S1), 500 parameter sets were sampled using Latin Hypercube Sampling (Mishra, 2009). Latin Hypercube Sampling combines Simple Random Sampling as in Monte Carlo analysis and stratified sampling techniques, yielding statistically significant results with considerably fewer realizations beneficial for computationally demanding models (Mishra, 2009). This was used to compute the 5% and 95% interquartile ranges of the model outputs of simulations where the Nash-Sutcliffe Efficiency (NSE) of runoff and groundwater was >0.5.

3.6. Data

The model integrates multiple data sets, including climate and biophysical data for hydrological modeling (Table S1 in Supporting Information S1), crop data for estimating water requirements, yields, costs, and revenue (Tables S2 and S4 in Supporting Information S1), and farmer census data for characterizing agricultural stakeholders (Table S5 in Supporting Information S1). Comprehensive details and explanations of each data set are provided in the supplementary information (Text S1 to S4 in Supporting Information S1), forming a detailed model description.

4. Results

4.1. Model Performance

Figures 5a and 5b show the performance of the calibrated HB_{on} model in simulating runoff and groundwater levels. The model exhibited satisfactory performance during the calibration period (1991–2008), achieving a NSE of 0.59 for runoff with a Percent Bias (PBIAS) of 2.76%, and an NSE of 0.65 for groundwater levels. The model performed similarly during the validation period (2009–2015), with NSE of 0.56 for runoff and 0.61 for groundwater levels. The observed and simulated runoff shows that most of the runoff is generated in a few peaks with no characteristic flow recession at monthly scale and low flows for most of the other times. The model underestimates high runoff peaks except in 2010 and overestimates a few smaller ones. For the groundwater levels (meter below ground level, mbgl), the model simulates the observed pre- (May month) and post-monsoon (November month) patterns satisfactorily with a small bias towards deeper pre-monsoon (May groundwater levels) in the later years.

A comparison between the calibrated version of the model with embedded human behavior (HB_{on}) and the version without (HB_{Off}) revealed significantly better ($p < 0.01$) performance (unpaired independent t-test) of the former in terms of higher NSE values for runoff (HB_{on} = 0.59 vs. HB_{off} = 0.54) and groundwater levels (HB_{on} = 0.65 vs. HB_{off} = 0.55) (see Table S10, Figure S6 in Supporting Information S1). The better performance reflects the importance of farmers evolving agriculture practices in explaining the variations in hydrological fluxes, which the HB_{on} model accounts for. The HB_{on} model accounts for the farmers feedback in terms of cultivated area and investment (in drip irrigation and borewells), which influence soil moisture and groundwater storage, specifically through crop water needs, irrigation application and its corresponding efficiencies. The calibrated parameter values for the two versions were the sensitive soil storage parameters (field capacity, saturated capacity, and capillary rise, see Table S10 in Supporting Information S1).

Considering the better performance of the HB_{on} model in representing groundwater storage, we henceforth utilize the calibrated parameters from the HB_{on} model to simulate both the scenarios with human behavior on (HB_{on}) and off (HB_{off}).

Figure 6a presents a comparison of the simulated wheat area, simulated based on a human behavior rule (see methods), with the observed area. The performance was good, with an simulation accouting for ~70% of the variation (R^2 of 0.71). The remaining 30% of variation likely arises from factors unrelated to water, which the current model does not account for. Although the model simulated the observed patterns reasonably well, there was an overestimation for most years, especially in the period 2000–2010. Concerning crop yields, the model demonstrated satisfactory performance with R^2 values of 0.36, 0.46, and 0.52 for cotton, groundnut, and wheat yields, respectively (Figure S7 in Supporting Information S1). In general, there was less inter-year variation in simulated yields, especially for groundnut yields which could be attributed to the model's consideration of higher irrigation for groundnut (70% groundnut area being irrigated in the calibrated model), while that may not be the case in the field (Table S10 in Supporting Information S1). Also, the model only accounts for the effect of water

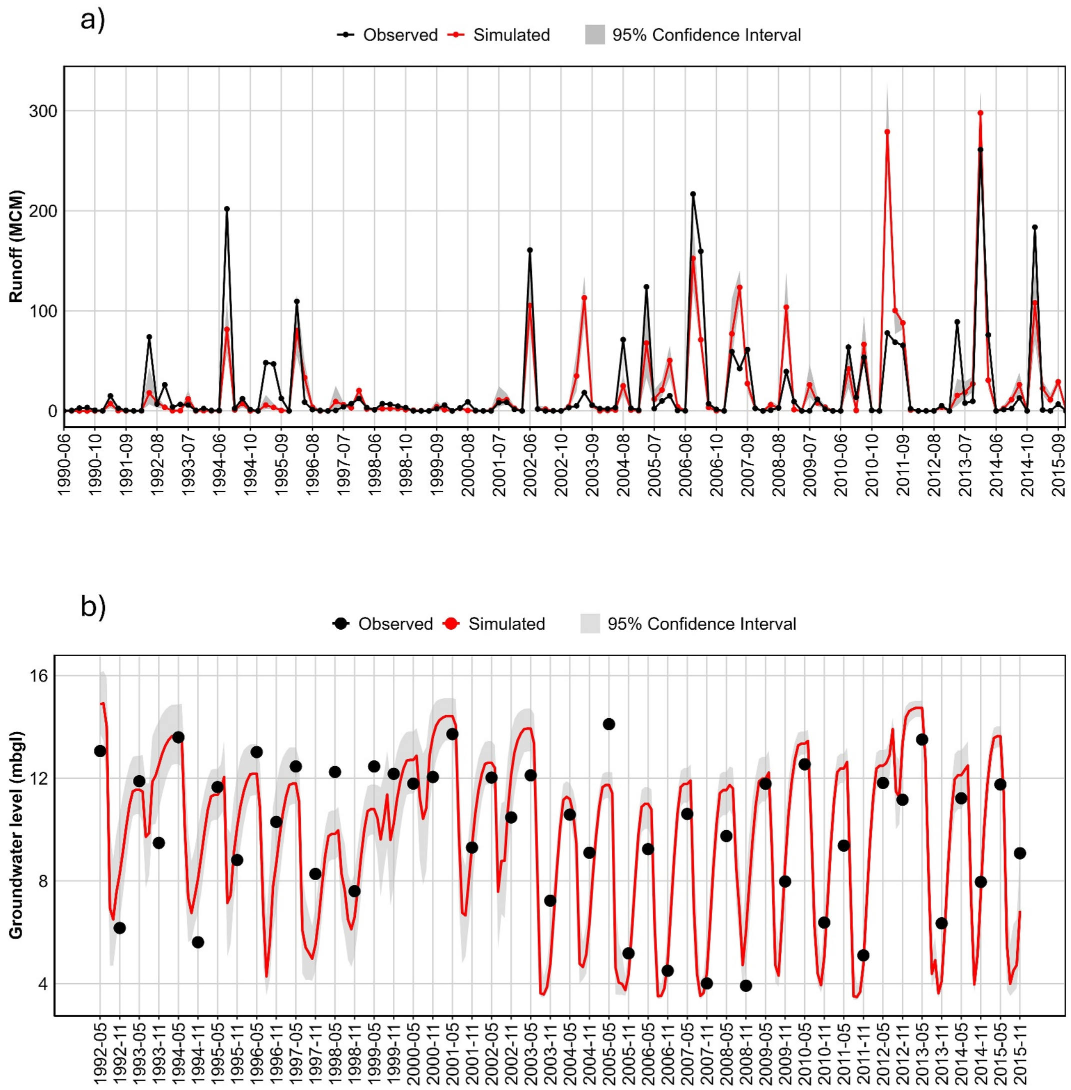

Figure 5. Simulated (HB_{on}) and observed runoff (a) and groundwater levels (b).

stress on yields, while achieving actual yields are more nuanced, involving other factors such as pest and extreme weather events. Cotton is especially impacted by pests, which may explain the lowest R^2 for cotton yields.

The overall model simulated annual ET at catchment scale was also compared with the remote sensing-based estimates of ET from MODIS (Mu et al., 2014) (Figure 6b). The comparison of model-simulated ET for the years MODIS ET was available (2000–2013) shows a good correlation ($R^2 = 0.79$), though small underestimation for most years were observed, indicating that the model can capture the crop water dynamics well at the catchment scale.

4.2. Increase in Supply (Recharge) From Check Dams

Figure S8 in Supporting Information S1 shows the increase in supply through recharge by CDs in the grid cells where CDs are located (453 grid cells out of 1,319). On average, each year CDs capture 18.5 MCM of runoff, resulting in a recharge of 16.8 MCM, with the remainder evaporated. Recharge is dependent on rainfall, with higher rainfall generally leading to increased recharge (28–34 MCM in 2005–2008 and 2011), while low rainfall years result in negligible recharge (<4 MCM in 2004, 2012, and 2014). The low recharge during years with low rainfall, when additional water is most needed, suggests that the CDs may not be able augment the supply to

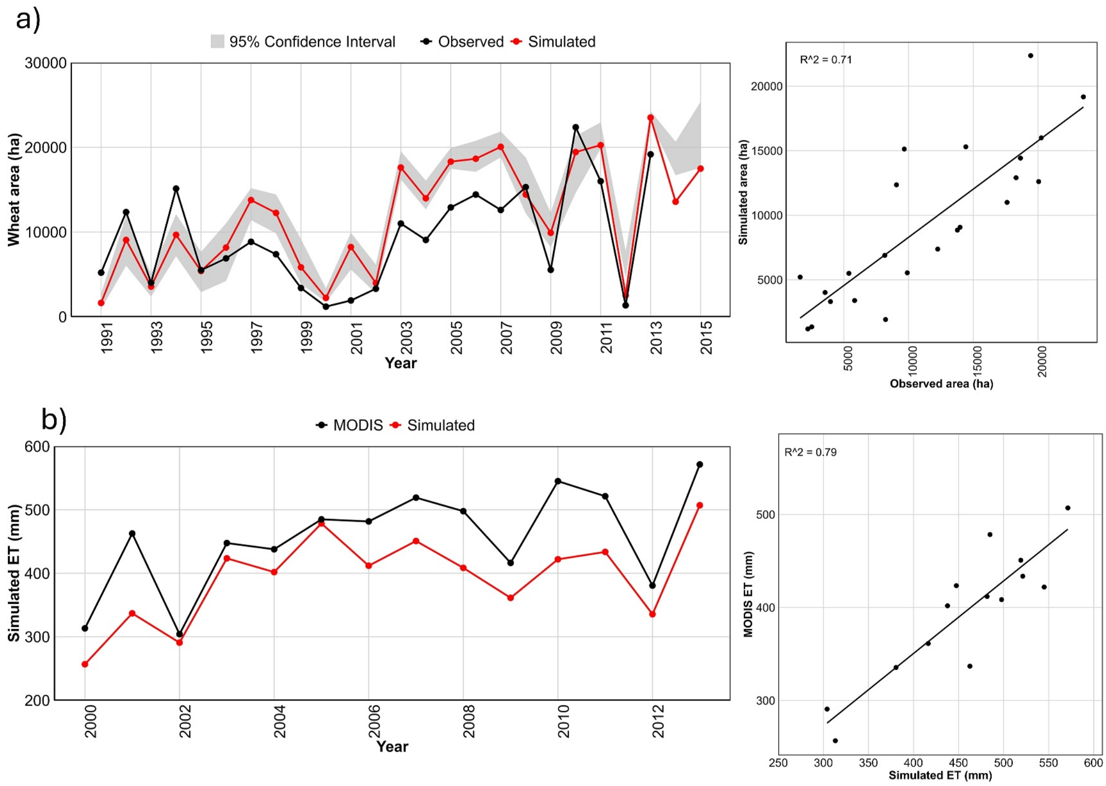

Figure 6. (a) Simulated and observed post-monsoon wheat area (ha); (b) Comparison of modeled ET with remote sensing-based MODIS ET, averaged over the catchment.

mitigate drought impacts. This is especially so because groundwater is depleted annually and there is no transfer over the years of recharge from good years to bad. In grid cells with no CD storage, there is no increase in supply.

4.3. Increase in Cotton and Wheat Area in Response to Increase in Recharge

Figure 7 shows the increases in the areas (per grid cell) of cotton (5a and 5b) and wheat (5c and 5d) in the catchment after the introduction of CDs in 2002 (post-CD period). The comparison is made for the whole catchment area (5a and 5c) and for farmers living in grid cells with CDs (5b and 5d) between models with human behavior (HB_{on}) and without human behavior (HB_{off}). In the HB_{off} model, the farmers do not respond to the increase in supply due to CDs since the behavior rules are switched off. The comparison between HB_{on} and HB_{off} models shows that human behavior as described leads to an increase in the area of both cotton and wheat in the catchment over the post-CD period. On average at the catchment scale, at the end of the simulation (in the year 2015), the cotton area (36.5 ha/grid cell) is higher by 4.3% (Figure 7a), and the wheat area (13.3 ha/grid cell) is higher by 15.5% (Figure 7c) in the HB_{on} model when compared to the HB_{off} model. The difference is greater in good rainfall years when higher rainfalls mean more recharge by CDs and fewer irrigation needs for the monsoon cotton crop. The results effectively captures the observed intensification of water intensive crops in the catchment validating hypothesis that this is driven by individual change in farmers behavior.

The spatial distribution of increased crop area (Figure 8) reveals heterogeneous impacts across the catchment, with changes concentrated in grid cells containing CDs. In these cells, the average cotton area is 41.3 ha/grid cell in the HB_{on} model—11.9% higher than in the HB_{off} model (36.9 ha/grid cell; Figure 7b). Similarly, wheat area increases by 36.1%, from 11.9 to 16.2 ha/grid cell (Figure 7d). The spatially heterogeneous patterns (Figure 8) support the hypothesis that impacts are unevenly distributed, with concentrations near CDs that reinforce spatial disparities within the catchment. Moreover, these heterogeneous impacts and spatial interactions may drive cross-catchment dynamics, contributing to the observed supply–demand feedback and further shaping system behavior. However, the current ABM does not capture such cross-catchment interactions, as knowledge exchange in the model is confined to individual grid cells.

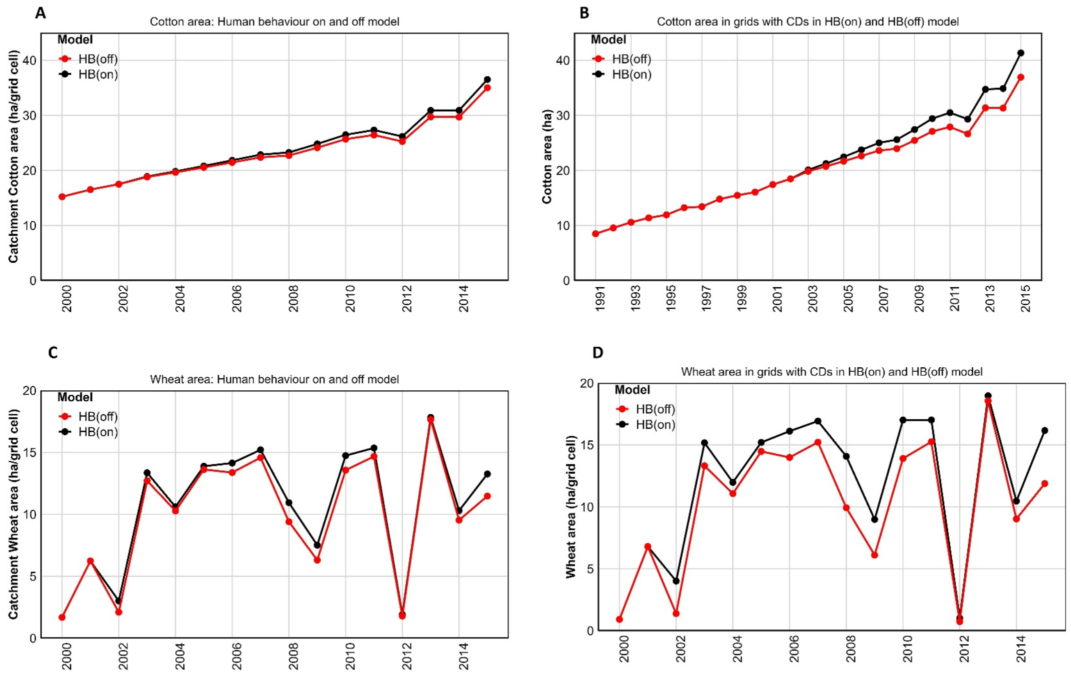

Figure 7. Total catchment (a) cotton area (top left) and (c) wheat area (bottom left) in the HB_{on} and HB_{off} model. Mean (b) cotton area (top right) and (d) wheat area (bottom right) in the grids with check dam in the HB_{on} and HB_{off} models. The figures show the period starting from 2000 because there is no difference in crop areas in the pre-CD period (1991–2001).

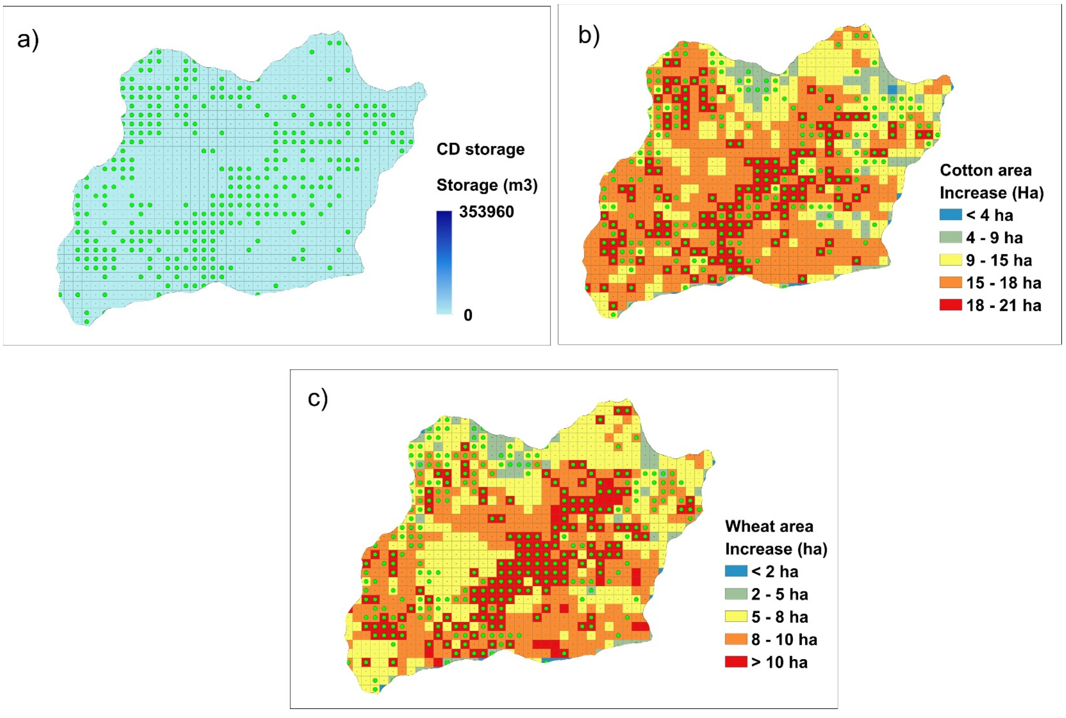

Figure 8. Spatial pattern of (a) check dam (CD) storage; (b) increase in cotton area and (c) wheat post introduction of CDs in 2002 (post-CD period). Green dots in the figure shows the presence of CD in the grid cell.

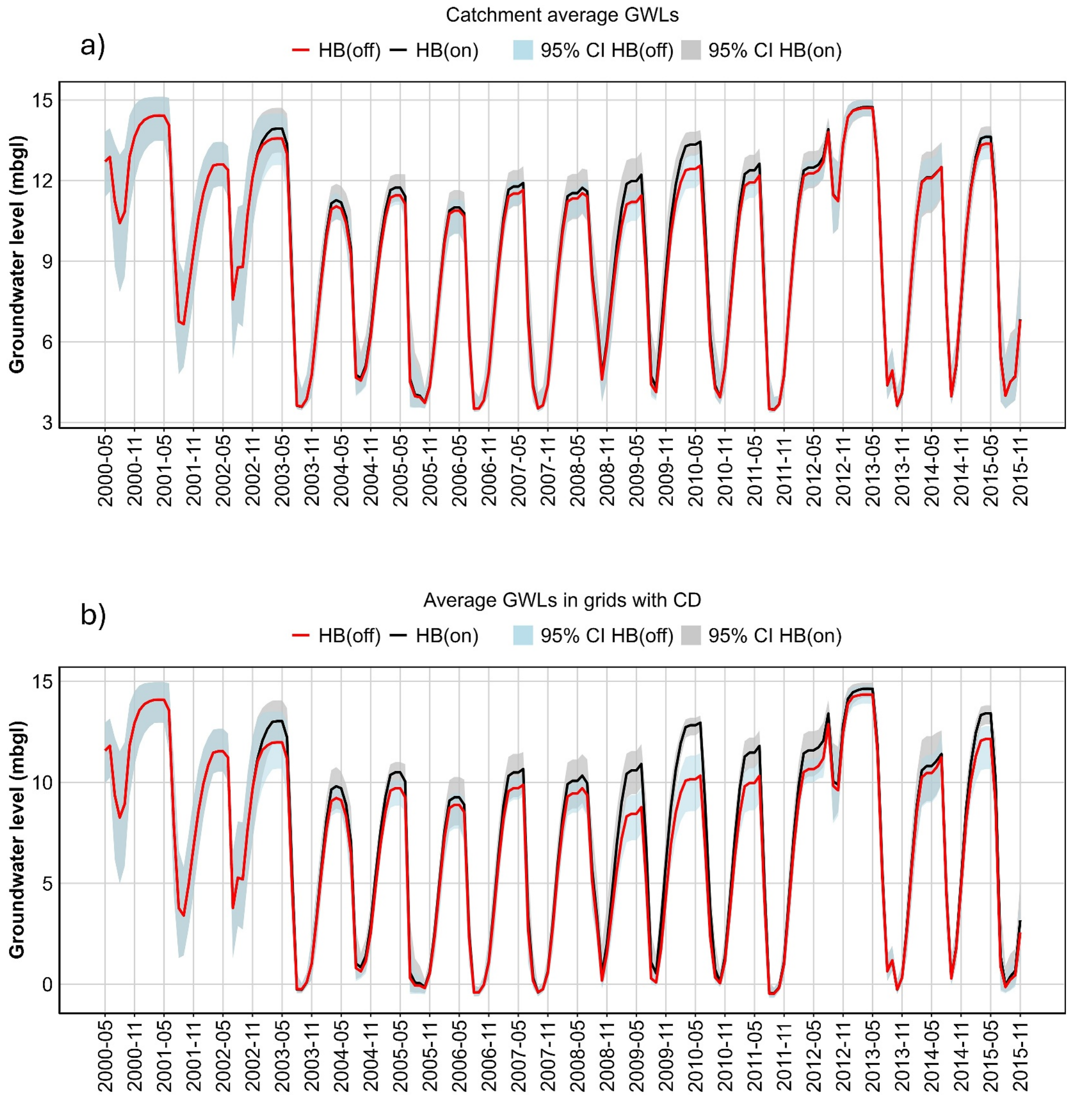

Figure 9. (a) Overall catchment groundwater level (top) and (b) Groundwater level in grids with check dams (bottom) in the HB_{on} and HB_{off} models.

4.4. Impact of Increased Crop Area on Groundwater Levels

The expansion of cotton and wheat cultivated areas (Figure 7) results in an increased demand for groundwater irrigation and is reflected in the deeper groundwater levels. Figure 9 shows the characteristic pattern of groundwater levels in the shallow storage hard rock aquifer in the region with aquifer filling up, more in good rainfall years, during monsoon season (June-November) and drying in the post monsoon season (December-May). This limits the evolution of any long-term trend, but the impact of increased use or additional recharge is discernible when comparing average groundwater levels. Due to increased crop area, groundwater levels averaged across the entire catchment are slightly deeper in HB_{on} model compared with HB_{off} model in the post-CD period over the years on average (by 0.18 m) and difference is more pronounced in the pre-monsoon season (by 0.32 m) (after the end of the cropping season). This reflects the impact of increased irrigation abstractions to support the expanded areas of cotton and wheat (Figure 7).

However, the differences become more pronounced when comparing grid cells with CDs in both the HB_{On} and HB_{Off} models (Figure 9b). In the grid cells with CDs, where the expansion of crop areas occurs, groundwater levels over the year are on average 0.62 m deeper (Figure 9b). The difference is much higher at the end of a cropping season in the pre-monsoon (May month) with groundwater levels on average deeper by 1.03 m

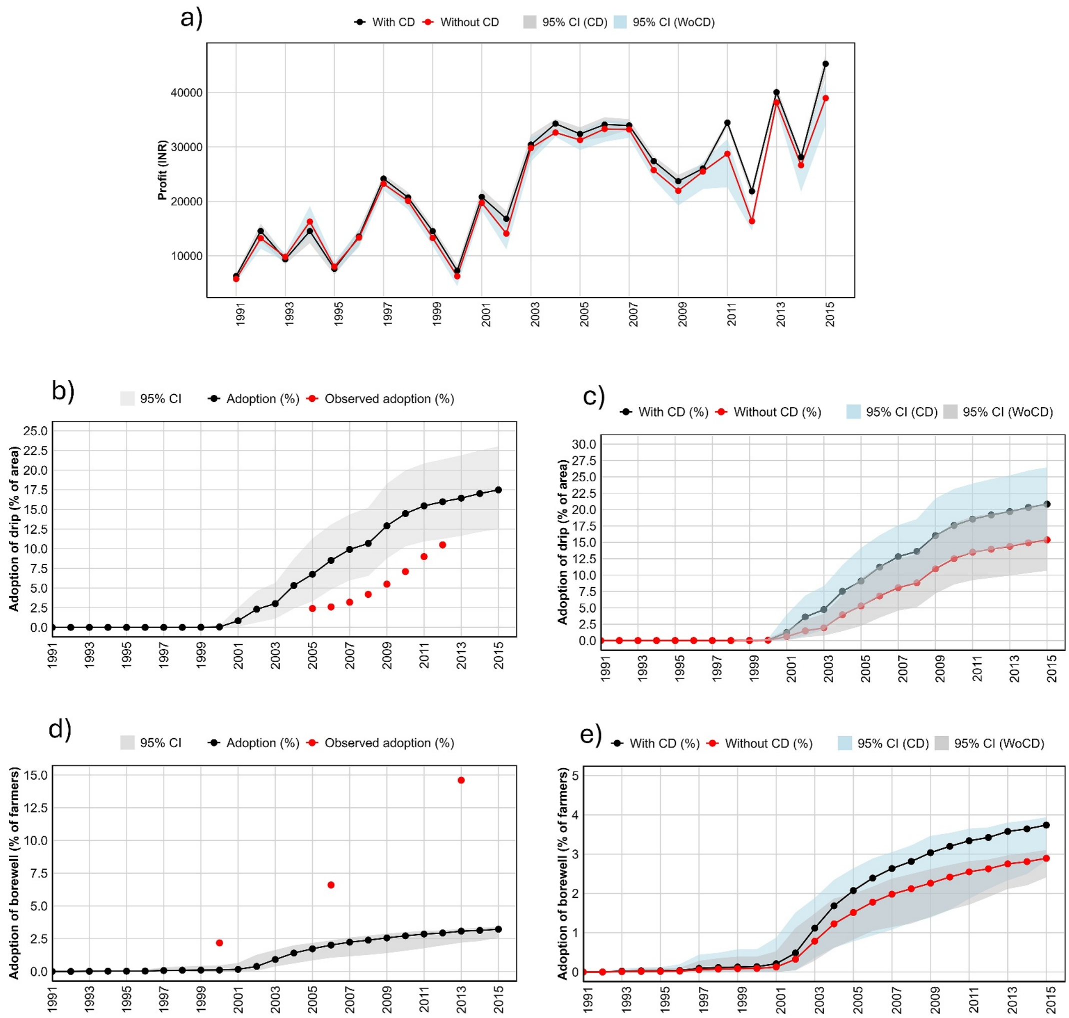

Figure 10. (a) Average profit (INR) from crop production for farmers with and without a CD; (b) overall adoption (% of area) of drip in the catchment; (c) Adoption (% of area) of drip with (check dam (CD)) and without a CD (WoCD); (d) overall Adoption (% of farmers) of borewell in the catchment; (e) Adoption (% of farmers) of borewell for farmers with (CD) and without a CD (WoCD) [Source: Observed drip adoption (GAPL, 2014) and Borewell adoption (MoWR, RD & GR, 2024)]. Both CD and WoCD are from the HB_{on} model.

(0.3–2.7 m) in the HB_{on} model when compared to the HB_{off} model. This suggests that the additional recharge from CDs may have raised groundwater levels by an average of 1.03 m by the end of a hydrological year. This increase is significant for the shallow aquifer, accounting for approximately 7% (ranging from 2% to 18%) of dynamic storage (∼15 m, Figure 8). Also, the decrease in GWLs directly impacts wheat area cultivation which depends on post monsoon GWLs (see methods, Equation 2). On average groundwater level of 6 m below ground level (mbgl), a 1-m increase in groundwater levels could result in an approximately 12% increase in the wheat cultivation area. Furthermore, this additional groundwater storage buffer could have provided resilience against delayed monsoons or reduced rainfall in the following year. These results support the hypothesis that individual behavioral changes on crop intensification, when aggregated at catchment scale, have led to increased groundwater use across the catchment.

4.5. Unintended Impact on Income and Adoption

Figure 10a shows the effect of an increase in crop areas on farmer profits resulting from enhanced crop production over time. Following the introduction of CDs, farmers' profit shows a marginal increase (Figure 10a), in line with the expansion of crop area (Figure 7). There is a general increase in profit over the years which is due to higher yields over time. The comparison between farmers living in grid cells with CDs and those in grid cells without CDs shows that the average profit in the post-CD period (2002–2015) for CD farmers amounts to INR 30,627 (369 USD) year^{-1} [29,267–31,740 INR/year], representing an 8.2% increase compared to non-CD farmers (INR 28,307 years^{-1}). In contrast, their pre-CD period profit was INR 13,943 (USD 168) year^{-1} [12,621–15,057 INR/year], which was only 2.9% higher compared to the non-CD farmers (INR 13,547 years^{-1}).

Farmers reinvest a portion of their profits in agricultural water interventions, as assessed through the adoption of drip irrigation and borewells and simulated based on the RANAS behavioral model. Figure 10b illustrates the adoption rate (% of area under drip irrigation) of drip irrigation over the years. The simulated adoption of drip irrigation slightly over-estimates the observed adoption but overall shows a satisfactory performance with adoption increasing in the post-CD period and tapering towards the end, reflecting the characteristic S-shaped adoption curve. By the year 2015, the simulated adoption percentage in the catchment reached 17.5%. While the rate of adoption is more gradual in simulated adoption, the observed adoption exhibits exponential growth starting 2007 compared to the simulated gradual increase. Nevertheless, by the end of 2022, with observed adoption reaching 16.5% in the region (Alam et al., 2024), it can be inferred that the observed growth deviates from pure exponential growth to the S-shape adoption curve and aligns with the S-shape of the simulated adoption curve.

The impact of increased profit on adoption is evident when comparing the farmers living in grid cells with and without CDs (Figure 10c). Farmers with CDs, experiencing increased crop area and profit, show on average a much higher adoption rate (20.8% [15.4%–26.4%] in 2015) than farmers without CDs (15.4% [10.7%–21.0%] in 2015). Though the increase in profit is small (Figure 9a), the relatively higher difference in the adoption rate implies that even smaller increases in profit followed by a marginal higher rate of adoption in farmers with CDs can lead to favorable social norm and attitudes, leading to much larger impact on adoption over the years. The higher adoption is also reflected in the household survey conducted in the region (Alam et al., 2024). It shows higher rate of adoption amongst the farmers with CD (23.5%) (defined as those having nearest CD < 500 m) when compared to the farmers without CD (20.7%) and the difference is significant ($p < 0.05$; chi-square test).

In contrast to the adoption of drip irrigation, the model underestimates the observed borewell adoption (percent of farmers) patterns (Figure 10d). Simulated borewell adoption is much lower (3.3% in 2015) than observed borewell adoption, with the adoption rate increasing at a slower pace than observed. However, similar to the case with drip irrigation, the farmers in grid cells with CDs show higher adoption rates (3.9% [2.9%–4%]) than the farmers without CDs (2.9% [2.4%–3.1%]) (Figure 10e). The adoption of both drip irrigation and borewells contributes to higher yields among the adopters, as depicted in Figure S9 in Supporting Information S1, further enhancing farmers' benefits. These results support the hypothesis that change in crop shifts contributed to income disparities and uneven adoption of technologies such as drip irrigation and borewells.

The underestimation of borewell adoption can be attributed to various factors. Firstly, borewells have a higher cost of adoption, especially in the absence of subsidies, and high failure rates. Also, the model imposes financial constraints by restricting access to debt, which farmers often resort to fund borewell drilling (Taylor, 2013). Additionally, there could be other unaccounted factors, such as farmers' networks, power dynamics, and variations in farm soil types, which may play a role in influencing the adoption patterns and are not included. This omission is partly evident in the lower predictive power of the logistics model for borewell adoption (65.9% accuracy) compared to drip adoption (85.9% accuracy) (Table S7 and S8 in Supporting Information S1). Thus, the findings underscore the necessity to broaden the model's scope by incorporating additional social, behavioral, and biophysical factors that impact farmers' adoption decisions. However, the simulations highlight that, assuming other unknow factors as constant, the positive impact of additional recharge and associated crop changes on income significantly influences the adoption rates.

4.6. Impact on Overall Water Use

The evolution of supply demand feedback, resulting in an increased crop area (Figure 7) and the dynamics of drip adoption (Figure 10), leads to unintended changes in total water use relative to CD recharge. The expansion of the cotton area (Figure 7) increases water use (Table S11 in Supporting Information S1). However, the growing adoption of more efficient drip irrigation (Figure 10), which improves efficiency from 0.6 to 0.9 (a 50% increase), mitigates this effect. Consequently, cotton water use increases most in grid cells with high cultivated area and low drip adoption, while it decreases in areas with high cultivated area and high drip adoption due to water savings outweighing the increased crop area (Tables S11 and S12 in Supporting Information S1).

This shift impacts post-monsoon groundwater levels, influencing farmers' decisions on wheat area (Equation 3, see methods). Grid cells with high drip adoption exhibit better (shallower) post-monsoon groundwater levels (Table S13 in Supporting Information S1), leading to a higher wheat area in those grids (Table S14 in Supporting Information S1). The expansion of wheat cultivation suggests that the water saved with drip irrigation is being redirected to support the increased wheat area. This reflects the development of another supply demand feedback loop, for post-monsoon crops, in response to enhanced water supply (increased groundwater levels). As a result of increased wheat area, the improvement in post-monsoon (November) groundwater levels diminish or disappear by the end of the hydrological year, that is, pre-monsoon (May of the following calendar year) (Table S15 in Supporting Information S1). This is more pronounced in years with where supply augmentation is higher that is, years with large differences (>1 m) in post-monsoon levels (e.g., 2002, 2008, 2009, 2015). In these years, the increased water use for wheat exceeds the savings from cotton, depleting the water saved through drip irrigation (Table S15 in Supporting Information S1). In years with smaller differences (<1 m) in post-monsoon levels, the water saved from drip irrigation outweighs the increased water use for wheat cultivation. These results support the hypothesis that change in crop area and impact on technologies affected overall water use dynamics in an unintended way.

Overall, an average of 54% of additional recharge by CDs is used (annual increase in irrigation water use (HB_{on}-HB_{off})/annual CD recharge) for expanding irrigation for cotton and wheat (Figure S10 in Supporting Information S1). The percentage is higher (80%–100%) for low rainfall years (e.g., 2008, 2009, 2012) when the recharge was limited and demand was higher and is towards the lower end (10%–20%) when the rainfall was higher (e.g., 2005, 2011).

5. Discussion

The application of the sociohydrology based ABM-AWM model in the study area demonstrates how integrating human behavior into hydrological models, designed to evaluate agricultural water interventions, can reproduce/mimic observed human-water feedback, thus providing a valuable tool to devise strategies for preventing inequitable and unsustainable outcomes for informed policy making. The model successfully replicates the observed supply demand phenomenon with increase in water intensive crop cultivation, supported by increase in groundwater use, in response to the (perceived) increase in supply after introduction of CDs. The results validate the hypothesis that farmers' perception of increased water availability from CDs drives a spatially uneven shift toward more water-intensive crops, primarily benefiting those near the structures, which cumulatively leads to greater groundwater extraction across the catchment. While other factors may also contribute to the observed changes in cotton cultivation (see Methods), the purpose of this model is to demonstrate how human behavior can be integrated with hydrological models and how neglecting it may lead to unexpected and negative externalities. The results and discussion focus on this supply demand feedback interpretation of the data.

For programmes and policies focused on supply side interventions like CDs, the findings offer critical lessons. While such water supply related investment aim to both enhance groundwater storage and increase irrigation supply (Alam et al., 2022b; Patel et al., 2020; Shah et al., 2009), these objectives can conflict due to supply demand feedback. As results and validated hypothesis show that as farmers perceive greater water availability, they tend to increase water use, undermining the potential groundwater gains. For instance, simulations show pre-monsoon groundwater levels to be 1.03 m deeper when farmer behavior shifts, negating the recharge benefits from CDs. This aligns with results reported elsewhere (Adla et al., 2023; Kallis, 2010) showing that increased supply often triggers increased demand, limiting long-term storage gains. Conversely, if the goal is solely to boost irrigation, CDs appear effectively expanding cultivated areas and incomes. However, this is not sustainable. In dry years, recharge is minimal, making CDs unreliable for drought mitigation (Section 4.2). Moreover, the shift to water-intensive crops increases vulnerability when water is scarce in dry years (Alam et al., 2022b). Without demand management, this cycle fuels further infrastructure investment to enhance supply. This is evident in the region with both rising number and depth of borewell and large-scale schemes like Sauni, which transfers floodwater across 1,000+ km to fill regional reservoirs (WRD, 2024).

While increased supply measures are necessary and are integral part of agricultural water interventions, results indicate that focusing solely on supply interventions will not result in expected sustainable outcomes and could lead to self-reinforcing supply demand cycles (Alam, Pavelic et al., 2022; Di Baldassarre et al., 2018) and increasing vulnerability. Instead supply measures should be accompanied/be part of broader set of holistic measures that includes demand management measures. These include providing incentives to reduce water usage (e.g., pricing saved water and/or electricity) (Mitra et al., 2023) implementing market mechanisms to prevent a shift to more water-intensive crops (Chand, 2012) and, if possible, establishing quotas on irrigation water use (Perry & Steduto, 2017). Additionally, it is essential to clearly identify end goals—such as enhancing groundwater storage, expanding irrigation, or reallocating water for other uses—to enable clearer and more objective assessments.

Further, the model brings out the unintended consequences on farmers' investment (as hypnotized). Changes in cropping patterns following the introduction of CDs increased farm profits —especially for those located near the CDs—leading to higher adoption of both drip irrigation and borewells (Alam et al., 2022b). This profit-driven reinvestment leads to the evolution of a new supply demand feedback loop, where increased water availability drives the adoption of technologies that further intensify water use. These shifts significantly affect water use dynamics. e.g., while drip irrigation can improve efficiency which translates to better post-monsoon groundwater levels. However, better post-monsoon groundwater levels lead to expanded wheat cultivation—showing supply gain from improved efficiency is quickly offset by increased demand. Additionally, results show higher income drives more borewell investments. Though the model underestimates actual adoption, the rising trend is concerning, as it leads to deep groundwater overexploitation. In effect, the result show investments aimed at enhancing shallow groundwater storage are encouraging extraction from deeper, non-renewable aquifers—undermining the original intent of the CDs to augment groundwater storage.

These reflect how ABMs can replicate the observed human-water feedbacks and unintended consequences, showcases the value of ABMs as a valuable tool for planning agricultural water interventions to unravel unintended consequences. However, there are limitations and areas of future research.

First, limitations in modeling human behavior remain. Results reveal discrepancies between the observed and simulated adoption rates, especially concerning borewells. This underscores the need to refine the behavior module by incorporating factors like social networks, institutional access, governance, power dynamics, and farm-level biophysical differences (e.g., farm soli types) all of which may impact adoption patterns. Also given the uncertainty and challenges involved with modeling human behavior, the focus of the study is less on precise prediction but more on interpreting unintended outcomes. While the improved behavior prediction will indeed lead to better quantifiable predictions, it is unlikely to alter the overall trajectory of resulting dynamics.

Second, the findings indicate that increased cropped area does not fully deplete the additional recharge—in contrast to a previous water balance study (Alam et al., 2022b), which found that expanded cultivation exhausted the recharge from CDs. Both studies, however, confirm that water use increased post-CD implementation and that recharge is fully exhausted during dry years. The incomplete exhaustion findings highlight limitations of the ABM-AWM model. For example, the model omits groundwater lateral flow, which can lead to overestimated groundwater levels in CD grid cells and underestimates the influence of recharge on adjacent areas. Also, model do not capture farmer behavioral changes post-drip adoption. Since drip irrigation can prolong cotton cultivation as the timing and frequency of cotton harvesting depend on groundwater availability, it may lead to higher water use and complete recharge exhaustion—effects not fully represented in the model.

Further, current model and results do not capture catchment-level interactions, which may have a contribution to the observed supply demand feedback, due to both model limitations and the study's scope. Although farmers are hydrologically connected through surface water flows, farmer interactions are currently modeled only at the grid level, capturing local neighbor effects but not broader social or hydrological interactions across the catchment. Capturing wider social networks (beyond the grid where a farmer is located) and cross-catchment interactions would require additional data, conceptual development, and model enhancements—an important direction for future work.

On the results side, the primary focus was on temporal dynamics—how individual farmer behavior evolves over time. The spatially explicit ABM was necessitated by the need to capture individual behavior response in response to spatial variability in water availability, as outlined in methods, this spatial dimension was not the focus of detailed analysis. However, the model's spatial structure offers potential to explore other relevant dynamics—such as upstream–downstream interactions and socio-economic disparities (e.g., differential access to water between small and large farmers)—though these were beyond the current study's scope. These remain areas for future investigation. For instance, upstream water harvesting could reduce downstream reservoir inflow, affecting command area irrigation.

Despite these limitations, the model demonstrates the potential of ABMs to uncover unintended outcomes of water interventions, especially the risk that water supply investments may drive unsustainable supply demand feedback leading to negative externalities and unintended consequences. Such insights are difficult to capture using conventional modeling approaches, reinforcing the unique value of socio-hydrological ABMs in planning. To avoid negative externalities and unintended consequences, understanding and modeling human-water feedback is therefore essential. Empirically grounded behavioral rules—reflecting real-world decision-making by farmers— integrated with hydrological modeling through ABMs provides a valuable tool to planners and policymakers to make more informed decisions.

6. Conclusions

The implementation of agricultural water interventions can trigger human-water feedback mechanisms, leading to unintended negative externalities. This study examined the supply demand feedback phenomenon—where increased water availability, or the perception of it, drives higher irrigation demand—in the Kamadhiya catchment, India. Following the introduction of CDs aimed at recharging groundwater (the main irrigation source), farmers' irrigation demand increased significantly. To model and understand this dynamic, an agent-based model for agricultural water management (ABM-AWM) was used. The model effectively captured these human-water feedback effects, demonstrating both the rise in irrigation demand and its unintended consequences on farmers' investments. These findings reveal that while supply side measures are vital components of agricultural water management, focusing exclusively on them is insufficient for achieving sustainable outcomes. Such interventions risk perpetuating self-reinforcing supply demand cycles. This underscores the critical need to understand and incorporate empirically grounded behavioral insights into planning and policy-making. By addressing the nuances of human-water feedback, stakeholders can design long-term water resource investments that are both sustainable and equitable.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data used can be accessed from Alam (2025), Buchhorn et al. (2020), ICRISAT (2021), DoA (2021), DoES (2015), ISRIC (2023), Jarvis et al., (2008), MoWR, RD & GR, (2024), MoA&FW (2021) and Pai et al. (2014). The code can be accessed from Alam (2025) and https://github.com/faiz-iwmi/AWM_ABM.

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