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Planning Sustainable and Equitable Agricultural Water Management Interventions: An Agent-Based Sociohydrology Approach

Mohammad Faiz Alam

Planning sustainable and equitable agricultural water management interventions: an agent based sociohydrology approach

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To my family and friends.

Contents

Summary

Sustainable and resilient agriculture is essential for global food security, especially in the Majority World, where agriculture is vital not only for food security but also for income security, employing a large portion of the population. Given agriculture's dependence on water and its vulnerability to weather extremes, which are further exacerbated by climate change, climate adaptation has become increasingly important. With climate change primarily affecting agriculture through the intensification of the water cycle, agricultural water management (AWM) interventions hold significant potential.

However, AWM interventions can lead to unintended negative externalities, resulting in unsustainable outcomes such as groundwater depletion and inequitable consequences such as increased income disparity. These externalities arise from the feedbacks between human and water systems, where changes in water availability influence human decisions and vice versa. To unpack these externalities, approaches used in sociohydrology that explicitly account for human-water feedback are essential.

This thesis uses a sociohydroloical approach to develop an agent-based model (ABM) to simulate bi-directional human-water feedback and uncover the potential externalities associated with AWM interventions. It develops a multi-method approach to interpret two emergent phenomena typical of agricultural water systems, “supply demand feedback” and “success to the successful”, and suggest ways to resolve the associated externalities that lead to the phenomena. The "supply-demand feedback” phenomenon suggests that increased water availability, or the perception of it, leads to a rise in demand potentially reducing the expected supply benefits. On the other hand, the "success to the successful”

phenomenon indicates that individuals or groups who are already advantaged are more likely to capitalize on new opportunities or interventions.

The thesis begins with a systematic review of how ABMs have been used in agricultural systems, highlighting existing limitations such as the absence of spatially explicit and integrated hydrological models, an overreliance on the assumption of rational human behavior, and a lack of differentiation among farmer representations (Chapter 2). These limitations hinder ABMs ability to reveal agricultural water externalities, which are often spatially explicit and unequally impact different groups of farmers.

The thesis applies this approach to the Kamadhiya catchment in India, which has seen intensive construction of check dams (CDs) aimed at recharging groundwater, which is the primary source of irrigation. Through a combination of water balance analysis (Chapter 3) and farmer surveys (Chapter 4), the thesis illustrates the evolution of supply-demand feedback in the catchment. The findings show that as (perceived) groundwater supply increases due to CDs, farmers respond by cultivating more water-intensive crops, thus increasing groundwater usage. Over time, this increased demand negates the benefits of CDs, resulting in no significant improvement in groundwater storage. Additionally, the increased reliance on groundwater irrigation heightens vulnerability. This is because the underlying low-storage hard rock aquifer system cannot sustain the additional demand, especially during low-rainfall years when CDs recharge is negligible. Moreover, the benefits of CDs are unequally distributed, primarily accruing to farmers situated near the check dams, thereby exacerbating spatial inequities within the catchment.

The thesis further examines how farmers perceive and adopt two other major agricultural water interventions in the area—drip irrigation and borewells—

which are farmer-led initiatives, in contrast to the government-implemented CDs (Chapter 5). The research utilizes the RANAS behavioral theory to understand the decision-making processes of farmers regarding these practices. The results underscore the importance of incorporating sociopsychological factors such as risk perception, attitude, ability, and social norms when designing programs and policies aimed at increasing adoption and scaling. Incorporating these psychological factors significantly enhances the explanatory power of the adoption model, suggesting that program and intervention designs should also focus on influencing behavior, rather than relying solely on financial incentives such as subsidies.

In the final chapters (Chapter 6 and 7), the thesis synthesizes the developed understanding of the case study area and farmer behavior to create an agent-based model for AWM (ABM-AWM) interventions. The model is then used to interpret emergent “supply demand feedback” and “success to the successful” phenomena. The ABM-AWM model integrates a spatially distributed hydrological model with the decision-making processes of approximately 38,000 individual farmers. Model simulations demonstrate that increased water supply from CDs has led to a rise in the cultivation of more water-intensive cotton, which in turn increases groundwater usage and diminishes the expected benefits on groundwater storage – thereby offering an interpretation of the supply demand feedback phenomenon.

Furthermore, the ABM-AWM reveals unexpected externalities of CDs on the adoption of drip irrigation and borewells, showing an inequitable distribution of benefits that influences adoption patterns, particularly for farmers located near CDs. The results also indicate that impacts are not evenly distributed among all farmers; larger farmers, with more resources and better access to groundwater, gain more benefits and exhibit lower vulnerability during dry years compared to small and marginal farmers (Chapter 7) – thereby offering an interpretation of success to the successful phenomenon. Overall, Chapters 6 and 7 illustrate how the application of ABM-AWM can be valuable for informing future investments.

The thesis findings emphasize the need for more careful consideration of negative externalities when planning and investing in AWM interventions. Planning should account for the feedback between the interventions and farmer behavior. Specifically, for achieving sustainable outcomes with supply-side interventions such as CDs, the thesis advocates to make them part of a more holistic approach that includes demand management measures. These include providing incentives to reduce water usage (e.g., pricing saved water and/or electricity), implementing market mechanisms to prevent a shift to more water-intensive crops, and, if possible, establishing quotas on irrigation water use. Understanding farmer behavior is crucial for enhancing the adoption rate of agriculture water interventions. Additionally, the thesis demonstrates the value of ABMs as a tool for planning agricultural water interventions and mitigating negative externalities. Through such mixed methods as presented in the thesis, sociohydrological approaches can help achieve long-term sustainable and equitable outcomes.

Samenvatting

Duurzame en veerkrachtige landbouw is essentieel voor de werldwijde voedselzekerheid, vooral in de meerderheidswereld, waar de landbouw niet alleen van groot belang is voor de voedselzekerheid, maar ook voor de inkomenszekerheid en werkvoorziening. Gezien de afhankelijkheid van de landbouw van water en de bijbehorende kwetsbaarheid voor extreme weersomstandigheden, die nog worden verergerd door de klimaatverandering, is klimaatadaptatie steeds belangrijker geworden. Nu de klimaatverandering vooral de landbouw treft door de intensivering van de watercyclus, hebben agrarische waterinterventies een aanzienlijk potentieel.

Ongeplande landbouwwaterinterventies kunnen echter tot onbedoelde negatieve externe effecten leiden, wat tot niet duurzame uitkmosten leiden ~~zoals~~ met name uitputting van het grondwater en onrechtvaardige gevolgen zoals grote inkomensverschillen. Deze externe effecten komen voort uit de feedback tussen mens- en watersystemen, waarbij veranderingen in de beschikbaarheid van water beslissingen beïnvloeden en omgekeerd. Om deze externe factoren te belichten zijn sociohydrologische benaderingen, die expliciet rekening houden met de feedback tussen mens en water.

In dit proefschrift wordt gebruik gemaakt van een sociohydrologische benadering om een Agent-Based Model (ABM) te ontwikkelen om bidirectionele mens-waterfeedback te simuleren en de potentiële externe effecten die verband houden met interventies te ontdekken. Het betreft een aanpak van meerdere methoden om twee opkomende fenomenen te interpreteren die typisch zijn voor landbouwwatersystemen: ‘feedback van vraag en aanbod’ en ‘succes voor de succesvolle’, en stelt manieren voor om de daarmee samenhangende externe factoren op te lossen die tot deze fenomenen leiden. Het fenomeen ‘feedback tussen vraag en aanbod’ suggereert dat een grotere beschikbaarheid van water, of de perceptie daarvan, leidt tot een stijging van de vraag, waardoor de verwachte aanbodvoordelen mogelijk afnemen. Aan de andere kant geeft het fenomeen ‘succes voor de succesvolle’ aan dat individuen of groepen die al bevoordeeld zijn, makkellijker kunnen profiteren van nieuwe kansen of interventies.

Dit proefschrift begint met een systematische review van hoe ABM’s ~~zijn~~ gebruikt worden in landbouwsystemen, waarbij bestaande beperkingen worden benadrukt. Voorbeelden daarvan zijn de afwezigheid van ruimtelijk expliciete en geïntegreerde hydrologische modellen, een overdreven vertrouwen op de aanname van rationeel menselijk gedrag en een gebrek aan differentiatie tussen boerenrepresentaties. (Hoofdstuk 2). Deze beperkingen belemmeren het vermogen van ABM's om externe factoren zichtbaar te maken, die vaak ruimtelijk expliciet zijn en een ongelijke impact hebben op verschillende groepen boeren.

Het proefschrift past deze aanpak toe op het Kamadhiya-stroomgebied in India, waar Check Dams (CD's) zijn gebouwd, gericht op het aanvullen van grondwater, de belangrijkste bron van irrigatie. Door een combinatie van waterbalansanalyse (Hoofdstuk 3) en boerenenquêtes (Hoofdstuk 4) wordt de evolutie van de feedback tussen vraag en aanbod in het stroomgebied aangetoond. De resultaten tonen dat naarmate de (vermeende) grondwateraanvoer toeneemt als gevolg van CD's, reageren boeren door meer waterintensieve gewassen uit te breiden, waardoor het grondwatergebruik toeneemt. Na verloop van de tijd doet deze toegenomen vraag de voordelen van CD's teniet, met als uitkomst een niet significante verbetering van de grondwateropslag. Bovendien vergroot de toegenomen afhankelijkheid van grondwaterirrigatie de algemene kwetsbaarheid. Dit komt omdat het onderliggende hardgesteente aquifersysteem, met lage opslagcapaciteit, de extra vraag niet kan ondersteunen, vooral tijdens jaren met weinig regenval, in het geval dat de aanvulling van de regenval beperkt is en de aanvulling van cd's verwaarloosbaar is. Bovendien zijn de voordelen van CD's ongelijk verdeeld en komen deze voornamelijk ten goede van boeren die in de buurt van de controledammen zijn gevestigd, waardoor de ruimtelijke ongelijkheid binnen het stroomgebied wordt verergerd.

Het proefschrift onderzoekt verder hoe boeren twee andere belangrijke landbouwpraktijken in het gebied waarnemen en toepassen – druppelirrigatie en boorputten – wat geleide initiatieven zijn, in tegenstelling tot de door de overheid geïmplementeerde CD's (Hoofdstuk 5). Het onderzoek maakt gebruik van de RANAS-gedragstheorie om de besluitvormingsprocessen van boeren met betrekking tot deze praktijken te begrijpen. De resultaten onderstrepen het belang van het meenemen van sociaalpsychologische factoren zoals risicoperceptie, houding, bekwaamheid en sociale normen bij het ontwerpen van programma's en beleid gericht op het vergroten van de adoptie en schaalvergroting. Het incorporeren van deze psychologische factoren vergroot de verklarende kracht van het adoptiemodel aanzienlijk, wat suggereert dat programma- en interventieontwerpen zich ook moeten richten op het beïnvloeden van gedrag, in plaats van uitsluitend te vertrouwen op financiële prikkels zoals subsidies.

In de laatste hoofdstukken (hoofdstukken 6 en 7) wordt het ontwikkelde inzicht in het casestudygebied en het gedrag van boeren gecombineerd om een Agent-Based Model (ABM-AWM) voor interventies op het gebied van landbouwwaterbeheer (ABM-AWM) te creëren. Het model wordt vervolgens gebruikt om opkomende 'aanbod-vraag-feedback' en 'succes voor de succesvolle' fenomenen te interpreteren. De ABM-AWM integreert een ruimtelijk verdeeld (distributed) hydrologisch model met de besluitvormingsprocessen van ongeveer 38.000 individuele boeren. Modelsimulaties tonen aan dat de toegenomen wateraanvoer uit CD's heeft geleid tot een toename van de teelt van meer waterintensief katoen, wat tot toename leidt van het grondwatergebruik en de verwachte voordelen op het gebied van grondwateropslag vermindert. Daarmee wordt een interpretatie van het fenomeen van feedback op de vraag naar aanbod gegeven.

Bovendien onthult de ABM-AWM onverwachte externe effecten van CD's op de adoptie van druppelirrigatie en boorputten, wat een ongelijke verdeling van de voordelen laat zien die de adoptiepatronen beïnvloedt, vooral voor boeren die in omgeveing van CD's wonen. De resultaten geven ook aan dat de gevolgen niet gelijkmatig over alle boeren zijn verdeeld; grotere boeren, met meer hulpbronnen en betere toegang tot grondwater, verkrijgen meer voordelen en zijn tijdens droge jaren minder kwetsbaar dan kleine en marginale boeren (hoofdstuk 7) – waardoor een interpretatie van succes aan het succesvolle fenomeen wordt geboden. Over het geheel, illustreren de hoofdstukken 6 en 7 hoe de toepassing van ABM's in de context van waterinterventies in de landbouw waardevol kunnen zijn voor het informeren van toekomstige investeringen.

De bevindingen van dit proefschrift benadrukken de noodzaak van een zorgvuldige afweging van negatieve externe effecten tijdens het plannen en investeren in waterinterventies in de landbouw. Bij planning moet rekening worden gehouden met de feedback tussen de interventies en het gedrag van boeren. met Voor het verduurzamen doormiddel van interventies aan de aanbodzijde, zoals CD's, pleit het proefschrift ervoor om deze onderdeel te maken van een meer holistische benadering die maatregelen voor vraagbeheer omvat. Deze omvatten het bieden van stimulanten om het waterverbruik te verminderen (bijvoorbeeld het beprijzen van bespaard water en/of elektriciteit), het implementeren van marktmechanismen om een verschuiving naar meer waterintensieve gewassen te voorkomen, en, indien mogelijk, het vaststellen van quota voor het gebruik van irrigatiewater. Het begrijpen van het gedrag van boeren is van cruciaal belang voor het vergroten van de acceptatiegraad van waterinterventies in de landbouw. Bovendien toont dit proefschrift de waarde aan van ABM's als instrument voor het plannen van waterinterventies in de landbouw en het verminederen van negatieve externe effecten. Via dergelijke gemengde methoden, kunnen sociaalhydrologische benaderingen helpen duurzame en rechtvaardige resultaten op de lange termijn te bereiken.

Preface

I am excited to write this preface, marking the end of a journey that began four years ago. It was back in 2016 when I joined IWMI in Delhi that I got exposed to the challenges of water management in agriculture. Engaging with farmers, understanding the on-ground realities, and collaborating with researchers from other disciplines piqued my interest in applying my technical expertise in hydrology within a more interdisciplinary framework. Around same time, I came across the emerging field of sociohydrology, which aims to do the same. With this background and motivation, my PhD journey officially began in 2020.

The chapters in a way reflect this journey and motivation. Chapters 1 and 2 establish the motivation and provide background on the problem. Chapter 3 focuses on hydrological methods to address the issue, while Chapters 4 and 5 incorporate social and behavioral surveys to deepen the understanding. Chapters 6 and 7 synthesize these elements, developing a model that integrates hydrological, social, and behavioral sciences. Chapter 8 offers a synthesis and reflects on the implications of this thesis for agricultural water management.

This achievement would not have been possible without the unwavering support of my supervisory team—Saket, Michael, and Alok. I was fortunate to have a perfect blend of mentors who each supported and guided me in their unique ways. To my family, I could not have done this without you. Please read the introduction, which may finally answer your perennial question about what I do, and the acknowledgements, which express what your support means to me.

Mohammad Faiz Alam

Delft, June 2024

1. Introduction[1]

[1] This chapter is partially based on an article published in Environmental Research Letters:

Alam, M.F., McClain, M., Sikka, A., Pande, S., 2022. Understanding human–water feedback of interventions in agricultural systems with agent based models: a review. Environ. Res. Lett. 17, 103003. https://doi.org/10.1088/1748-9326/ac91e1

1.1 Agricultural Water Management interventions for climate change adaptation

Climate change manifested in increased variability of the water cycle is increasing the frequency of extreme events and reducing the predictability of water availability (United Nations, 2019). This is a growing global threat to agriculture with strong implications for food security and poverty reduction (GCA and WRI, 2019; Mendelsohn, 2009). Already extreme weather events of floods and drought account for more than 80 % of agricultural losses (in crop and livestock production) (FAO, 2015) and have resulted in a loss of over 3.8 trillion USD over the past three decades due to damage to crop and livestock production (FAO, 2023). Climate change has reduced global agricultural total factor productivity by an estimated 21 % since 1961 (Ortiz-Bobea et al., 2021). Thus, there is an urgent need for adaptation in agriculture without which global agriculture yields could be reduced by up to 30 percent by 2050, impacting 500 million small farms the most (GCA and WRI, 2019).

With climate change's impact on water and agriculture's reliance on water, adaptation in agriculture is inextricably linked to how water is managed (United Nations, 2019). For this reason, improving dryland agriculture crop production and making water resources more resilient are two of the five key identified adaptation areas globally with net benefits of 2.1 trillion USD (GCA and WRI, 2019). As a climate change adaptation measure, Agricultural water management (AWM) interventions are extensively promoted and implemented globally (Sharda et al., 2012; Shah et al., 2021; Evans and Giordano, 2012). AWM interventions can be broadly defined as interventions on land that alter the water balance or partitioning of rainfall into different components (soil, surface, and sub-surface storages, transpiration, evaporation, and losses) (Barron et al., 2009, Calder et al., 2008). They can be broadly categorized under supply-side and demand-side interventions (Sikka et al., 2018; Barron et al. 2009). Supply-side AWM interventions increase water storage by either using in-situ soil and water conservation practices (e.g. mulching, field bunding) or ex-situ storage interventions (e.g. ponds, aquifer recharge, dams). Demand-side AWM interventions reduce water demand either by increasing water application efficiency (e.g. micro-irrigation, irrigation scheduling) or by broader measures such as changes in cropping and production systems (agroforestry, inter-cropping) and shifting crop sowing window.

The benefits of implementing AWM interventions have been widely reported and established. This includes enhancing natural resource systems by increasing the availability of surface water, groundwater, and soil water leading to improved agricultural yields, benefiting farmers through increased income, and additionally contributing to raising community awareness regarding water usage and environmental conservation (Joshi et al., 2008; Calder et al., 2008; Glendenning et al., 2012; Sikka et al., 2018). Collectively, these outcomes play a crucial role in climate change adaptation and building farmers' resilience to its impacts.

1.2 Externalities of Agricultural Water Management Interventions

Despite overwhelming documented positive impacts, there is a concern that studies highlighting the benefits of AWM interventions may be biased towards well-managed and successful projects (Kerr, 2002) and often miss out on reporting negative externalities (Barron et al., 2008, 2009; Kerr et al., 2007; Glendenning et al., 2012). Externalities, defined as indirect or accidental feedback associated with interventions, of AWM can be both positive and negative. Negative externalities often result from ill-planned implementations of AWM interventions that do not account for their hydrological impacts (especially across spatial scales) or social feedback. Though the focus of this thesis is on negative externalities, it is important to highlight that the benefits of AWM, along with multiple positive externalities of AWM, are well documented (Reddy, 2012, Sikka et al., 2018). Positive externalities of AWM include those that lead to enhanced surface and groundwater storage, reduced flood damage, enhanced baseflows during dry seasons, reduced soil erosion, and reduced sedimentation of reservoirs (Bouma et al., 2011; Reddy, 2012; Alam and Pavelic, 2020).

Negative externalities of AWM interventions result from the coevolutionary dynamics of human-water systems. Here, we term and classify negative externalities of AWM interventions linked to water and human systems as negative hydrological externalities and unexpected societal feedback (Figure 1.1). *Negative hydrological externalities* are unintended or unexpected changes in the spatial and temporal availability and allocation of water flows (Figure 1.1). They arise from the interaction of AWM interventions with hydrological flows (Calder et al.,2008 Barron et al., 2009; Kumar et al. 2006; Bouma et al., 2011; Van Oel et al. 2010). For example, water harvesting or storage interventions could lead to reduction in downstream flows and efficient irrigation interventions could lead to reduction in recharge from percolation and return flows (Table 1.1).

The impact of AWM interventions on hydrology is not unidirectional and is further influenced and shaped by the societal response to the interventions and hydrological externalities. This response, influenced by socio-economic and cultural contexts here termed unexpected societal feedback, is usually non-linear and highly heterogeneous and is typically not expected at the stage of planning (Di Baldassare et al., 2019; Pande and Sivapalan, 2017; Walker et al., 2015) (Figure 1.1). Examples include increased water use, rather than expected decrease, in response to efficient irrigation interventions (Jevons paradox) and increased demand in response to supply-side interventions (supply-demand feedback) (Table 1.1). Under the phenomenon of supply-demand feedback, demand rises following increased water availability or perception thereof (Di Baldassarre et al., 2018; Adla et al., 2023). This can lead to the development of more irrigated agriculture, which can offset the benefits of increased supply or can further decrease the amount of water available for downstream users (Glendenning et al., 2012). This is of particular concern as significant portions of agricultural water interventions pertain to the supply side, such as the construction of small storages and groundwater recharge interventions (Sikka et al., 2022; Joshi et al., 2008).

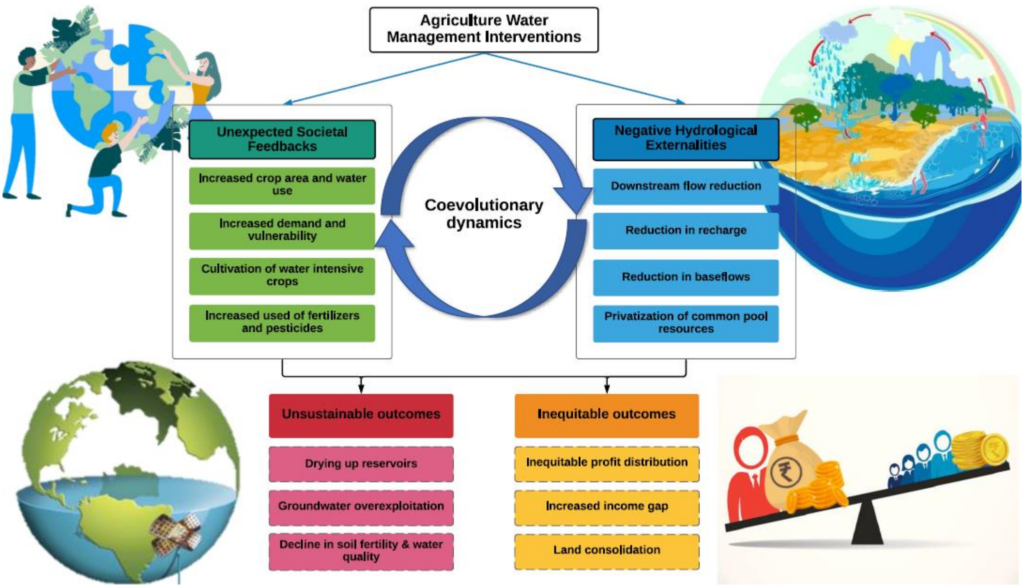

Figure 1.1: A conceptual diagram illustrating unsustainable and inequitable outcomes resulting from the coevolutionary dynamics of unintended negative hydrological externalities and unexpected societal feedback of AWM interventions.

These coevolutionary dynamics of hydrological externalities and unexpected societal feedback in society, unequally structured with unequal capacity and power, can lead to outcomes for social and biophysical systems that are unsustainable and inequitable (Figure 1.1) (Calder et al., 2008; Pande and Sivapalan, 2017; Barron et al., 2009; Bouma et al., 2011; Kerr, 2007). Examples of unsustainable outcomes include the drying of downstream lakes or reservoirs, groundwater overexploitation, reduced environmental flows, and water quality deterioration (Table 1). Further, these AWM impacts are often mediated and exacerbated by socio-economic inequalities in financial capital and knowledge, and gender and power relations (Sharma et al., 2008; Namara et al., 2010; Linton and Budds, 2014). Often, the benefits of AWM (and their negative impacts) are distributed unequally (Shiferaw et al. 2008; Shah et al., 2021; Linton and Budds, 2014) with rich or influential farmers having more access to social, financial, and biophysical capital capturing more advantages, more subsidies, and more benefits (Namara et al., 2010; Kafle et al., 2020) and resource-poor farmers disproportionately bearing the negative impacts (Table 1.1). The social-water relationship and how this perpetuates or even exacerbates inequality, exclusion, and impoverishment in response to development has been central to hydro-social studies (Linton and Budds, 2014).

Table 1.1: Illustrative examples of negative externalities linked with AWM interventions

	Negative externalities	Examples
Water harvesting, storage interventions	Hydrological externalities	Reduction in runoff leading to upstream-downstream impacts (Calder et al., 2008; Bouma et al., 2011)
	Societal unexpected feedback	Supply-demand feedback where more supply may lead to more demand (Adla et al., 2023)
	Unsustainable outcomes	Groundwater depletion; Drying of downstream lakes or reservoirs (e.g., Aral Sea) and reduction in environmental flows (Nepal et al., 2014; Wood and Halsema, 2008).
	Inequitable outcomes	Benefits concentrated to nearby farms in low-lying areas and to richer farmers having the financial capacity to invest in irrigation infrastructure (Bouma et al., 2011; Calder et al., 2008; Shah et al., 2021)
Irrigation efficiency interventions	Hydrological externalities	Reduction in return flows and percolation leading to a reduction in groundwater recharge (Fabbri et al., 2016; Perry and Steduto, 2017)
	Societal unexpected feedback	Increased water use, rather than expected reduction in the absence of any regulation limiting water use or abstraction (Birkenholtz, 2017).
	Unsustainable outcomes	Groundwater Depletion; wetland degradation and reduction of environmental flows (Zhang and Shan, 2008; Kopittke et al., 2019; Albert et al., 2021)
	Inequitable outcomes	The increased cost of pumping and drilling, well failure, and abandonment of wells are disproportionately borne by resource-poor farmers (Shiferaw et al. 2008, Reddy, 2012)

Subsidies (inputs, electricity etc.)	Hydrological externalities	Increased evapotranspiration demands from shifting toward more profitable and water-intensive crops (Shiferaw et al., 2008, Sarkar, 2011)
	Societal unexpected feedback	Increased water use; Increased use of fertilizers and pesticides (Berka et al., 2001; Zhang and Shan, 2008)
	Unsustainable outcomes	Hasten groundwater depletion (e.g., Northwest India) (Mukherji, 2020); water quality deterioration of rivers and aquifers (Zhang and Shan, 2008)
	Inequitable outcomes	Male, high-value crop cultivators and wealthier farmers benefit the most from investments made in farmer-led irrigation projects (Kafle et al., 2020; Namara et al, 2010)

1.3 Shortcomings in traditional modeling approaches to unravel AWM externalities

With agricultural water demand accounting for 70 % of freshwater withdrawals globally, and up to 95 % in developing countries (FAO, 2021), how water is managed in agriculture will have important implications for agriculture and other linked sectors (Satoh et al., 2017). Investments in AWM interventions must lead to sustainable and equitable impacts. Modeling presents one tool to understand and predict the impacts of proposed interventions and investments by unraveling their potential negative externalities. Given the interaction of AWM interventions with hydrology and society, understanding the impacts of AWM interventions requires that developed models be able to capture the coevolutionary dynamics of negative hydrological externalities and unexpected societal feedback to avoid inequitable and unsustainable outcomes (Figure 1.1).

Conventional modeling approaches used to study the impacts of AWM interventions (e.g., hydrological models, hydro-economic, and water resource models) have generated a wealth of information and knowledge on future availability and use of water, the impacts and benefits of AWM interventions, required agronomic conditions, and socio-economic constraints (Garg et al., 2012; Andersson et al., 2011; Satoh et al., 2017; Harou et al., 2009; MacEwan et al., 2017; Hassaballah et al., 2012). However, they do not explicitly model the feedback between human and water systems, thus missing out on the coevolutionary dynamics that limit their prediction power over the long term (Srinivasan et al., 2017; Pouladi et al., 2020; Sivapalan et al., 2012). In these models, human actions (or societal feedback) are mostly externally prescribed, often as scenarios (Srinivasan et al., 2017; Pouladi et al., 2020; Satoh et al., 2017). However, they typically treat human and water subsystems as independent of each other, disregarding the reality that humans think and respond dynamically to changes in environmental and socio-economic conditions (e.g., irrigation and cropping decisions, land use) (Srinivasan et al., 2017; Pouladi et al., 2020; Van Niekerk et al., 2019).

For example, hydrological models can assess and predict the hydrological impacts of proposed AWM interventions based on various assumptions about human processes (e.g., population growth, adoption of interventions, adaptation responses) (Garg et al., 2012; Andersson et al., 2011; Satoh et al., 2017). Similarly, hydro-economic modeling and water resource systems that incorporate human modifications such as dams and canals largely focus on the economic value of water, optimization of costs and design, and ignore feedback such interventions have on human decision-making, e.g., with regards to the perception of scarcity (Srinivasan et al., 2017; Harou et al., 2009; MacEwan et al., 2017; Hassaballah et al., 2012).

The interventions could lead to long-term unintended consequences exacerbating social inequalities and vulnerabilities without accounting for these human-water feedback in their design (Di Baldassarre et al., 2019; Sivapalan et al., 2012; Srinivasan et al., 2017; Pouladi et al., 2020; Pande and Sivapalan, 2017).

For example, studies have shown that infrastructure systems for mitigating floods (e.g., levees) can expose the population to less frequent but more catastrophic events (Pande and Sivapalan, 2017; Di Baladassarre et al., 2015). Thus, there is a need to expand conventional AWM models to integrate human-water dynamics, especially for longer-term planning horizons when human-water feedback becomes increasingly important.

1.4 Sociohydrology: An approach to unravel AWM externalities

Sociohydrology, an interdisciplinary science of coupled human-water systems, was introduced to understand and model the coevolutionary dynamics of human-water systems on multiple spatial and temporal scales (Sivapalan et al., 2012). In contrast to conventional modeling approaches, sociohydrology explicitly allows for changing and adaptive responses by humans and how those responses affect the environment, thus capturing unexpected, emergent behavior of human-water systems (Sivapalan et al., 2012; Srinivasan et al., 2017; Di Baldassarre et al., 2019; Pande and Sivapalan, 2017). Sociohydrology models are being increasingly applied to understand and model the coevolutionary dynamics of coupled human-water systems (Di Baldassarre et al., 2016; Pande and Sivapalan, 2017). The approach has been used for examining human-flood, human-drought systems (Di Baldassarre et al., 2013; 2017), smallholder agricultural human-water systems (Pande and Savenije, 2016), water security challenges (Gober and Wheater), and the evolution of ancient societies (Kuil et al., 2016; Pande and Ertsen, 2014).

1.4.1 Agent-Based Modelling: A promising tool for sociohydrology

The two main methods that have been used to model sociohydrological systems are agent-based modeling (ABM) and system dynamics (Di Baldassarre et al., 2019, Pande and Sivapalan, 2017). In the system dynamics approach, the focus is on the dynamics and evolution of complex overall lumped systems (e.g., a city, population), represented through feedback loops, stocks, and flows, over time and not the micro-level behavior and interactions (Di Baldassare et al., 2019; Yu et al., 2017; Martin and Schlüter, 2015). However, modeling lumped systems misses out on micro-level (e.g., individual farmers) interactions, constraints, heterogeneity, and inequality that give rise to overall system behavior. This also means that inequitable impacts within the population that are at the core of AWM externalities (Figure 1.1, Table 1.1) cannot be fully explored.

In contrast, Agent-based models (ABMs) can explicitly account for micro-level constraints, individual behavior, and their interactions with society and the environment (Berger and Troost., 2014; Berger et al., 2006; Berger and Ringler, 2002; Khan et al., 2017). This allows for a natural representation of the real world where social behaviors and dynamics at the macro-level can be attributed to both micro-scale and macro-scale factors (Di Baldassare et al., 2019, Khan et al., 2017). For this capability, ABMs have been widely used to study the evolution of different systems including land use, urban, forests, ecosystems, epidemiology, social-ecological, and agricultural systems (Le Page et al., 2017). This also makes it a promising tool for sociohydrology to understand and explore the evolution of coupled human-water systems, and to unravel and understand AWM externalities that may result in unsustainable and inequitable outcomes. Thus, ABMs can expand and complement conventional AWM studies to integrate human-water feedback. Table 1.2 provides some illustrative examples of the strengths of ABMs and how they can expand or complement the AWM studies to capture externalities generated by AWM interventions.

Table 1.2: Illustrative examples of the potential capabilities of ABM to expand or complement AWM studies to capture externalities.

	Externalities	**ABMs potential to expand or complement AWM studies**
Introduction of drip irrigation	Farmers increase crop irrigated area leading to increased water use rather than conserving water	*While AWM studies* can capture (and focus on) changes in evapotranspiration requirements, return flows, water productivity, and water savings (e.g. Nouri et al., 2020), *ABMs* potential lies in its capacity to simulate farmers' behaviors and decisions regarding changes in irrigation or cropping patterns. This in return influences the hydrological fluxes such as increased water use in response to increased efficiency measures.
Water harvesting	Increased water supply leads to increased demand (Supply – demand feedback); Downstream-upstream impacts	*While AWM studies* can capture the increase in water availability, and reduction in downstream flows in response to water harvesting interventions (e.g., Garg et al., 2012), *ABMs* can potentially simulate the long-term feedback loop between the perceived increase in water availability (water system) to water demand (human system) that may lead to long term unintended impacts.
Groundwater development policies	Long-term groundwater depletion, inequitable distribution of benefits	*While AWM studies* can model the impacts of groundwater incentives on groundwater abstraction and resulting water tables based on exogenous scenarios (Wada et al., 2016), *ABMs* can potentially make these scenarios endogenous by simulating individual farmers' decisions based on their socio-economic characteristics in response to the incentives and makes it possible to assess the distribution of benefits or impacts within a population.

1.5 Objective, Research Questions, and Approach

With this background, this study is motivated by the overarching research goal:

"T*o improve understanding and consideration of potential hydrological externalities and unexpected societal feedback resulting from the implementation of AWM interventions to avoid or mitigate unsustainable and inequitable outcomes using modeling approaches incorporating dynamic and coupled human-water systems interaction.*"

The overarching research goal is addressed by pursuing four main research questions:

RQ 1: How have agent-based sociohydrology approaches been used to unravel the negative hydrological externalities and societal unexpected feedback associated with AWM interventions?

RQ 2: How sustainable and equitable are the impacts of AWM interventions implemented to enhance water supply for agriculture?

RQ 3: How to assess and represent human behavior associated with the implementation and uptake of AWM interventions to simulate their externalities and impacts?

RQ 4: How to apply an agent-based sociohydrology approach to model human-water feedback from AWM interventions for planning long-term sustainable and equitable outcomes?

Figure 1.2 provides the overall methodological approach of the research and the method associated with each research question.

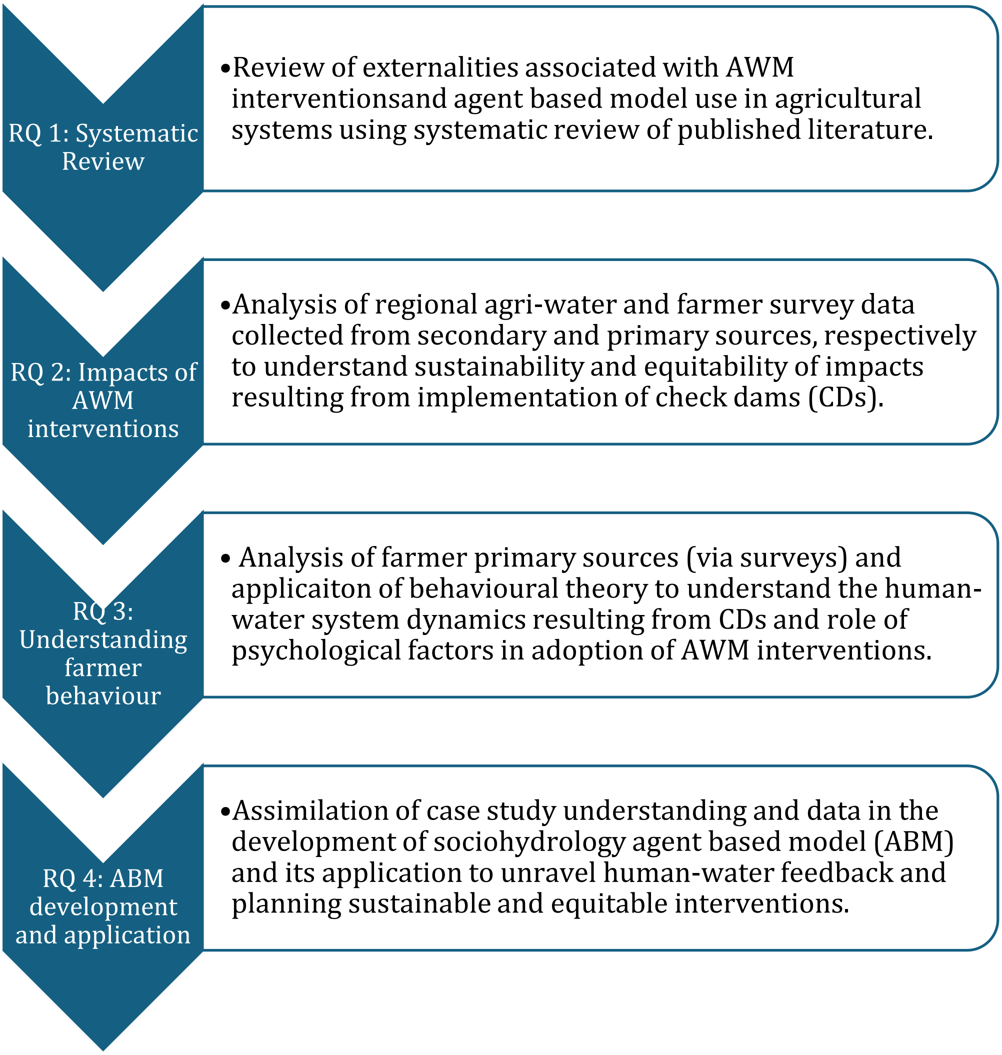

Figure 1.2: Overall workflow of the research questions and methods employed for each research question

1.5.1 Research Question 1

Chapter 2 addresses research question 1 by undertaking a systematic scoping review of peer-reviewed journal articles focusing on ABM use in agricultural systems and more specifically where AWM interventions are involved. The review enhances the understanding of the ABMs use in agricultural systems and brings forward the gaps in methods employed that require further research, especially to interpret spatially explicit and inequitable outcomes associated with negative externalities of AWM interventions.

1.5.2 Research Question 2

Chapters 3 and 4 addresses research questions 2 and 3, employing a mixed-method approach combining quantitative and qualitative data collection and analysis. The research for RQs 2, 3 and 4 takes place in the Kamadhiya catchment in the Saurashtra region of Gujarat state in India representing a typical case of where AWM interventions have been implemented (Figure 1.3, section 1.6). The region has seen large-scale intensive development of check dams (CDs) supported by government programs to enhance groundwater storage for irrigation supply and drought mitigation (section 1.6).

In Chapter 3, a catchment water balance method is used to assess the impact of CDs on groundwater storage, food production, and resilience. This is done by estimating and comparing changes, across periods of low and high CD development, in potential recharge from CDs, rainfall trends, cropping area changes and irrigation demand. This develops a broad understanding of the dynamics of agriculture and water storage at the catchment scale.

In Chapter 4, farmer surveys are used to explore the impact of CDs from a farmer's perspective. The survey data is used to assess how farmers perceive the benefits of CDs and the equitability of benefits. This complements the understanding developed from catchment water balance in chapter 3.

1.5.3 Research question 3

Chapters 4 and 5 addresses research questions 3 using the farmer survey data to examine the socio-economic and psychological factors in their behaviour towards maintaining CDs and adoption of AWM interventions. Two contrasting and dominating agricultural water interventions in the area, drip irrigation and borewells, are evaluated. The chapters employs Risks-Attitudes-Norms-Abilities-Self-regulation (RANAS) behavioral theory (Mosler, 2012) to develop understanding on farmers behaviour. The chapter shows the significance of psychological factors in explaining farmers' behaviour and adoption decisions.

Combined together chapters 3 and 4, and 5 offer a comprehensive understanding of the interplay between CDs, perceptions and adoption behaviors of farmers, and associated human-water feedback at both catchment and farmer scales.

1.5.4 Research Question 4

Chapters 6 and 7 addresses research question 4 through the development and application of agent-based socio-hydrology model. In chapter 6 and 7, the developed understanding (and gaps) on the use of ABMs for agricultural systems (chapter 2) is combined with data and insights from case study area (chapter 3, 4 and 5)to develop an agent-based sociohydrology model. The model integrates spatially explicit watershed hydrological processes with constraints, decisions, and interactions at the farmer/farm scale.

In Chapter 6, an agent-based sociohydrology model explicitly designed to emulate the phenomenon of supply-demand feedback in response to the intensive development of CDs is developed. In Chapter 7, the developed agent-based sociohydrology model is applied for assessing the (in)equitability of impacts.

The thesis concludes by synthesizing responses to the aforementioned research questions, discussing resulting implications for agriculture water management, exploring other potential applications of the developed agent-based model, and suggesting avenues for further research (Chapter 8).

1.6 Case study area

Kamadhiya catchment is located in the Bhadar basin in southwestern Saurashtra region of Gujarat state, India (Figure 1.3). The region experiences a semi-arid climate with an average annual rainfall of 638 mm (1983–2015), characterized by significant inter-and intra-year (Pai et al., 2014). Climate projections for the area suggest rising temperatures, accompanied by an increase in both total rainfall and the number of rainy days. However, this is coupled with a rise in the frequency of heavy rainfall events, indicating an intensification of the water cycle and greater variability (CSTEP., 2022).

To manage inter-and intra-year variability of rainfall, the Saurashtra region has been the focus of managed aquifer recharge projects, mostly through the development of check dams (CDs) (Shah et al., 2009; Patel et al., 2020). The project was supported by government and non-government actors under the government participatory scheme Sardar Patel Participatory Water Conservation Programme (SPPWCP). As part of SPPWCP, the government shared almost 60 percent of its funding; 40 percent was to be borne by the direct stakeholders and the beneficiary groups including NGOs involved in monitoring the quality of check dam construction. In Gujarat state, after the year 2000, more than 100,000 managed aquifer recharge (MAR) structures, of which an estimated 27,000 are CDs, have been constructed across Saurashtra till 2018 (NWRWS, 2018; World Bank. 2020). In the Kamadhiya catchment, the CD count reached 575 by 2006, contributing to a density of approximately one CD per 2 km^2 (Patel, 2007). The farmers do not directly use (lift) water from CDs, but indirectly with additional recharge from CDs feeding their wells.

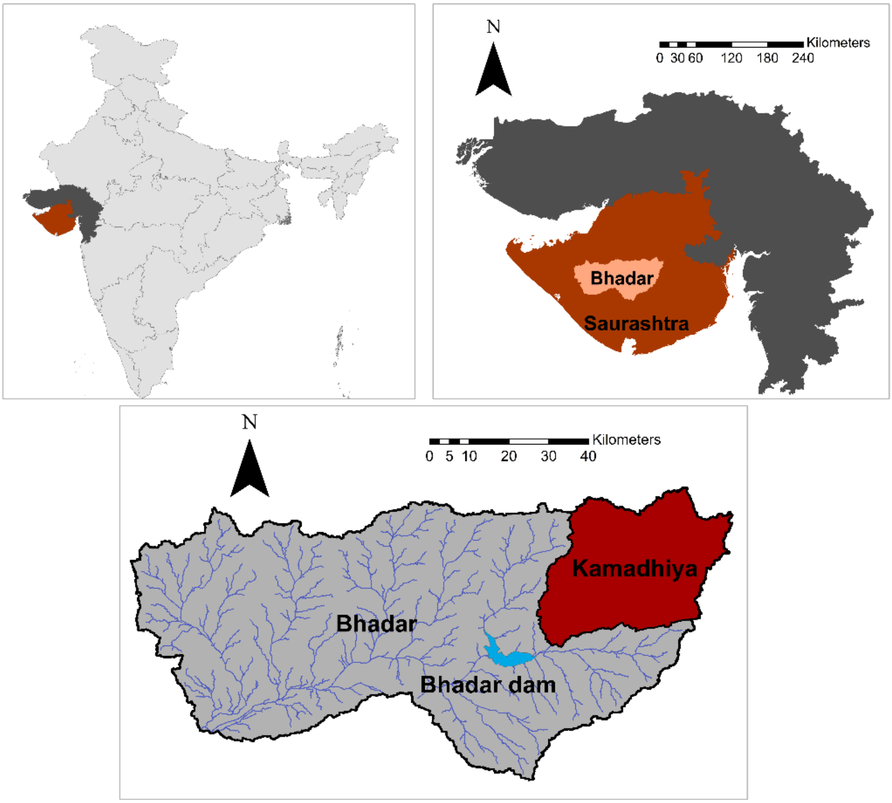

Figure 1.3: Location of Kamadhiya catchment in the Saurashtra region of the state of Gujarat, India

Several studies have analyzed the impact of intensive CD development in Saurashtra and Gujarat but the efficacy of CDs remains unresolved (Kumar and Perry, 2018; Bhanja et al., 2017; Jain, 2012; Shah et al., 2009; Praharsh et al. 2020). The challenge to assess groundwater storage impact from CDs arises from the fact that any change in groundwater storage is a result of long-term dynamics of several supply and demand factors including, climate, the intensity of MAR, changing cropping patterns, area, and irrigation practices. Previous studies have not fully accounted for these complexities and most specifically have ignored the increasing demand arising from increasing cropping area and irrigation (Patel et al., 2020; Bhanja et al., 2017; Kumar and Perry, 2019), which this thesis aims to explore. These studies have largely used the hydrological lens to evaluate CD impact but have largely ignored the feedback between human-water systems.

Additionally, drip irrigation and borewells are other major agricultural water interventions where farmers invest individually. Drip irrigation is a demand management intervention to increase the efficiency of irrigation water applied. The adoption of drip irrigation is supported by a government capital subsidy program called Pradhan Mantri Krishi Sinchai Yojana (PMKSY - Prime Minister Farm Irrigation scheme) (Nair and Thomas, 2022; DAC&FW, 2017). On the other hand, farmers drill borewells 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).

2. Application of agent based models towards understanding human-water feedback of interventions in agricultural systems: a review[2]

[2] This chapter is based on the article published in Environmental Research Letters (starting section 4 of the paper)

Alam, M.F., McClain, M., Sikka, A., Pande, S., 2022. Understanding human–water feedback of interventions in agricultural systems with agent based models: a review. Environ. Res. Lett. 17, 103003. https://doi.org/10.1088/1748-9326/ac91e1

2.1 Agent Based Modelling for Agricultural systems

Explicit modelling of coupled natural-human systems to unravel unintended and unexpected dynamics enables planners and managers to enhance positive benefits while mitigating/reducing negative externalities of agricultural water management (AWM) interventions (Pande and Sivapalan, 2017; Di Baldassarre et al., 2019; Khan et al., 2017). Most of the current conventional modeling approaches do not explicitly model the feedback between the human and water systems, thus missing out on the coevolutionary dynamics that limit their prediction power over the long term (Srinivasan et al., 2017; Pouladi et al., 2020; Sivapalan et al., 2012). In these approaches generally, human actions are explicitly given as exogenous scenarios thus ignoring endogenous and co-evolutionary dynamics (Van Niekerk et al., 2019; Lobanova et al., 2017). This absence of bi-directional feedback can exacerbate social inequalities, vulnerabilities, and ineffectiveness of AWM solutions (Di Baldassarre et al., 2019; Troost and Berger, 2014).

Sociohydrology, an interdisciplinary science of coupled human-water systems, was introduced to understand and model the coevolutionary dynamics of human-water systems on multiple spatial and temporal scales (Sivapalan et al., 2012). In sociohydrology, the use of agent-based modeling (ABM) has been gaining popularity. ABMs can explicitly account for micro-level constraints, individual behavior, and their interactions with society and the environment (Berger and Troost., 2014; Berger et al., 2006; Berger and Ringler, 2002; Khan et al., 2017). This allows for a natural representation of the real world where social behaviors and dynamics at the macro-level can be attributed to both micro-scale and macro-scale factors (Di Baldassare et al., 2019, Khan et al., 2017). These capabilities are critical to assess spatial, temporal, and often inequitable negative externalities of AWM interventions.

The applications of ABMs in sociohydrology have already begun and are broadening (Michaelis et al., 2020, Tamburino *et al*., 2020; Ghoreishi et al., 2021). For example, Tamburino *et al*. (2020) developed an ABM to simulate the impact of water use behavior on crop yield and economic gain in smallholder farming systems and how this is influenced by farmers' attitudes and behavior. Ghoreishi et al. (2021) developed an ABM to study the rebound phenomenon, i.e. increased water demand in response to more efficient irrigation, and its controlling factors in Bow River Basin in Canada.

However, with or without explicit mention of sociohydrology, ABMs have a long history of application in agricultural systems (Berger et al., 2001, Berger and Ringler, 2002). This includes ABMs for modeling the adoption of AWM interventions (Schreinemachers et al., 2007, 2009; Berger 2001), modeling the impact of farmers' agricultural decisions on hydrological systems (Van Oel et al., 2010; Becu et al. 2003) and simulating a range of policy, trade, and market mechanisms (Aghai et al., 2020; Farhadi et al. 2016; Schlüter and Pahl-Wostl, 2007).

While ABMs have the potential ingredients to capture AWM externalities and applications are increasing in sociohydrology, there is limited understanding of what can be or has been achieved through ABM methodological approaches and what are the remaining methodological gaps that further need to be bridged to unravel the negative externalities of AWM interventions. With the aim to synthesize the learnings, challenges, and gaps in modeling AWM externalities through ABMs, we here carry out a systematic review of methodological approaches taken in agent based model for agricultural water management (ABM-AWM) studies. Since AWM and associated externalities are the focus here, the scope of review is limited to ABM application for modeling AWM interventions. Similarly, other recent reviews have focused more specifically on

ABM applications for agricultural policy evaluation (Kremmydas et al., 2018), for Food–Energy–Water Nexus (Magliocca, 2020) and flood risk models (Taberna et al., 2020).

2.2 Review of ABMs application to agricultural water systems (ABM-AWM)

Developed ABMs for agricultural systems model biophysical, economic, and social processes by integrating and coupling biophysical sub-models (e.g., hydrology, crop growth) and social (e.g., behaviors, decisions, network interaction) systems at different spatial and temporal scales (Berger et al., 2001; Troost and Berger, 2014; Dziubanski et al., 2020). Methods employed for modeling these biophysical, economic, and social processes differ substantially (Kremmydas et al., 2018**,** Le Page et al., 2017) and have a direct bearing on the ABMs ability to resolve negative hydrological externalities and unexpected societal feedback of AWM interventions (Figure 1.1). For example, whether ABM-AWM can model spatially explicit hydrological impacts depends on the hydrological models employed and the simulations of realistic societal feedback depends on behavioral theories used.

Since ABMs differ substantially in terms of methods employed, our review focuses on assessing ABM-AWM methods for their capability to unravel negative hydrological externalities, assess inequitable impacts and capture societal unexpected feedback. We broadly focus on three overarching questions (derived from Figure 1.1). 1) How does the ABM-AWM resolve negative hydrological externalities? 2) How are farmers' responses, behavior and interactions simulated? And 3) How does the ABM-AWM resolve inequitable impacts by accounting for the heterogeneity of society? These were broken down into sub-questions (Table 2.1) for which information was collected and synthesized from the reviewed papers. The sub-questions therefore also serve as criteria to evaluate the extent to which ABMs can unravel negative externalities, thereby identifying the remaining gaps that further need to be bridged to comprehensively understand the impacts of AWM interventions on sustainable and equitable water use.

Table 2.1: Overview of questions on different components of ABM-AWM models for the review.

Overarching Question	**Sub-questions**	**Link to AWM externalities and outcomes (conceptual framework in Figure 1.1)**
How does ABM-AWM resolve negative hydrological externalities?	Can hydrological models used in ABM-AWM: A. resolve the spatially explicit impact of AWM on water flows? B. model surface-groundwater interactions?	Negative hydrological externalities (e.g., Spatio-temporal changes in water flows) Unsustainable outcomes (e.g., groundwater depletion)
How are farmers' responses, behavior, and interactions simulated?	A. Which individual behavioral theories have been used? B. How social interactions have been simulated?	Unexpected societal feedback (e.g., increases in crop area and water use)
How does ABM-AWM resolve inequitable impacts?	A. Whether individual agents, critical to modeling inequitable impacts within a population, are represented and simulated? B. How are individuals' socio-economic and biophysical characteristics defined to represent the heterogeneity of the population?	Inequitable outcomes (e.g., inequitable profit distribution)

2.2.1 Review design

For our review, search criteria from Kremmydas et al. (2018) were modified to focus specifically on ABM developed for AWM interventions to synthesize the learnings, challenges advances, and gaps in unraveling AWM externalities through ABMs. Kremmydas et al. (2018) reviewed ABM use for agricultural policy evaluation. To capture a wide range of articles and for that, we interpret AWM in a broad sense including ABM-AWM studies that not only model AWM interventions but also simulate management, market, and trade mechanisms and agents' behavioral aspects that directly impact agricultural water use. We reviewed articles published in peer-reviewed journals with their title, abstract or keywords including:

- One or more of "agent-based", "agent based", "abm", "multi-agent" or "multi agent"
- AND any word beginning from "water", "groundwater", "gw"
- AND any word beginning from "farm", "agricul", or "crop".

This is equivalent to the following SCOPUS search command:

TITLE-ABS-KEY ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TITLE-ABS-KEY (farm*) OR TITLE-ABS-KEY (agricul*) OR TITLE-ABS-KEY (crop*) AND TITLE-ABS-KEY (water*) OR TITLE-ABS-KEY (groundwater) OR TITLE-ABS-KEY (gw*) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "ch") OR LIMIT-TO (DOCTYPE , "re"))

The search produced 206 documents that were further refined based on the criteria detailed below:

Criteria 1: Agricultural systems and ABM

Papers were excluded which were not related to ABM or focusing on agricultural systems. Examples include papers from chemistry, Pest, diseases, marine, urban etc.

Criteria 2: Focus on AWM interventions

- Paper is considered to be relevant if the agricultural water management is a key component of the model that directly affects the model outcome and consequently the paper focuses on the relation of the policy to the model outcome.
- Excluded ABMs where the focus is exclusively on land use or urban or ecosystems but not AWM
- Additionally, review papers were also excluded.

Additionally, papers not in SCOPUS search but in authors knowledge were added. Finally, we reviewed 69 papers.

2.3 Review results

2.3.1 Modeling negative hydrological externalities

Modeling negative hydrological externalities resulting in unsustainable outcomes (e.g., groundwater depletion, upstream-downstream conflicts) requires integration/coupling of hydrological models in ABMs. These hydrological models employed in ABM-AWM are concerned with modeling and simulating spatial and temporal patterns of water flows and the impact of AWM on the same. To capture and predict the hydrological changes, with spatial variability and cutting across surface-groundwater systems (Section 2.1), the hydrological models should at least be: 1) semi-distributed to account for the spatial heterogeneity of water quantity and quality processes and 2) include groundwater-surface water interactions (Khan et al., 2017; Glendening et al. 2012). The following section explores the extent to which these criteria are met.

2.3.1.1 Hydrological models in ABM-AWM

Whether spatially explicit hydrological changes and interactions can be modeled or not depends to a large extent on spatial scales considered and the type of hydrological models integrated/developed in ABM-AWM studies. ABM-AWM where spatial scale is either individual farm or administrative region (Figure 2.1a, 27 %), is not conducive for modeling hydrological flows and interactions. In these ABM-AWM, water flows are largely modeled at individual plot/farm levels either using one-dimensional soil water balance (Wens et al., 2020; Tamburino et al. 2020) or empirical models (Zagaria et al., 2021; Van Duinen et al. 2016). ABM-AWM with a focus on individual farms are largely concerned with modeling individual farmers' socio-economic temporal dynamics resulting from their response, behavior, and adoption of AWM interventions. For example, Wens et al. (2020) modeled individual farmers' adaptive behavior, simulated using multiple behavioral theories, to estimate future drought risk in a region in Kenya. In the study, hydrology is modeled at an individual plot scale using FAO crop model AquacropOS.

ABM-AWM at an administrative scale in addition to individual farmers' socio-economic dynamics can also model spatial dynamics (e.g., crop changes, land-use change, adaptation diffusion) emerging from individual farmers' decisions, direct or indirect social environmental interactions (Schreinemachers et al. 2007; Troost and Berger, 2014; Barnaud et al. 2013; Hampf et al. 2018). However, hydrology, if modeled, is still mostly modeled at individual farm scales (Schreinemachers et al. 2007; Troost and Berger, 2014). With hydrological impact not the focus in many ABM-AWM at an administrative scale, more than 50 % of such studies do not employ any hydrological model (Figure 2.1a). For example, Troost and Berger (2014) modeled regional land user and crop production dynamics resulting from individual farmers' decisions at farm-level to adapt to climate change in a mountainous area in southwest Germany. Water flows were not modeled with the study focusing on analyzing the effect of inco crop changes, and agriculture supply.

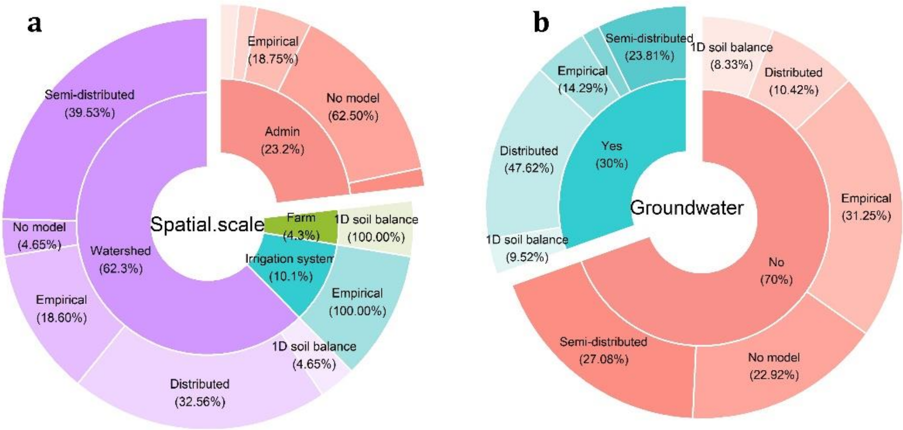

Figure 2.1: Proportion of ABM-AWM reviewed across a) different spatial scales considered in ABM-AWM and proportion of the type of hydrological models used under each, b) Inclusion of groundwater in ABM-AWM and proportion of the type of hydrological models used under each.

Hydrological flows and interactions, via surface and groundwater, can be explicitly modeled in ABM-AWM where the spatial scale is either watershed/basin (Van Oel et al., 2010; Becu et al. 2003; Berger, 2001; Schreinemachers et al.,2009; Ng et al., 2011) or irrigation systems (Barreateau et al. 2004; Schlüter and Pahl-Wostl, 2007; Ghazali et al., 2018). Overall, 62 % and 10 % of ABM-AWM have the watershed and irrigation systems as their spatial scale, respectively (Figure 2.1a). In these ABM-AWM negative hydrological externalities can be captured as agents' actions impact other agents' water flows and availability, simulated as the change in surface water flows (Pouladi et al., 2020, Van Oel et al., 2010; Becu et al., 2003), groundwater depth (Du et al., 2020; Noël and Cai, 2017; Hu and Beattie, 2019) and water quality (Pouladi et al. 2019). In ABM-AWM modeling irrigation systems, water flows and availability are determined by canal flows, rather than watershed hydrology (Barreateau et al., 2004; Barreateau and Bousquet, 2000). This is done largely using empirical models (Figure 2.1a).

In ABM-AWM at the watershed scale, both semi-distributed and distributed hydrological models have been used (Figure 2.1a). In semi-distributed hydrological models, aggregated hydrological response (e.g., runoff, recharge, drainage) of sub-units (sub-watershed, HRUs) is modeled at the overall basin/watershed outlet (Becu et al., 2012; Dziubanski et al., 2020). Examples of semi-distributed models include using SCS curve number method to assess the impacts of land cover changes, aggregated at sub-basin unit, resulting from decisions made by different agent types (Dziubanski et al., 2020) or linking hydrologic-agronomic model SWAT in Salt Creek watershed in Central Illinois, USA to simulate farmer behavior regarding best management practices and its effect on stream nitrate load (Ng et al. 2011). In semi-distributed models, flow at each point/grid is not simulated so they are more useful where the query of interest is assessing the impact on hydrology from the aggregated response of agents. This may limit their utility to assess the impact on individual agents from changes in hydrology, especially when there are significant differences in socio-economic-biophysical capital of farmers in the aggregated units (sub-watershed, HRUs).

In contrast, in distributed hydrological models, hydrology is modeled at each part/grid and can be linked to underlying individual agents. Examples of distributed models are by Becu et al. (2003) and Bithell et al. (2009) both of which developed spatially distribute models as part of ABM-AWM and linked each point/grid in space with underlying agents. This allows for modeling two-way feedback between individual actions/decisions and hydrology. The most often used distributed models in ABM-AWM come from studies assessing groundwater management and sustainability (~ 47 %, Figure 2.1b). In these studies, the use of the distributed model, MODFLOW, have been frequent (Farhadi et al. 2016; Nouri et al. 2019; Noel and Cai, 2017). For example, Noel and Cai (2017) developed an integrated ABM-MODFLOW model where farmers' daily irrigation decisions are used as input to MODFLOW which in turn provides updated water-table and baseflow information to agents in Republican River Basin, USA. In contrast, only a few studies (~ 10 %, Figure 2.1b) modeling surface water flows have used spatially distributed models (Becu et al., 2003, Bithell et al. 2009; Du et al. 2020). This could be due to relatively more ease in integrating stock variables (e.g., groundwater head, lake storage) in comparison to output fluxes (i.e., streamflow) in ABMs code (Khan et al., 2017).

2.3.1.2 Groundwater-surface water interactions in ABM-AWM

The examples of negative hydrological externalities discussed earlier (section 2.1) show that they often result from interactions of surface-groundwater (SW-GW) systems. Examples include the change in potential recharge from surface storage structures and changes in return flows (as brought on by efficiency improvements practices). Resolving these processes requires that hydrological models should be able to capture surface-groundwater interactions. However, our review shows that there are large gaps in this part. First, only ~ 30 % of reviewed papers had considered groundwater (figure 2.1b). Even in these studies, many simulate integrated SW-GW systems in a very simplistic way, such as modeling groundwater irrigation but not process-based recharge and storage modeling (Holtz and Pahl Wostl, 2012, Wens et al., 2020; Tambourino et al., 2020).

Second, very limited studies use integrated models with SW-GW interactions in place (~ 14 % of studies) (Du et al., 2020, Mirzaei and Zibaie, 2020, Van Oel et al., 2010). Most studies model surface water (Dziubanski et al., 2020; Nikolic et al., 2012) or groundwater (Aghaei et al., 2020; Farhadi et al., 2016; Nouri et al. 2019; Noël and Cai, 2017) in isolation. One explicit case of distributed integrated SW-GW model use in ABM-AWM is by Du et al. (2020) where GSFLOW (an integrated SW-GW model) was integrated with an ABM to model water use and understand its impact on hydrology in the Heihe River Basin, China, under the influence of collective water management policies. This lack of inclusion of groundwater and integrated surface-groundwater process means that many of the AWM externalities cannot be captured or predicted.

2.3.2 Modeling society unexpected feedback in ABM-AWM

Incorporating agent responses and feedback to the environment to capture unexpected society feedback is central and critical in ABM-AWM studies. Modeling this requires a suitable and dynamic representation of agent behavior, goals, and decision-making processes (Müller-Hansen et al., 2017). Multiple studies have reviewed the use of decision-making behavioral theories in ABM focusing on natural resources (An, 2012; Müller-Hansen et al., 2017; Schlüter et al., 2017). Based on our review, we broadly categorized ABM-AWMs into two types: ABM-AWM where agent behavior is modeled in isolation without accounting for social interactions, and ABM-AWM where the influence of social interactions on individual behavior is incorporated. We review individual behavior theories and social interaction theories used separately in the following sections.

2.3.2.1 Simulating individual farmers' responses and behavior in ABM-AWM

Individual decision-making and behavior in ABM-AWM include taking decisions regarding crop production, irrigation, investment in AWM interventions, and other agronomy aspects (fertilizers, labor, etc.). These decisions differ among agents based on the assumptions made about three key determinants of human choices: goals and needs, constraints, and decision rules (Müller-Hansen et al., 2017; Schlüter et al., 2017). Based on these three key determinants, Schlüter et al. (2017) categorized theories used for modeling agent decision making. We use these categories to analyze how frequently they appear in ABM-AWM (Figure 2.2a).

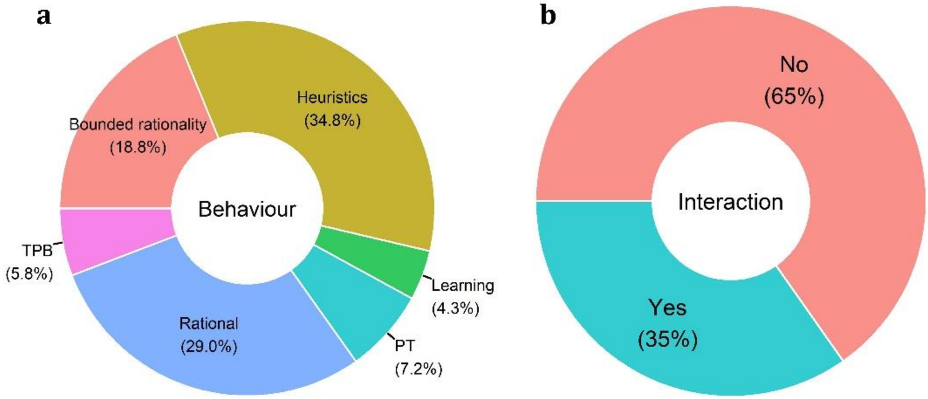

Figure 2.2: a) Proportions of different individual decision-making behavioral theories used for modeling agents in reviewed papers; b) Proportions of papers implementing social interactions.

Our review shows that the most used theories in ABM-AWM are rational choice and bounded rationality (including heuristics) (Figure 2.2a). *Rational and bounded rationality* are both based on expected utility maximization where an agent's decision-making is goal oriented. Agents choose a strategy, under given constraints, with the best-expected outcome or utility (Schlüter et al., 2017; An, 2012). The rational choice theory assumes that agents make rational choices. These rational choices achieve outcomes that maximize their advantage or income by optimizing their decision regarding crops, irrigation, and resource use under given constraints. An example of rational theory used in ABM-AWM is the application of the MP-MAS model where farmers' investment decisions are simulated to maximize expected long-term average levels of net farm and non-farm incomes. (Berger, 2001; Schreinemachers et al. 2007; 2009).

However, field evidence suggests that farmers are not always rational (Dessart et al., 2019; Howley et al., 2015; Bluemling et al., 2010). Examples include farmers' unwillingness to covert land to forestry even with expected higher economic returns as that does not align with their attitudes (Howley et al., 2015) or the economic cost of increased pumping being an insignificant factor in choosing efficient irrigation technology (Blueming et al., 2010). This is because human decisions are complex, and decisions are made under the influence of experiences, rules, psychological factors, and social influences (Du et al. 2020; Van Duinen et al., 2016; Dessart et al., 2019).

Bounded rationality theory, a modification of rational choice theory, aims to account for these factors by putting constraints or bounds on the agent's information receiving, understanding, and cognitive capacity (Schlüter et al., 2017; An, 2012). There are many different approaches to formalize bounded rationality with respect to limited information, quality of information, and cognitive capacities of decision-makers (Schlüter et al., 2017; Van Duinen et al., 2016). The most often used approach is heuristics, where agents are assigned rules, derived from empirical data or observations, that drive their decision-making (An, 2012; Schlüter and Pahl-Wostl, 2007; Van Oel et al., 2010). In heuristics, decisions emanate from farmers' experience, accumulated knowledge, and preferences (Schlüterand Pahl-Wostl, 2007). Examples of heuristics include ‘if/then/else’ rules where agents make cropping decisions based on the predefined threshold such as capital, soil pH, and groundwater levels (Castilla-Rho et al., 2015) or sensitivity to crop water stress (Noël and Cai., 2017). Though heuristics can mimic an agent’s behavior and decisions, it fails to explain the underlying reasons for the same as this is without a strong theoretical basis (An, 2012). While this can suffice for modeling behavior to known stimuli/changes/options but has limited utility in case of unexpected and unforeseeable scenarios.

Thus, to drive actual motivations and incentives behind the decisions, there is an increasing realization and call for grounding agent decisions in established social-science theories (e.g., protection motivation theory, theory of planned behavior, learning) rather than rational or simple heuristics (Wens et al. 2020; Schlüter et al., 2017; Taberna et al., 2020). Protection motivation theory (PMT), a version of bounded rationality, offers an example (Zagaria et al., 2021; Wens et al., 2020; Dziubanski et al., 2020). In PMT, farmers’ adaptation is simulated as the integration of farmers' perceived risk and appraisal of their capacity to adapt (Zagaria et al., 2021; Wens et al., 2020). Wens et al. (2020) applied PMT to explore the adaptation decisions of farmers in Kenya. Their results show that bounded rationality can model complex human adaptation decisions more realistically over theory based on rational agents.

In contrast, there is a relatively lower application of other theories in ABM-AWM, namely the Habitual or Reinforcement Learning Theory, Theory of Planned Behavior (TPB), and Prospect Theory (PT) (Figure 2.2a). In Habitual or Reinforcement learning, positive and negative experiences (history) are stored in the state (knowledge) and reflected in the habit formation of agents (Schlüter et al., 2017; Nikolic et al., 2012; Yuan et al., 2021). Castilla-Rho et al. (2015)

partially include this in heuristics behavior by including 'history' of risk accumulating where agents learn to avoid risky investments. Theory of Planned Behavior (TPB) focuses on farmer intention, shaped by agent attitudes, subjective norms, and perceived control, as the main determinants of implementing a certain behavior (Pouladi et al. 2019; Kaufmann et al., 2009, Yang et al., 2020). Pouladi et al. (2019) used TPB to assess farmers' decisions on the conservation of water resources in the Zarrineh River Basin, Iran. Prospect Theory (PT) takes into account the differences in risk preferences of agents with the idea that people are much more sensitive to losses (risk-averse) and evaluates possible future outcomes differently based on the subjective probabilities rather than objective probabilities (Gonzalez-Ramirez et al., 2018; Ng et al., 2009; Ding et al., 2015; Balbi et al., 2013). Ng et al. (2011) applied PT to model farmers' crop and best management practice decisions where farmers maximize total utility as a function of their perceptions of future conditions and risk attitude.

2.3.2.2 Simulating social interactions in ABM-AWM

Social interactions among individuals play a critical role in influencing individual responses and decisions (Barreute et al., 2004; Schreinemachers et al., 2007, 2009; Ng et al., 2011). The specific sets of individual behaviors influenced by neighbor's decisions and behavior are also referred to as sideward looking theories (Müller-Hansen et al., 2017). Agents can interact, observe, or share information with other similar agents (i.e., horizontal interactions) or with higher authorities, governments, markets (i.e., vertical interactions), or both. We focus on the former as the latter act more like constraints or incentives for individual behavior (Aghaie et al., 2020). Of the reviewed papers, only one-third incorporate agent social interactions or sideways looking theories (Figure 2.2b).

These ABM-AWM have used social interactions to model diffusion and adoption of adaptation practices (Berger 2001, Schreinemachers and Berger, 2011; Schreinemachers et al., 2007, 2009; Ng et al., 2011), mimicking of behaviors (such as cooperative or non-cooperative behavior) and decisions regarding cropping practices (Farhadi et al., 2016; Nikolic et al., 2012; Castilla-Rho et al., 2015; Barreteau et al., 2004; Bazzana et al. 2020; Cai and Xiong, 2017; Ghazali et al., 2018).

The model of diffusion is based on a principle that agents mimic and learn from other farmers' decisions. Most ABM-AWM have employed social influence as a model of diffusion (Young, 2009), where adoption of practices is modeled as threshold functions. In these models, agents adopt practices or interventions once a certain threshold of the population has adopted them (Schreinemachers et al., 2007; 2009; Schreinemachers and Berger, 2011; Farhadi et al. 2016; Cai and Xiong; 2017). Order of adoption between agents is based on agent behavioral values such as innovativeness or risk behavior, which can be either based on empirical data or randomly allocated to agents.

Another model of diffusion used is the contagion model, where agents adopt interventions when they meet others who have adopted them (Young, 2009; Holtz and Pahl Wostl; 2012). In this model, the diffusion of an innovation is modeled as a self-reinforcing process that tends toward a final saturation level of adopters (Holtz and Pahl Wostl; 2012). For example, Nikolic et al. (2012) modeled social interactions where farmers are able to imitate the cropping patterns of neighbors resulting in higher yields during the previous season.

The third type of diffusion mode is the social learning model of diffusion where agents also rationally evaluate, rather than adopting it based on whether others have, the evidence of proposed benefits of interventions generated by prior adopters (Young, 2009). The use of social learning in ABM-AWM is however limited (Ng et al. 2011; Daloglu et al. 2014; Perello-Moragues et al., 2019). For example, Ng et al. (2011) used social learning where agent adoption is influenced by variances of the net return on the adoption of interventions, which decreases as more people adopt it.

Extensive use of the social influence diffusion model, with its roots in the study of hybrid seed corn in the USA in the 1940s (Rogers, 2004), has been a leading theory of agriculture extension work employed in many international rural development programs and research (AgriFutures, 2016). Application of the diffusion model in the field often includes identifying lead or progressive farmers (more innovative or more risk-taking) who are trained or provided support for interventions with the assumption that others will learn and mimic their practices (Tsafack et al., 2015; Franzel et al., 2019).

However, the application of the theory can be a source of inequity as the expectation that introduced practices will trickle down from lead farmers (mostly more progressive and economically well-off) may not happen (AgriFutures, 2016; Monu, 1995). This is so because diffusion models often assume homogenous social systems with respect to the introduced technology, which is often not the case (Monu, 1995). Empirical field research has shown that the decision making on adoption is influenced by a range of factors including preferences and socio-economic and ecological constraints (Shilomboleni et al., 2019), social groups, clans, acceptability (de Roo et al., 2019), attitude, cultural norms, and abilities (Daniel et al., 2019; Kaufmann et al., 2009). Thus, there is a need to internalize and incorporate the wealth of empirical field research and move away from the use of a simplistic threshold-based approach as often done in ABM-AWM (Kaufmann et al., 2009).

2.3.3 Modeling inequitable outcomes of AWM interventions in ABM-AWM

Modeling inequitable outcomes resulting from heterogeneities in social, economic and biophysical capital of farm/farmers requires an accurate and appropriate representation of agents in the modeling domain. Representation of ABM-AWM deals with how agents (farmers or farms) are defined in terms of their socio-economic characteristics and location in space. This requires two main considerations: 1) Each farmer located within the study domain should be represented to simulate their impact on hydrology and vice versa and 2) farmer characterization in the model should capture their relevant socio-economic characteristics and associated biophysical endowments.

2.3.3.1 Representation of farmers in ABM-AWM

Our reviews show there are two broader methods of representing spatially distributed farmers: modeling individual farmers (Schreinemachers et al., Berger, 2001; Arnold et al. 2015) and modeling aggregate farmers (Hu and Beattie; 2019, Farhadi et al. 2016; Hu et al., 2015). The latter has also been termed as areal agents by Wens et al. (2019). There can also be non-spatial agents such as institutions and markets (Wens et al., 2019). These are not reviewed here explicitly as the focus is on farmers or farms, but they are implicit in agents' behavior where they set rules and constraints.

In ABM-AWM modeling individual agents, agents are assigned to discrete spatial units (e.g., plots, grids) in the model spatial domain where each agent interacts and provides feedback to the underlying environment and hydrological flows (Schreinemachers et al. 2009, 2007; Berger, 2001, Arnold et al., 2015; Van Oel et al., 2010; Noel and Cai, 2017). These ABM-AWM differ depending on whether the entire population is modeled (Schreinemachers et al. 2009; Arnold et al. 2015) or only a subset of the population is modeled (Ng et al., 2011; Holtz and Pahl Wostl, 2012). For example, Schreinemachers et al. (2007) modeled soil fertility and poverty dynamics of all 520 farmers in two village communities in Uganda by dividing the spatial domain into grid cells of area 0.5 ha, corresponding to the size of the smallest agricultural field cultivated in the study area. In contrast, Holtz and Pahl Wostl (2012) divided the farmers based on land size and simulated only 100 farmers per land size class in Upper Guadiana, Spain. Results were extrapolated from this representative population to assess the influence of farmer characteristics on land-use change and associated groundwater over-use.

Modeling a subset of the population, taken as representative of the total population, limits model runs when the spatial domain is large, saving computational costs. Conclusions on broader dynamics may be drawn from this representative population (Ng et al., 2011; Holtz and Pahl Wostl, 2012; Troost and Berger, 2014). However, this may restrict the complete representation of all possible spatial and social interactions among the agents. The challenge is also to build the best representative typologies that can explain the farmer's decision/behavior.

In ABM-AWM modeling aggregated agents, individual agents are aggregated and are represented as one super-agent, over a larger region such as a sub-basin, watershed, or a city (Hu and Beattie, 2019; Nouri et al. 2019; Nikolic et al. 2011; Xiao et al. 2018). It is the aggregated responses and feedback of agents that are simulated and integrated with biophysical systems (Hu et al., 2017; Hu and Beattie; 2019; Nikolic et al., 2011). For example, Hu and Beattie (2019) modeled 46 counties with each county aggregated as one farmer, Farhadi et al. (2016), and Nikolic et al. (2011) modeled 13 and 28 sub-watershed/basins, each acting as one independent agent. Aggregation of agents can facilitate practical model development, especially where large basins are modeled. However, aggregated agents limit the model's capability to include local variability and heterogeneity, missing out on equity dynamics within a population (Berger and Ringler, 2002). This is critical, especially in an unequal society where the adoption and response to AWM and the impact of AWM externalities could be quite different within the population.

2.3.3.2 Representing farmer heterogeneity in ABM-AWM

Agent characterization in ABM-AWM is a way to represent the heterogeneity of a population. Representing population heterogeneity is important to model inequities in cost and benefits sharing and capacities of the agents to adapt AWM practices. Agents are characterized by their socio-economic characteristics, biophysical endowments, and behavioral characteristics. Behavioral characteristics define agent behavior and decision-making and are discussed in the next section.

Our review shows that most of the studies consider socio-economic characteristics of households and farms (family, family composition, household composition, age, sex, area) (Table 2.2). This determines the availability of labor, consumption, and expenses of agents. Other often used socio-economic characteristics, based on the objective of ABM-AWM, are ownership of assets, machinery, and capital, access to extension services, credit, markets, and off-farm income sources. These all determine the economic, social, and knowledge endowment of agents. The use of a wide range of characteristics already shows the importance and centrality of considering the heterogeneity of agents in ABM-AWM studies. The data for these socio-economic characteristics are either collected from existing microeconomic datasets (obtained from sample surveys, censuses, and administrative systems) (Noel and Cai, 2017) or through primary surveys (such as household surveys and focus group discussions) (Wens et al., 2019; Van Oel et al., 2010, Pouladi et al., 2019).

Table 2.2: Range of Socio-economic, biophysical endowments and BH that have been used in the ABM-AWM to characterize agents.

Characteristics	Type	Example studies
family and farm size, labour, household composition	Socio-economic	Wens at al., 2020; Becu et al., 2003; Arnold et al. 2015; Schreinemachers and Berger (2011); Schreinemachers et al. 2007
Access to extension services, market; Social network		Wens at al., 2020; Arnold et al. 2015; Barreteau et al. 2004
Off-farm income sources [livestock etc]		Wens at al., 2020; Schreinemachers and Berger (2011)
Land and Water rights		Arnold et al. 2015; g et al. 2011; Wens at al., 2020; Ng et al. 2011
Assets ownership, machinery, capital		Arnold et al. 2015; Troost and Berger (2014); Holtz and Pahl Wostl (2012)
Soil characteristics	Biophysical endowments	Arnold et al. 2015; Ng et al. 2011; Schreinemachers et al. 2007
Precipitation;irrigation water		Arnold et al. 2015; Van Oel et al., 2010
Location of the agents farms[upsteam/downstream, command area , flood plain]		Schreinemachers and Berger (2011); Van Oel et al., 2010; Schluter and Pahl-Wostl (2007)
Foresight, and risk aversions	Behavioral	Ng et al. 2011; Dziubanski et al.2020
Membership in a population cluster; Innovation segment		Schreinemachers and Berger (2011); Barreteau et al. 2004
Knowledge		Schreinemachers et al. 2007; Hu and Beattie (2019)
(non)Cooperative behavior		Farhadi et al. 2016
Sensitivity to crop water stress		Noel and Cai (2017); Hu and Beattie (2019)

Biophysical endowments of agents are mostly derived from underlying maps of biophysical datasets (e.g., soil, elevation, rain). Biophysical endowments characteristics considered (Table 2.2) differ markedly between studies but most consider data on soil type, elevation, precipitation, and irrigation sources. In addition, relative locations of the agents' farms (such as upstream or downstream of other agents, command area, flood plains, etc.) have been used to differentiate agents. These data are mostly acquired through secondary data and geographical databases such as cadastral maps, digital elevation models, land use maps, soil maps, etc.

One critical aspect that is of importance while providing biophysical endowments to agents is how agent's location in space is determined. Agent location in space is of paramount importance as this determines their biophysical endowments (e.g., soil quality, water availability), interactions with hydrology, neighbors, and social groups. Our review shows that despite the importance of location, only a few studies use real location data to distribute agents spatially (Schreinemachers et al., 2007; Noel and Cai, 2017; Arnold et al., 2015; Van Oel et al., 2010). For example, Noel and Cai (2017) use certified irrigated acres from the existing database on pumping wells to delineate the agents. The results of our review are similar to the conclusion of Kremmydas et al. (2018), who found that only 2 of the 32 reviewed papers used observed location data.

2.4 Synthesis

The review confirms the ability of ABM-AWM to expand the capabilities of conventional AWM studies by incorporating human-water feedback (a key limitation of conventional AWM studies and models) and capturing the negative externalities possibly generated by AWM interventions and unravelling the unintended consequences including unsustainable and inequitable outcomes.

The review shows that methods employed by ABM-AWM can successfully integrate a range of farmer behavior including the adoption of AWM interventions (Wens et al., 2020; Ng et al., 2011; Schreinemachers and Berger, 2011), investing in farming inputs, choice of crops (Becu et al., 2003; Arnold et al., 2015; Schreinemachers and Berger, 2011; Schreinemachers et al. 2009) and land use (Troost and Berger, 2014) and irrigation (Van Oel et al., 2010; Nikolic et al., 2012; Xiao et al., 2018). This modeling of farmers' behaviors and decisions makes the scenarios endogenous, thus allowing the modeling of long-term coevolutionary dynamics. For example, Ghoreishi et al. (2021), show how ABM that includes farmers' behavior can shed light on long-term rebound phenomenon where adoption of efficient improving measures leads to increased water use.

Farmer's decisions and resulting co-evolutionary dynamics resulting from AWM interventions have been successfully linked to their subsequent impacts on natural and social systems (Wens et al., 2020; Schreinemachers et al., 2007, 2009; Berger 2001; Dziubanski et al., 2020). This includes explicitly modeling AWM hydrological externalities including agricultural water use impact on groundwater overexploitation (Du et al., 2020), water quality (Daloğlu et al. 2014), and downstream flows (Pouladi et al. 2019). ABM-AWM do this by linking farmers and societal modules (human systems) with coupled spatially distributed surface (Du et al., 2020; Becu et al., 2003) and groundwater hydrological models (Noel and Cai, 2017; Hu and Beattie, 2019) (water systems). For example, Hu and Beattie (2019) successfully modeled the impact of farmers' irrigation decisions on groundwater table levels in the High Plains Aquifer in the USA and Van Oel et al. (2010) simulated the impact of farmers' decisions on spatial and temporal distribution of surface water resources in a river basin in Brazil.

Further, the modelling of human-water feedback in ABM-AWM can capture inequitable impacts of AWM interventions on human-water systems. It does so by capturing and modeling individual farmers based on their heterogeneous socioeconomic characteristics (Barreteau et al., 2004; Ng et al., 2011; Ohab-Yazdi and Ahmadi, 2018; Yuan et al., 2021). For example, ABM-AWM have modeled inequitable adoption of AWM interventions based on land size and financial resources (Wens et al., 2020; Holtz and Pahl Wostl, 2012); (in)equity in water allocation (Mirzaei and Zibaie, 2020), and inequitable water distribution and interaction between upstream and downstream farmers (Becu et al, 2003; Van Oel et al., 2010; Barreteau et al. 2004). Yet the review also brings to fore the remaining methodological gaps of ABM-AWM in resolving AWM externalities and the resulting unsustainable and inequitable outcomes.

2.4.1 Gaps and future research need in ABM-AWM to unravel negative externalities

Despite all the advances, some methodological gaps remain that need to be filled to fully exploit the strengths of ABMs in context of AWM interventions. These gaps mainly arise from missing necessary methodological ingredients (Table 2.1) in ABM-AWM that limit their capacity to unravel one or more of the externalities. In the section below, we identify these gaps under each component of ABM-AWM and the research needed to bridge these gaps (Table 2.3).

Table 2.3: Identified remaining research gaps and future ABM-AWM research needs to bridge these to fully unravel the negative externalities of AWM interventions.

		Gaps and future research
Negative hydrological externalities	**Gaps**	No consideration of hydrological impacts in ~ 25% of studies, thus ignoring any negative hydrological externalities of AWMs. Lack of inclusion of spatially distributed hydrological models and integrated surface-groundwater systems limiting ABMs capacity to model spatially distributed and inequitable impacts of AWM interventions
	Future research	Supplement or complement studies where the effects related to AWM interventions are simulated (e.g., their adoption, socio-economic impacts) but subsequent impacts of the same on hydrology are not accounted. This is needed to link the impacts of farmers' decisions (e.g., adoption of AWM interventions) on water use. Expand the use of spatially distributed and integrated hydrological models to capture spatially explicit AWM externalities. This will help better resolve hydrological externalities like downstream – upstream impacts and interactions of linked surface-groundwater stocks.
Society feedback	**Gaps**	Over-reliance on rational behavior and simple heuristics to model individual behavior and decisions. Also, there is lack or very simplistic representation of social interaction based on simple diffusion and contagion models
	Future research	Move away from rational and simple heuristics to behavioral theories grounded in social science (e.g., Theory of planned behavior, bounded rationality, prospect theory) and use rich empirical data collected from the field to formalize these theories. This is needed to include the impact of a range of socio-economic-cultural-behavioural (e.g., farmers' perception of risk, confidence) characteristics on farmers' decisions. Assimilation of more nuanced and holistic social interaction and diffusion models, thus moving away from simple diffusion and contagion models. This is needed to account for empirical field research studies that show community or neighbors' influence on farmers' decisions is mediated through a range of social-cultural and behavioral factors.

Inequitable impacts	**Gaps**	Limited ability to account for inequitable impacts of AWM interventions among farmers in ABMs where aggregated farmers (e.g., watershed, city, basin) are simulated. Limited inclusion of farmers' spatial locations with most of ABMs using random allocation of farmers in the study area. This ignores the criticality of spatial location that determines farmers' biophysical and social capital.
	Future research	Supplement or complement ABMs where aggregated agents are modelled with studies that model individual agents, thus accounting for the heterogeneity of farmer population. One way is to model a subset of agents based on predefined typologies and extrapolate the results for the population. This presents a way forward, especially for studies where the numbers of farmers to be simulated are very high and thus computationally expensive. This is needed to bring out inequitable access of a population to, and subsequent impacts of, AWM interventions (and associated externalities) (e.g., access to groundwater, subsidies, inequitable adoption). Attribute more realistic spatial locations to farmers either using collected data or using existing microeconomic databases (e.g., census, sample surveys). This is needed to account for differences in biophysical capital among farmers that may drive differential adoption of, and benefits from, AWM interventions (e.g., location near water harvesting structures, more productive lands).

2.4.1.1 Modeling negative hydrological externalities

Despite AWM interventions being intricately linked with hydrology (Section 2), our review shows that a quarter of ABM-AWM simulate dynamics at individual farms or administrative regions (Figure 2.1a) where spatial scale is not conducive to model hydrological interactions. In these studies, the subject of inquiry is not hydrological changes but dynamics such as emergent land use, adoption of interventions, and changes in the cropping system. Given that AWMs are intricately linked with hydrology, the simulated dynamics can cause hydrological externalities leading to unsustainable and inequitable outcomes. Thus, there is a need to supplement/complement these studies with hydrological models to account for and predict any negative hydrological externalities.

Additionally, even in ABM-AWM with the capability to model water flows (i.e., the spatial scale of the watershed, and basins), methodological gaps limit their capacity to completely resolve the hydrological externalities of AWM interventions. This includes a lack of incorporation of spatially distributed models, limited inclusion of groundwater systems, and almost non-existent integrated surface-groundwater models (Figure 2.1a and 2.1b). Spatially distributed hydrological models are required to capture the spatial heterogeneity of both biophysical systems and agents in the region and capture spatially explicit hydrological externalities of AWMs. The lack of spatially distributed models means that the impact of hydrological changes on individual farmers and vice versa cannot be modeled. This limits the capability of ABM-AWM to resolve inequitable impacts. Additionally, the non-inclusion of the groundwater system and lack of integrated SW-GW limits ABM-AWM capability to capture the holistic hydrological impact of AWM interventions that often leads to reallocation/changes within SW-GW systems.

Our review shows a clear need to enhance the representation of hydrological systems in ABM-AAMs if they are to be used to assess the negative hydrological externalities of AWM interventions. This requires coupling ABMs with spatially distributed and integrated models. This can be done by developing hydrological models as part of ABMs or coupling ABM code with existing open-source models (e.g., GSFLOW, SPHY). An example of the latter is by Du et al. (2020) where GSFLOW, an integrated surface-groundwater model, was tightly coupled with ABM at the source code level.

2.4.1.2 Modeling society feedback

A realistic representation of individuals' behavior and interactions forms the basis of modeling society's unexpected and emergent dynamics. This requires a suitable, accurate, and dynamic representation of agent behavior and decision-making processes. Though a range of farmer decision-making behavior has been simulated, there remain gaps in terms of incorporating appropriate behavioral theories in ABM-AWM. The empirical field research has shown that human behavior is shaped by a range of factors such as socio-economic, cultural norms, risk attitudes, perceptions, and other psychological characteristics (Daniel et al., 2019; Pouladi et al. 2019; Kaufmann et al., 2009). However, there is a large gap in incorporating the same in ABM-AWM. Our review shows that the use of rational choice theory and simple heuristics is still dominant (Figure 2.2a). The rational theory assumes agents make rational choices and discount the impact of a range of factors such as socio-economic, cultural norms, risk attitudes, and other psychological characteristics or both. Similarly, farmer heuristics devised based on experience, accumulated knowledge, and preferences lack the theoretical background to explain the underlying reasons for the same.

There is limited but increasing use of theories grounded in social science and field research to account for these constraints (e.g., Protection Motivation Theory, prospect theory, and Theory of Planned Behavior). There is a greater need to formalize these theories in ABM-AWM. A general lack of sufficient and good-quality primary data on agent behavior makes derivation, validation, and verification of agent behavioral rules difficult (Hu et al., 2017). Multiple studies have shown that this can be done with primary data collection through surveys or focus group discussions (Kaufmann et al., 2009, Pouladi et al. 2019; Wens et al., 2020). Additionally, there is a need to incorporate further behavioral models such as risk-, attitude-, norm- , ability-, self-regulation- (RANAS) model originally developed for the WaSH sector (Mosler, 2012). RANAS combines multiple important behavioral theories (including the theory of planned behavior) to explain and change behavior and can be adapted to a range of situations and already provides a standard template of questions to quantify behavioral factors and analyze the behavior (Callejas et al, 2021).

Another gap in ABM-AWM studies is the lack of incorporation of social interactions among agents (Figure 2.2b). In limited studies where social interaction is in place, social interaction is largely modeled simplistically following simple thresholds or contagion-based diffusion model approaches. These approaches assume agents adopt interventions or behaviors once certain other people have adopted, or they come in touch with someone who has (Schreinemachers et al., 2007, 2009; Ng et al., 2011). These are found to ignore a range of factors influencing adoption, including preferences and socio-economic and ecological constraints as has been showcased in multiple empirical field research studies (Daniel et al., 2019; Kaufmann et al., 2009). Thus, like individual theories, there is a need to expand the ABM-AWM social interactions theories in use, employing more holistic adoption and diffusion models.

2.4.1.3 Modeling inequitable outcomes

There remain gaps in fully exploiting the ABM capabilities to resolve spatially explicit and inequitable externalities of AWM interventions. Multiple ABM-AWM aggregate agents over an area (e.g., region, basin, watershed) and simulate their aggregated response. In large areas, this paves the way for easy implementation of the model where the computational cost of modeling each agent could be very high. However, such representation may mask both the heterogeneity of responses within the population and the inequitable impacts of AWM interventions. Thus, while these studies may be beneficial to simulate lumped dynamics, there is a need to supplement/complement them with disaggregated studies that can account for this heterogeneity of farmer populations. One other way to reduce computation cost and time are to model a subset of agents based on predefined typologies and extrapolate the results (Ng et al., 2011; Holtz and Pahl Wostl, 2012). However, to completely account for spatial interaction and individual farmer dynamics, the best way is to model individual agents.

Another main gap is that farmer characterization lacks spatial location/attribution. This is critical as the spatial location of farmers determines their biophysical capital and neighbors. A completely random allocation will not reflect reality, especially where good and productive lands (better soil, more access to water) might be owned by better-off farmers (Bhattarai et al., 2002, Sharma et al., 2008). Thus, there is a need for ABM-AWM to locate agents based on some plausible evidence. Accessing the location of each farmer, especially in a large area, may not always be feasible given labor and cost constraints along with concerns of data privacy. A way forward could be the use of existing microeconomic datasets at multiple levels (e.g., census, sample surveys) to locate populations and their endowments within a constrained area. One example is the study by Noel and Cai (2017), who used the existing census of pumping wells with their spatial location to delineate the agents and irrigated area.

Despite the strength of ABM-AWM to model human-water feedback, one key tradeoff involved is the inherent uncertainty in its predictions, relative to conventional AWM models. This is because human actions are inherently uncertain and human-water feedback are still poorly understood, especially over longer time periods (Srinivasan et al., 2017; Di Baldassarre et al., 2016). The calibration and validation of ABM-AWM is more complex in comparison to that of the convention AWM models (Sivapalan and Blöschl, 2015; Pande and Sivapalan, 2017; Troy et al., 2015). Sivapalan and Blöschl (2015) discuss a way to deal with the parameter estimation, validation, and uncertainty assessment of sociohydrology models in this regard. However, ignoring the human water feedback in human dominated systems in favor of more conventional models using a scenario-based approach may lead to imprecise and unrealistic predictions (Sivapalan et al., 2012) and as we argue, lead to negative unexpected consequences over the long term. Thus, a balanced use of conventional AWM models and ABM-AWM is required. For long term strategic investment decisions, ABM-AWM are critical to understand the human-water dynamics and scale interactions and explore the whole space of possible future trajectories (including unintended and irreversible consequences) (Sivapalan and Blöschl, 2015; Srinivasan et al., 2017; Pande and Sivapalan, 2017).

2.5 Summary

AWM interventions have been widely implemented globally with well-documented benefits and positive externalities. However, ill-planned AWM interventions can lead to negative externalities resulting from unintended spatio-temporal changes in hydrological flows and unexpected societal feedback. These often lead to long-term unsustainable and inequitable impacts. To avoid this, interdisciplinary approaches that can model the coevolutionary dynamics of coupled natural-human systems are needed. Sociohydrology, studying bidirectional feedback in coupled natural-human systems with a focus on hydrology, has been proposed and increasingly used in this context. Among different methods employed in sociohydrology, the use of agent-based modeling (ABM) has been increasing as it provides the unique capability of modeling coupled natural-human systems while explicitly accounting for the role of individuals and micro-level constraints.

Our review shows that ABMs have been extensively used in agricultural systems to assess the adoption of AWM interventions and to simulate their impact on natural and social systems. Many of these studies have explicitly modeled unsustainable and inequitable outcomes. However, there are gaps in methods employed that require further research, especially to interpret spatially explicit and inequitable outcomes (Table 2.1). The main gaps include: 1) lack of spatially distributed and integrated hydrological models, which limits the capacity of ABM-AWM to resolve hydrological negative externalities; 2) over-reliance on rational and simple heuristics for modeling individual behavior and 3) lack of inclusion of social interactions. Our review highlights the need for further research and development of ABM-AWM to fill these limitations and gaps. Finally, with ABMs unique capabilities to unravel the dynamic interactions of heterogeneous biophysical and social systems, they should be widely used to plan, design, and implement AWM interventions to avoid negative hydrological externalities and unexpected societal feedback resulting in long-term unsustainable and inequitable outcomes.

3. Impact of high-density managed aquifer recharge implementation on groundwater storage, food production and resilience: A case from Gujarat, India[3]

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3.1 Introduction

Reliable and adequate availability of freshwater for irrigation is critical for global food security. With climate change and increasing climate variability leading to more extremes in water availability, expressed as droughts and floods, (United Nations, 2019; IPCC, 2021) irrigation is more important than ever (Smit and Skinner, 2002; Ignaciuk and Mason-D'Croz, 2014). Groundwater, being more reliable and more widely available than surface water and largely protected from evaporation losses, plays a critical role in providing irrigation water, especially in semi-arid areas (UN-WWAP, 2022), and supplies 38% of irrigated areas globally (Siebert et al., 2010). However, in many parts of the world, overdependence on groundwater irrigation has led to unsustainable use and depletion of groundwater resources (Doll et al., 2012; Bierkens and Wada, 2019).

To mitigate groundwater depletion and enhance groundwater security for irrigation, one strategy that is increasingly applied is managed aquifer recharge (MAR) (Zhang et al., 2020; Alam and Pavelic, 2020; Zheng et al., 2021). MAR involves strategically recharging aquifers with excess surface water through infrastructure such as check dams or recharge wells (Dillon et al., 2019; Alam and Pavelic, 2020). The benefits of MAR in these cases include enhanced groundwater storage in dry seasons and drought periods supporting continuous irrigation and/or mitigating depletion (Prathapar et al., 2015; Dillon et al., 2019; Zhang et al., 2020). MAR is contingent on the availability of harvestable source water for augmenting recharge and storage, like flood waters or treated wastewater, which may be seasonally or perennially available, respectively.

India, as the largest user of groundwater globally, is promoting MAR to mitigate negative impacts of extensive groundwater use through multiple central (CGWB, 2020) and state government programs and policies (Verma and Shah, 2019; CWGB, 2020). One notable example is Gujarat where more than

90,000 MAR structures (in the form of check dams) have been constructed since the year 2000 with the financial support (subsidies) of government and non-government organizations under the government participatory scheme '*Sardar Patel Sahbhagi Jal Sanchay Yojana* (Sardar Patel Participatory Water Conservation Program)' (Shah et al., 2009; NWRWS, 2018; Verma and Shah, 2019; Patel et al., 2020). An extended drought in 1999 – 2002, during which the average rainfall was about 35% less than normal (Pai et al., 2014), greatly accelerated the development of check dams, facilitated by government support (Patel, 2007; Patel et al., 2019).

Increased MAR implementation, as a result, has been widely reported as having a positive impact on groundwater storage in the region (Shah et al., 2009; Jain, 2012; Patel et al., 2020). While a number of studies have analyzed the increasing groundwater storage in Gujarat (Shah et al., 2009; Jain, 2012; Bhanja et al., 2017; Kumar and Perry, 2018; Patel et al., 2020), they disagree on the underlying explanation. Improved groundwater storage has been attributed to a number of factors: increased rainfall (Shah et al., 2009; Dinesh and Perry, 2018); reduced groundwater abstraction brought about by rationing schemes enabled by separating agriculture and non-agriculture electricity feeders (Shah et al., 2008; Bhanja et al., 2017); inter basin transfer of water (Kumar and Perry, 2018); and enhanced recharge from MAR, mostly through check dams (Shah et al., 2009; Jain et al., 2012; Patel et al., 2020). The diverging explanations among the studies demonstrate the lack of clarity in attributing the increase in groundwater storage, including the role of MAR. This is because any change in groundwater storage is a result of numerous factors associated with the short- and long-term dynamics of supply (e.g. rainfall amount and intensity, performance of MAR) and demand factors (e.g., changing cropping patterns, irrigated areas, irrigation practices). Previous studies have not systematically accounted for these complexities.

The main limitations associated with the previous studies include: 1) focusing on recharge enhancement while not accounting for increased groundwater irrigation demand for agriculture (Bhanja et al., 2017; Kumar and Perry, 2019; Patel et al., 2020); 2) neglecting the long-term change in rainfall and inter-annual variability in rainfall (Shah et al., 2009; Bhanja et al., 2017); 3) focusing on small scale assessments of MAR structures or micro-catchments (Patel et al., 2002; Sharda et al., 2006) leading to high uncertainty when attempting to extrapolate results to large scale; and 4) focusing on state level impacts (Shah et al., 2009; Bhanja et al., 2017) and thus discounting spatial variability and heterogeneity in biophysical factors (hydrogeology, soil, water demand) (Kumar and Perry, 2018) and the interconnectedness of MAR structures within a hydrologic unit (Mozzi et al., 2021).

With the progressive priority and increased investment being made in MAR in Gujarat and other states in India (Verma and Shah, 2019), there is clear and urgent need to assess the effectiveness of MAR at an appropriate intermediary scale and for relevant contexts. This requires a long-term integrated analysis, accounting for the dynamics of both supply and demand on a catchment scale, which this study aims to carry out. In this study, we analyze the dynamics of groundwater storage in conjunction with changes in rainfall, irrigation demand and increase in supply through MAR in Gujarat. With this, we aim to establish the contribution of MAR to groundwater storage and agricultural production relative to other key factors.

3.2 Study area

The analysis is carried out for Kamadhiya catchment (1,150 km^2), located in the Saurashtra region (~6,600 km^2) of the western state of Gujarat, India (Figure 3.1a). Kamadhiya catchment is an upstream catchment of the Bhadar basin, one of the larger river basins in the region. Kamadhiya catchment drains to Bhadar dam (~240 million cubic meters (MCM) (Figure 3.1b), the largest dam supplying both irrigation and drinking water in the Bhadar basin (NWRWS, 2010). While the catchment scale considered here provides a closed hydrologic unit for assessment and accounts for the limitation of the small spatial scales of earlier studies focusing on specific MAR structures or micro-watersheds, it still falls short of a basin-scale assessment as it represents only 17% of the entire basin area. Therefore, attempts to extrapolate these findings to the basin scale would require further investigation.

Saurashtra region has been the focus of development of MAR in India (mostly in the form of check dams, hereafter referred to as CD) (Shah et al., 2009; Patel et al., 2020). An estimated 27,000 CDs were constructed across Saurashtra before 2018 (NWRWS, 2018). Within Bhadar basin, the number of CDs increased from 484 (24.0 MCM storage) in 1999 to 4,385 (103.3 MCM storage) by the end of 2010 (Figure 3.1c) (Kamboj et al., 2011) with more than 90% of CDs constructed after 2000, primarily during 2001-2002, in response to the extended 2000 – 2002 drought (Patel, 2007; Patel et al., 2019).

In the Kamadhiya catchment, the total number of CDs in 2006 was estimated to be 576 with total storage capacity of 12.7 MCM (Patel, 2007). With lack of time series data for Kamadhiya catchment, we assume the same development curve as in Bhadar basin with ~90% of CDs (at the end of 2006) constructed post 2000 during 2001-2002. Also, we further assume that the rate of development of new CDs post 2006 will be approximately matched by the rate of attrition of existing

CDs, as they lose functionality from lack of maintenance (e.g., siltation, collapse) (Kumar and Perry, 2018; Mozzi et al., 2021). Thus, based on the density of CDs in the catchment, we term the period until 2002 as pre-CD, during which CD density was relatively low (10% of CDs in 2006 = 58 CDs ~ 1 CD per 20 km^2), and the period after 2002 as post-CD, during which CD density had increased ten-fold (100% of CDs in 2006 = 576 CDs ~ 10 CDs per 20 km^2).

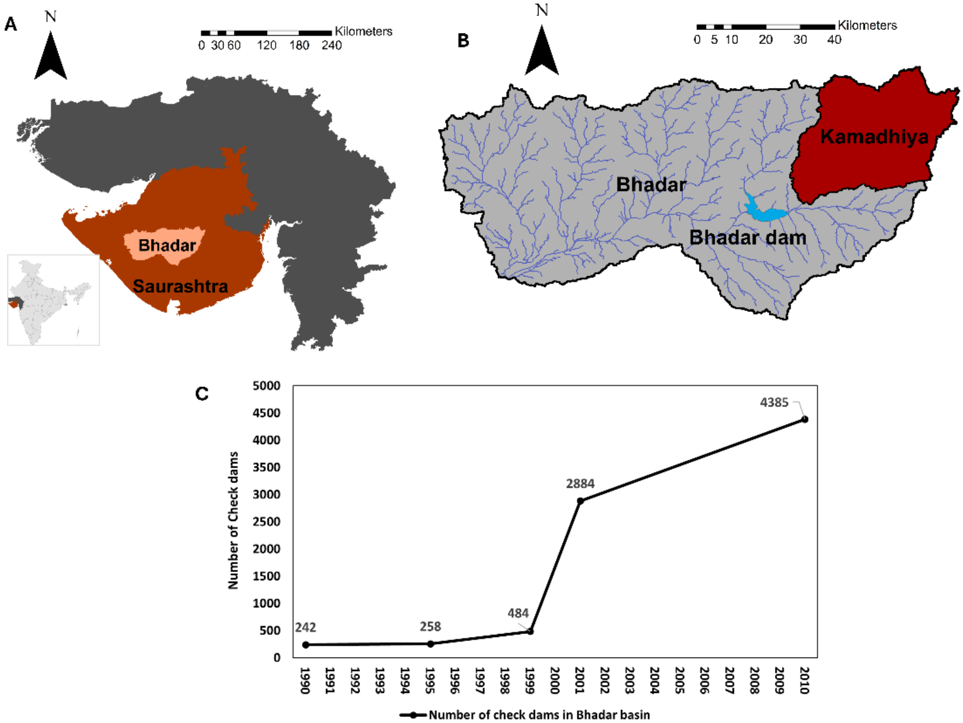

Figure 3.1: Location of A) Saurashtra region and Bhadar basin in Gujarat, India; B) Kamadhiya catchment, part of Bhadar basin; and C) timeline of number of check dams in the Bhadar basin.

3.2.1 Climate

The climate of the Kamadhiya catchment is semi-arid with an average annual rainfall of 638 mm yr^{-1} (1983-2015) (Pai et al., 2014). More than 90% of the rainfall is concentrated in the four monsoon months from June to September. Rainfall is also associated with high inter-annual variability with a coefficient of variation of 46%, estimated for the period 1983-2015 from the India Meteorological Department (IMD) gridded rainfall dataset (Pai et al., 2014). Average annual mean temperature is 27°C with minimum temperature observed in January with a mean of 20.6°C and the maximum temperature observed in May with a mean of 30.7°C (Srivastava et al., 2009).

3.2.2 Agriculture and irrigation

Agriculture and irrigation data were available only on an administrative level. Thus, we report and use data from Rajkot district and absolute values for the catchment are derived using the proportion of catchment area which lies within the district (86%). The kharif (monsoon) is the main cropping season where groundnut and cotton are the main crops occupying 48% and 41% of total sown area, respectively (DoA Gujarat, 2021). Other minor crops in the kharif season include bajra (pearl millet) and sesame. Rabi (post-monsoon) season has limited cropping area, which is reflected by low annual cropping intensity of 113% (DoES Gujarat, 2018). Wheat is the main rabi crop (DoA Gujarat, 2021). Of the total net cropped and gross cropped area, 39% and 42% is equipped for irrigation, respectively (DoES Gujarat, 2018). During the kharif season, cotton requires supplemental irrigation whereas groundnut is rainfed. Rabi crops rely entirely on irrigation (DoA Gujarat, 2021). Groundwater is the main source of irrigation in the district, accounting for 82% of the irrigated area (DoES Gujarat, 2018). The main source of surface water in the district is from Aji and Bhadar dams (GGRC, 2015). Irrigation and domestic water supply represent about 95% and 5% of the overall water demand, respectively (GGRC, 2015).

3.2.3 Hydrogeology

The groundwater in the Saurashtra region is found at shallow depths under unconfined conditions in aquifers characterized by parent basalt rock of the Deccan trap formation with little primary porosity (Mohapatra, 2013; Patel, 2007). In the region, deccan trap basalt has weathered upper parts to a depth of 20-30 m, forming good aquifers, which are tapped for irrigation mostly by large diameter open dugwells (Figure 3.2a) (Mohapatra, 2013; MoWR, RD & GR, 2017a).

Figure 3.2: A) Open dugwell commonly used for irrigation in the Bhadar basin; B) and C) check dam in the area in dry and wet season, respectively (images taken from downstream side).

The groundwater well yields are seasonally variable and highest after monsoonal recharge (Pavelic et al., 2012). The weathered aquifer is underlain by consolidated basalt rocks generally forms a poor aquifer with groundwater present in fractured and vesicular zones (secondary porosity) in successive basalt flows and tapped by deeper borewells of depth > 150 m (Mohapatra, 2013; Patel et al., 2020, MoWR, RD & GR, 2017a).

3.3 Methods and data

The analysis is carried out for the period from 1983 to 2015 (33 years). This period is divided into the pre-CD (1983-2002) and post-CD (2003-2015) period, where the post-CD period indicates the period after the 2000-2002 extended drought and after 90% of the CDs were constructed. We assess the impact of CDs by estimating and comparing changes, from the pre-CD to the post-CD period (Δ = post-CD – pre-CD), specifically in groundwater recharge (ΔGWR) and groundwater abstraction (ΔGWA). Since both groundwater recharge and groundwater abstraction for irrigation depend on rainfall, which is associated with high inter-annual variability, we only compare pre-CD and post-CD periods in similar rainfall years classified using standard precipitation index (SPI) (WMO and GWP, 2016). We define a year in terms of the hydrological year (June to May) and classify years as either dry, normal or wet. Years reported in the subsequent analysis refer to the hydrological year (e.g., the year 2001 covers June 2001 to May 2002).

We assume that positive difference in groundwater recharge (ΔGWR), between pre-CD and post-CD periods for years under the same SPI classification, will primarily come from increase in groundwater recharge from new CDs (i.e., $\Delta GWR = \Delta GWR_{CD}$). Balance of ΔGWR_{CD} (section 3.3.1) and ΔGWA (section 3.3.2) between the pre-CD and post-CD periods is used to estimate the change in groundwater storage (ΔGWS_E) between the two periods (equation 3.1).

$$\Delta GWS_{E_{(SPI)}} = \Delta GWR_{CD_{(SPI)}} - \Delta GWA_{(SPI)} \qquad .....3.1$$

ΔGWS_E, where E stands for estimated, will be positive if the increase in groundwater abstraction (ΔGWA) is less than the increase in recharge (ΔGWR_{CD}) and vice-versa. Estimated ΔGWS_E is compared with observed groundwater storage change (ΔGWS_O, section 3.3). Subscript SPI denotes classified years of dry ($SPI \leq -0.49$), normal ($-0.49 < SPI < 0.49$) and wet years ($SPI \geq 0.49$).

3.3.1 Change in groundwater abstraction (ΔGWA)

To estimate change in groundwater abstraction from pre-CD to post-CD, we focus our analysis on two main irrigated crops of the region: cotton and wheat. Cotton is supplementarily irrigated during the kharif season and wheat is fully irrigated during the rabi season. We assume the irrigation water volume derived from groundwater is proportional to the fraction of groundwater irrigated area in the area. Groundwater irrigated area data was taken from annual agricultural statistics as reported by the government (DoES Gujarat, 2018; ICRISAT, 2021) and was assumed to be the same for both crops (in the absence of crop-specific information). Also, we disregard groundwater abstraction for non-irrigation purposes, which is less than 5% in the district (CGWB, 2019). Figure 3.3 gives the conceptual flow diagram showing the approach taken to arrive at groundwater abstraction (GWA).

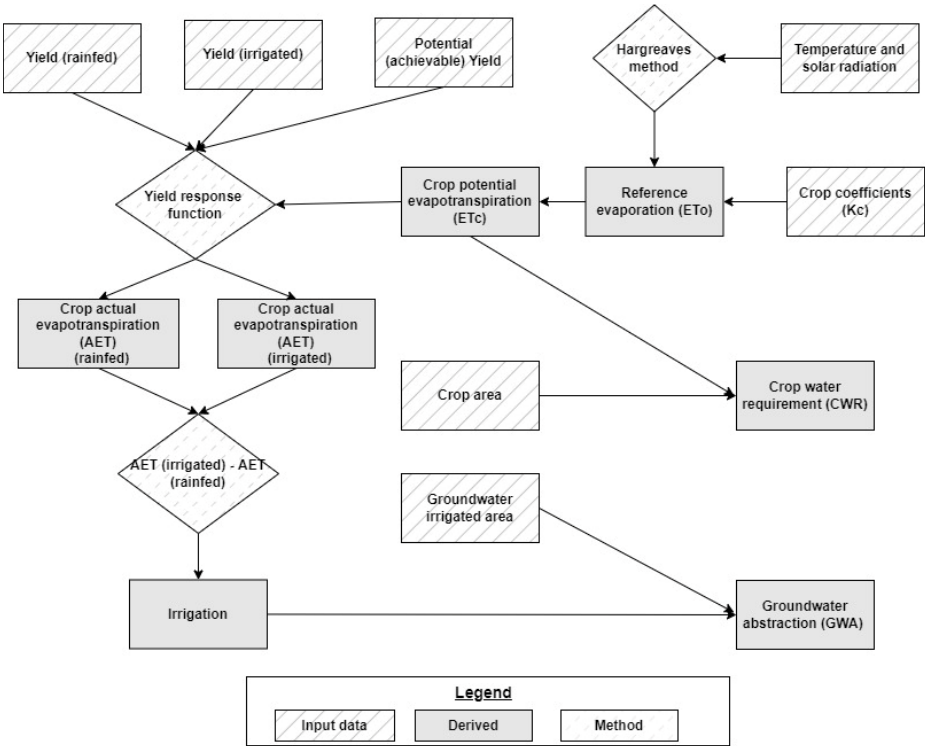

Figure 3.3: Conceptual flow diagram showing the approach taken to derive groundwater abstraction

To estimate groundwater abstraction for hydrological year *i*, we first estimate the annual net irrigation water applied (Irrigation) for crops. In the case of cotton, applied Irrigation volume (mm) is estimated as the difference between actual evapotranspiration (AET) of rainfed ($AET_{rainfed}$) and irrigated ($AET_{irrigated}$) cotton (equation 3.2a). For wheat, grown with 100% cultivated area under irrigation, we assume all crop water demand is met through irrigation, and Irrigation volume (mm) is equal to $AET_{irrigated}$ (equation 3.2b). We neglect any post-monsoon rainfall during the wheat growing season as for the period 1983-2015, this averaged only ~ 5 mm. $AET_{rainfed}$ and $AET_{irrigated}$ is calculated using FAO crop yield response to water (equations 3.4a and 3.4b) (Steduto et al., 2012).

$$Irrigation_{(c)(i)} = AET_{irrigated(c)(i)} - AET_{rainfed(c)(i)} \text{ \{for cotton\}} \quad ....3.2a$$

$$Irrigation_{(c)(i)} = AET_{irrigated(c)(i)} \text{ \{for wheat\}} \quad ....3.2b$$

$$AET_{ra\,inf\,ed(c)(i)} = ET_{c(i)} \times (1 - \frac{1}{K_{Y(c)}}(1\text{-}\frac{Yield_{ra\,inf\,ed(c)(i)}}{Yield_{Potential(c)}}) \quad .... 3.3a$$

$$AET_{irrigated(c)(i)} = ET_{c(i)} \times (1 - \frac{1}{K_Y}(1\text{-}\frac{Yield_{irrigated(c)(i)}}{Yield_{Potential(c)}}) \quad .... 3.3b$$

$$ET_{c(i)} = \sum_{s=1}^{4} ET_{o(i)} \times K_{c(s)} \quad ..... 3.4$$

Where, subscript *i* denotes year and *c* denotes crop (cotton and wheat). ET_c (equation 3.4) is the crop potential evapotranspiration demand and is estimated using FAO four stage (s) crop coefficient approach (Allen et al., 1998), and ET_o is reference evaporation estimated using Hargreaves method (Hargreaves and Samani, 1985). The Hargreaves method was chosen due to its simplicity, reliability and minimal data requirements as it requires only monthly average, minimum and maximum temperature along with solar radiation data. $K_{c(s)}$ is the crop coefficient for stage *s*; $Yield_{rainfed(c)}$ and $Yield_{irrigated(c)}$ is the observed rainfed and irrigated crop yield and $Yield_{Potential(c)}$ is the potential (achievable) yield. $Yield_{Potential(c)}$ is estimated as the five-year moving average of observed irrigated yield. Observed annual yield data, used to estimate rainfed $Yield_{rainfed(c)}$) and irrigated$Yield_{irrigated(c)}$) yield pertains to Rajkot district and were taken from annually reported government statistics (DoA, 2021; ICRISAT, 2021). $K_{y(c)}$ is the crop yield response factor representing the effect of a reduction in water use (relative to potential demand) on yield losses (Steduto et al., 2012). Values of K_Y for cotton (0.85) and wheat (1.15) were taken from the literature and are based on extensive analysis of data on crop yield, water relationships and deficit irrigation (Doorenbos and Kassam, 1979; Steduto et al., 2012).

Data on overall yield (average of rainfed and irrigated yield) for cotton was available for the whole time (1983-2015), whereas segregated data on rainfed and irrigated yield were only available starting 1995. Thus, for the time period of 1983-1994, segregated rainfed and irrigated cotton yield was derived based on the developed relationship between the ratio of overall yield to irrigated yield and irrigated area to the overall area (R^2 of 0.79, see Figure A.1) in the 1995-2015 period.

Derived irrigation volume is multiplied with annual groundwater irrigated area of a crop (equation 3.5) to get a volumetric estimate (million cubic meter, MCM) of groundwater abstraction (GWA_c). Annual groundwater irrigated area was taken from annually reported government statistics (DoES Gujarat, 2018; ICRISAT, 2021). Crop potential evapotranspiration demand (ET_c) is multiplied by annual crop area, taken from annually reported government statistics (DoES Gujarat, 2018; ICRISAT, 2021), to get a volumetric estimate (MCM) of total crop water requirement (CWR) (equation 3.6).

$$GWA_{c(i)} = Irrigation_{(c)(i)} \times Annual\ groundwater\ irrigated\ area \qquad .... 3.5$$

$$CWR_{c(i)} = ET_{c(i)} \times Annual\ crop\ area \qquad .... 3.6$$

Values for duration and crop coefficient for each crop stage were taken for Indian conditions (ICAR, 2014; Allen et al., 1998; Table A.1). The sowing dates for cotton and wheat were taken as 15th June and 15th November, respectively (DoA Gujarat, 2020). Thereafter, change in groundwater abstraction (ΔGWA_c) between the pre- and post-CD periods is estimated for years in the same SPI class by determining the mean GWA_c of each class for pre-CD and post-CD and taking the difference (equation 3.7).

$$\Delta GWA_{c(spi)} = \frac{1}{n_{postCD(spi)}}\left(\sum_{i=1}^{n_{postCD(spi)}} GWA_{(c)(i)}\right) - \frac{1}{n_{preCD(spi)}}\left(\sum_{i=1}^{n_{preCD(spi)}} GWA_{(c)(i)}\right) \qquad .... 3.7$$

Where, *spi* denotes the SPI class (dry, normal and wet) and $n_{pre\text{-}CD(spi)}$ and $n_{postCD(spi)}$ is the number of years in each SPI class in pre-CD and post-CD periods, respectively.

3.3.2 Potential groundwater demand met

We also estimate how much of crop annual potential groundwater demand (GWA_{Pot}) could be met through groundwater abstraction (GWA_c) (%met = $\frac{GWA}{GWA_{Pot}} \times 100$). For cotton, GWA_{Pot} is estimated as the difference between crop potential evapotranspiration demand (ET_c) and $AET_{rainfed}$ multiplied with cotton groundwater irrigated area (equation 3.8). As wheat is completely irrigated, wheat GWA_{Pot} estimated is equal to the crop potential evapotranspiration demand (ET_c) multiplied with wheat groundwater irrigated area (equation 3.9).

$$GWA_{pot(c)} = \left(ET_c - AET_{rainfed(c)}\right) \times groundwater\ irrigated\ area\ \{\text{for cotton}\} \quad \text{.... 3.8}$$

$$GWA_{pot(c)} = ET_c \times groundwater\ irrigated\ area\ \{\text{for wheat}\} \quad \text{.... 3.9}$$

Thereafter, the change in potential groundwater demand (ΔGWA_{Pot}) is estimated for each SPI class by obtaining the mean of GWA_{Pot} of each SPI category for pre-CD and post-CD period and taking the difference (equation 3.10).

$$GWA_{pot(c)(SPI)} = \frac{1}{n_{postCD(spi)}}\left(\sum_{i=1}^{n_{postCD(spi)}} GWA_{pot(c)(i)}\right) - \frac{1}{n_{preCD(spi)}}\left(\sum_{i=1}^{n_{preCD(spi)}} GWA_{pot(c)(i)}\right) \quad \text{.... 3.10}$$

Where, SPI denotes the SPI classification (dry, normal and wet) and $n_{preCD(spi)}$ and $n_{postCD(spi)}$ is the number of years under each SPI classification in pre-CD and post-CD, respectively.

3.3.3 Change in recharge from check dams (ΔGWR_{CD})

Groundwater recharge from CDs (GWR_{CD}) is simulated using an analytical dynamic tool (Mozzi et al., 2021). The tool integrates a daily water balance of individual CDs with a set of analytical infiltration equations (Bouwer, 1969; 2002) giving daily dynamics of storage, infiltration, and evaporation. The tool was previously applied to four structures in the Bhadar basin and validated at sites in Rajasthan where more extensive data were available (Mozzi et al., 2021). Application of the tool has shown good performance with validation results giving an average R^2 of 0.93 between the simulated and measured water levels in individual CDs. The tool requires input data on CD geometrical parameters, catchment area hydrogeology characteristics, daily inflow to CD and potential evaporation. Representative values of CDs in Kamadhiya catchment were applied (Table A.2).

To estimate GWR_{CD}, the tool is used to simulate recharge from a representative CD ($GWR_{CD(r)}$) with a storage capacity ($V_{CD(r)}$) of 21,486 m^3 (Table A.2). A simulation is carried out for the pre-CD period 1983-2002 where runoff is assumed to be representing the baseline conditions with low CD development. Annual recharge values are then averaged for each SPI class. Thereafter, to get relative CD recharge for pre-CD and post-CD periods at the catchment scale (GWR_{CD}) for each SPI classified year, the ratio of representative CD recharge ($GWR_{CD(r)}$) to its storage capacity ($V_{CD(r)}$) is multiplied with catchment cumulative CD storage capacity ($V_{CD(pre)}$ = 1.3 MCM and $V_{CD(post)}$ = 11.4 MCM) (equations 3.11a and 3.11b).

$$GWR_{CD(spi)(pre)} = \left(\frac{GWR_{CD(r)(spi)}}{V_{CD(r)}}\right) \times V_{CD(pre)} \quad \text{.... 3.11a}$$

$$GWR_{CD(spi)(post)} = \left(\frac{GWR_{CD(r)(spi)}}{V_{CD(r)}}\right) \times V_{CD(post)} \quad \text{.... 3.11b}$$

Thereafter, change in groundwater recharge (ΔGWR_{CD}) is estimated for each SPI class from the mean GWR_{CD} of each SPI category for pre-CD and post-CD and taking the difference (equation 3.12).

$$\Delta GWR_{CD(SPI)} = \frac{1}{n_{postCD(spi)}} \left(\sum_{i=1}^{n_{postCD(spi)}} GWR_{CD\ (post)}{}_{(i)}\right) - \frac{1}{n_{preCD(spi)}} \left(\sum_{i=1}^{n_{preCD(spi)}} GWR_{CD\ (pre)}{}_{(i)}\right) \quad \text{.... 3.12}$$

Where, *spi* denotes the SPI classification (dry, normal and wet) and $n_{preCD(spi)}$ and $n_{postCD(spi)}$ is the number of years under each SPI classification in pre-CD and post-CD periods, respectively. All GWR figures are calculated on daily time scales and thereafter aggregated to annual scale. We assume that all CDs are functioning, behave similarly, and do not interact.

3.3.4 Observed change in groundwater storage (ΔGWS_O)

The observed change in groundwater storage is the annual net balance of groundwater recharge and abstraction in the catchment. This is estimated using the water table fluctuation method (MoWR, RD & GR, GoI, 2017b; Pavelic et al., 2012). The water table fluctuation method has been used extensively and found suitable for climatic and hydrogeological conditions of unconfined weathered hardrock aquifers (Pavelic et al., 2012; Dewandel et al., 2010; Machiwal et al., 2017). The water table fluctuation method derives groundwater storage change (GWS_O) from the rise in monsoonal groundwater levels (GWL_r) estimated as the difference between pre (GWL_{PrM}) and post monsoon (GWL_{PM}) groundwater levels (equations 3.13-3.14).

$$GWS_{o(i)} = GWL_{r(i)} \times S_y \times catchment\ area \quad \text{.... 3.13}$$

$$GWL_{r(i)} = GWL_{PM(i)} - GWL_{PrM(i-1)} \quad \text{..... 3.14}$$

Where $GWL_{PM(i)}$ is the post monsoon of GWL of hydrological year i (taken in November), $GWL_{PrM(i-1)}$ is the pre monsoon GWL of previous hydrological year i (taken in May). Hence, pre monsoon GWL of previous hydrological year is the groundwater level/storage at the start of year i. S_y is the specific yield, which is taken as 0.02 as the recommended value for the region (MoWR, RD and GR, GoI, 2017; Patel et al., 2020).

Annual catchment averaged pre (GWL_{PrM}) and post monsoon (GWL_{PM}) groundwater levels are derived using observed data from monitored wells for the time period 1983-2015 from the Central Groundwater Board (CGWB, 2015). A total of 15 observation wells located within the catchment and up to a 10 km distance beyond the catchment boundary were used for the analysis. The data were filtered for outliers using interquartile range method with data outside an interquartile range of 1.5 removed. Only monitoring wells with observation records containing more than 2/3 of the years of pre and post GWL data points were used. GWL_{PM} and GWL_{PrM} for each year were then derived from spatially interpolating observation wells using inverse distance weighing (Li and Heap, 2008). Thereafter, GWL_r is calculated according to equation 3.15. Finally, the change in groundwater storage (ΔGWR_O) is estimated for each SPI classified category by getting mean of GWS_O of each SPI category for pre-CD and post-CD and taking the difference (equation 3.15).

$$\Delta GWS_{O_{(SPI)}} = \frac{1}{n_{postCD(spi)}}\left(\sum_{i=1}^{n_{postCD(spi)}} GWS_{O\,(i)}\right) - \frac{1}{n_{preCD(i)}}\left(\sum_{i=1}^{n_{preCD(i)}} GWS_{O\,(i)}\right) \quad ..3.15$$

Where, *spi* denotes the SPI classification (dry, normal and wet) and $n_{preCD(spi)}$ and $n_{postCD(spi)}$ is the number of years under each SPI classification in pre-CD and post-CD, respectively.

We compared observed (ΔGWS_O, equation 3.15) with estimated (ΔGWS_E, equation 3.1) change in groundwater storage to validate our results. Storage change derived from the water table fluctuation method incorporates all sources and sinks, including diffuse rainfall recharge, recharge from CDs, subsurface irrigation returns flows, groundwater evaporation, and any net lateral groundwater flow (Pavelic et al., 2012, MoWR, RD & GR, GoI, 2017b). It is assumed that net groundwater inflow/outflow is negligible as hardrock areas have limited lateral subsurface hydraulic connectivity at the regional scale (Bouma et al., 2011; Dewandel et al., 2010; Pavelic et al., 2012). Table 3.1 summarizes the datasets used in the analysis.

Table 3.1: Summary of data used in the analysis

Parameter	Temporal period	Temporal resolution	Source
Rainfall and temperature	1983-2015	Daily	India Meteorological Department gridded rainfall data (Pai et al., 2014)
Groundwater levels	1983-2015	Pre (May) and post	Central Ground Water Board (CGWB, 2015)
Crop area and yield	1983-2015	Annual	Government reported statistics (DoA, 2021; ICRISAT,2021)
Irrigated area and source	1983-2015	Annual	Government reported statistics (DoA, 2021; ICRISAT, 2021; DoES Gujarat,2018)
CD number and storage	Pre-CD (1983-2002) and Post-CD (2003-2015)		Patel (2007); NWRWS (2018)

3.4 Results

3.4.1 Rainfall

Figure 3.4 shows the annual rainfall time series, with individual years categorized as either 'wet', 'normal' or 'dry' based on SPI. For the overall period, average rainfall is 638.6 mm yr^{-1}. Average post-CD rainfall (809.8 mm yr^{-1}) is

~27% higher than the overall average, whilst the pre-CD rainfall (511.9 mm yr^{-1}) is ~25% lower than the average. Also, there is a high inter-annual variability characterized by a high coefficient of variation of ~45% across the whole time series. Wet rainfall years are concentrated in the post-CD (8 in post-CD vs 3 in pre-CD), whereas dry years are disproportionately occurring in the pre-CD period (8 in pre-CD vs 1 in post-CD) (Table 3.2).

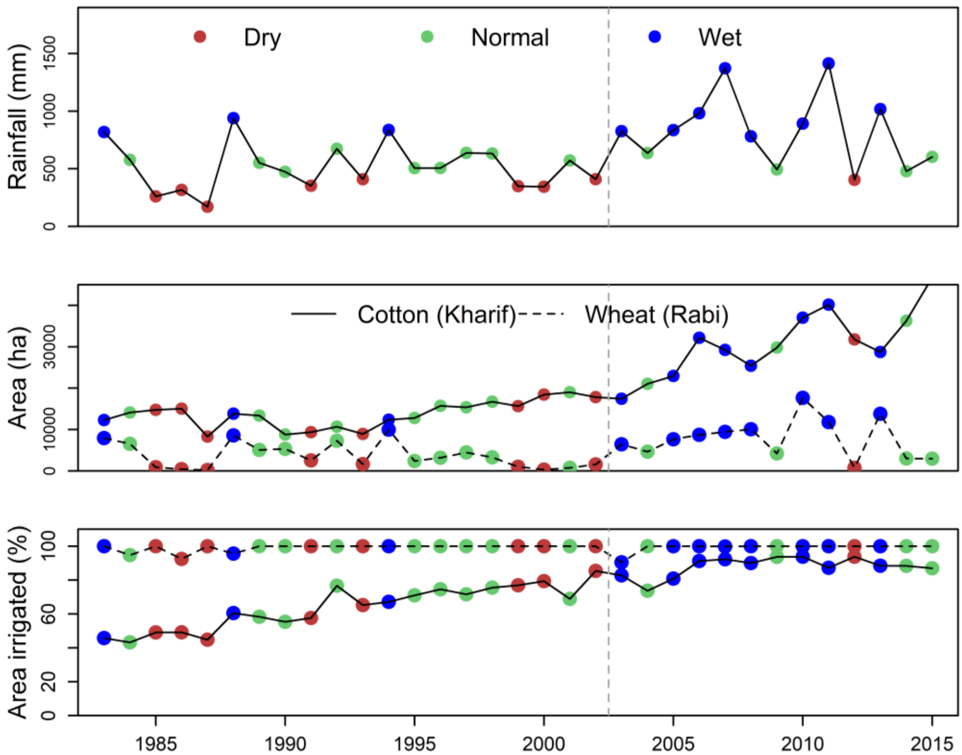

Figure 3.4: A) Annual rainfall (mm/year) for the time period 1983-2015; B) Cultivated area (ha) of cotton (kharif crop) and wheat (rabi crop); and C) Cotton and wheat irrigated area (given as percentage of total cultivated area of crop) Note: Years are indicated according to rainfall class (dry, normal and wet).

Table 3.2: Average values of key water and crop variables for all years and for SPI classified years, split into pre-CD and post-CD period.

Parameter	Overall		Dry		Normal		Wet	
	Pre-CD	Post-CD	Pre-CD	Post-CD	Pre-CD	Post-CD	Pre-CD	Post-CD
# of years	20	13	8	1	9	4	3	8
Rainfall (mm/year)	516.8	825.9	326.2	403.9	570.1	552.6	864.9	1015.3
Cotton								
Area[a]	136.7	306.7	135.5	317.8	140.7	334.6	128.4	291.4
Irrigated (%)	64.2	85.4	63.1	93.8	67.3	83.6	57.8	85.3
CWR[b]	84.6	183.6	85.7	196.2	86.1	199.7	76.6	173.9
GWA_{pot}[b]	41.5	94.2	51.2	147.6	37.4	100.3	27.9	84.5
GWA[b]	26.3	74.9	19.4	29.2	32.1	72.2	27.3	81.9
%met	79.1	90.2	53.6	30.0	94.9	86.2	100	100
Wheat								
Area	36.7	77.7	10.7	7.5	42.5	37.0	88.2	106.9
Irrigated (%)	99.1	99.2	99.1	100.0	99.4	100.0	98.6	98.8
CWR[b]	12.8	27.6	4.2	2.7	14.6	13.4	30.0	37.8
GWA_{Pot}[b]	12.8	27.6	4.2	2.7	14.6	13.4	30.0	37.8
GWA[b]	12.8	27.6	4.2	2.7	14.6	13.4	30.0	37.8
%met	100	100	100	100	100	100	100	100

[a] '00 ha

[b] in Million cubic meters (MCM)

3.4.2 Groundwater abstraction (GWA)

3.4.2.1 Cotton

Area under cotton cultivation has steeply risen, especially during the post-CD (Figure 3.4b). The average post-CD cotton area (30,670 ha) is ~124% higher than the pre-CD period (13,670 ha) (Table 3.3). At the same time, average irrigated cotton area has increased in post-CD (to an average of 85.4% of cropped area) compared to 64.2% in pre-CD (Figure 3.4b and Table 3.2). Results show that this increase in area and irrigation from pre- to post-CD is consistent for all SPI classified years (Table 3.2).

Increase in cotton area (Figure 3.4b) translates to more than two-fold increase in crop water requirement (CWR) in post-CD for both overall and SPI classified years (Table 3.2). With ~85% of crop area irrigated with groundwater, this translates into an increase in potential groundwater demand (GWA_{pot}) of 96.4 MCM (increase of 188%), 62.9 MCM (increase of 168%) and 56.6 MCM (increase of 203%) in dry, normal, and wet years, respectively (Table 3.2).

In normal and wet years, with practically all GWA_{pot} being met (%met between 86.2 and 100%) (Table 3.2), GWA increases by 40.1 MCM (increase of 125%) and 54.6 MCM (increase of 200%), respectively. However, for dry years most of GWA_{pot} remains unmet in post-CD (%met ~ 30%) reflecting that irrigation in dry years is limited by available groundwater storage. Thus, GWA increases by only 9.8 MCM in dry years between the two periods (Table 3.2).

3.4.2.2 Wheat

The wheat area in post-CD period (7,770 ha) is 112% higher than in the pre-CD (3,660 ha) (Table 3.2). In contrast to cotton, there is no or limited change in wheat area when compared across similar SPI classified years (Table 3.2), with area increasing only in wet years (~21%). However, across SPI years, wheat shows a large increase from dry (700-1,000ha) to wet (8,500-10,300ha) years. This shows that large overall increase (~118%) in wheat area in post-CD is largely due to higher number of wet years (Table 3.3). Wheat is completely irrigated (~99% area under irrigation) in both periods for all years (Figure 3.4c and Table 3.3).

Wheat CWR and GWA, similar to wheat area, show an increase of 115% for overall period in post-CD relative to pre-CD (Table 3.3). However, across SPI classified years, there is no or limited change in CWR and GWA. Only wet years show moderate increase in GWA by 7.8 MCM (~26% increase). Wheat yield does not show decrease across SPI years reflecting that 100% of demand is met (GWA_{pot} = GWA). Summing up cotton and wheat irrigation, overall GWA_{Pot} and GWA post-CD increases by 67.5 MCM (~124%) and 63.4 MCM (~162%) as compared to pre-CD.

3.4.3 Change in recharge from check dams (ΔGWR_{CD})

The average recharge from CDs (GWR_{CD}) increases from 2.4 MCM in pre-CD to 34.0 MCM in post-CD (Table 3.3). Overall, this means a 14-fold increase in recharge from CDs (ΔGWR_{CD}). Also, GWR_{CD} increases from dry to wet years with ΔGWR_{CD} (post-CD -pre-CD) increasing from dry (10.7 MCM) to normal (21.2 MCM) to wet years (37.2 MCM) (Table 3.3). Monthly recharge estimates (Table A.3) show that, on average, highest recharge takes place in July and August when sufficient runoff is available and groundwater tables are deeper. Table 3.3 shows that GWR_{CD} is constrained by inflow capture of the CDs, calculated as the difference between flow entering and leaving a check dam, which decreases from dry to wet years. On average, 67% of inflow is captured by CD with highest capture in dry years (94%), followed by normal years (85%) and wet years (55%). Besides rainfall, recharge and inflow capture are sensitive to CD geometry catchment area (Mozzi et al., 2021), and results reflect the first order average potential recharge from existing CD storage in the catchment (Table A.3).

Table 3.3: Average value of check dam groundwater recharge (GWR_{CD}), groundwater level monsoon rise (GWL_r), corresponding monsoon groundwater storage change (GWS_O) and pre (GWL_{PrM}) and post (GWL_{PM}) monsoon groundwater levels for all years and for SPI classified years, split into pre-CD and post-CD period.

	Overall		**Dry**		**Normal**		**Wet**	
	Pre-CD	**Post-CD**	**Pre-CD**	**Post-CD**	**Pre-CD**	**Post-CD**	**Pre-CD**	**Post-CD**
GWR_{CD}[a]	2.4	34.0	1.3	12.0	2.6	23.8	4.7	41.9
Inflow capture (%)[b]	67.1		93.7		84.7		55.0	
GWLr (m)[c]	3.1	4.7	0.8	0.7	3.6	2.8	7.4	6.1
GWS_O [a]	70.4	107.0	17.7	15.2	83.9	64.5	170.8	139.7
GWL_{PM} (m bgl)[d]	8.7	6.8	11.2	11.2	7.8	8.5	4.9	5.3
GWL_{PrM} (m bgl)[d]	11.8	11.4	12.6	13.5	11.8	12.8	9.4	10.5

[a] in MCM.

[b] Calculated as the difference between flow entering and leaving a check dam.

[c] $GWL_{r(i)} = GWL_{PM(i)} - GWL_{PrM(i-1)}$

[d] bgl = below ground level

3.4.4 Observed change in groundwater storage (ΔGWS_O)

GWLs show no statistically significant long-term declining or rising trend over the whole study period ($p > 0.05$), but high inter annual variability (Figure 3.5). Averaged over pre-CD and post-CD, post monsoon groundwater level (GWL_{PM}) below ground level (bgl) and average annual groundwater storage increase (GWS_o) are higher (GWLs closer to ground level) during the post-CD period (GWL_{PM} = 6.8 m bgl, GWL_{PrM} = 11.4 m bgl and GWS_O = 107.0 MCM) than in the pre-CD period (GWL_{PM} = 8.7 m bgl, GWL_{PrM} = 11.8 m bgl and GWS_O = 70.4 MCM) (Table 3.3). However, when compared across similar SPI classified years to account for the influence of rainfall, GWLs and GWS_O are lower in post-CD as compared to pre-CD (Table 3.3). For example, GWS_o in post-CD decreases by 2.5 MCM (pre-CD=17.7 MCM and post-CD= 15.2 MCM), 19.4 MCM (pre-CD=83.9 MCM and post-CD= 64.5 MCM) and 31.1 MCM (pre-CD=170.8 MCM and post-CD= 139.7 MCM) for dry, normal, and wet years, respectively. This shows that overall higher GWLs and GWS_O in post-CD is the result of disproportionally higher number of wet years in post-CD period (Table 3.3) and not due to the increased number of MAR interventions.

Dynamics of GWLs show that GWL_{PM} are sensitive to the magnitude of monsoon seasonal rainfall with average GWL_{PM} highest during wet years (~5 m bgl) and much deeper in dry years (~11 m bgl). On the other hand, pre monsoon groundwater levels (GWL_{PrM}) are relatively less sensitive to monsoonal rainfall with average GWL_{PrM} fluctuating from ~9.4-10.5 m bgl in wet years to ~ 12.6-13.5 m bgl in dry years (Figure 3.5 and Table 3.3). This reflects the properties of low storage aquifer systems where storage is filled during monsoon months (to an extent depending on rainfall and storage capacity of the aquifer) and irrigation leads to desaturation at the end of hydrological year (Pavelic et al., 2012). The lower GWL_{PrM} and their low sensitivity to annual rainfall shows that there is limited inter-annual groundwater storage carry-over from the dry season to the wet season in the catchment.

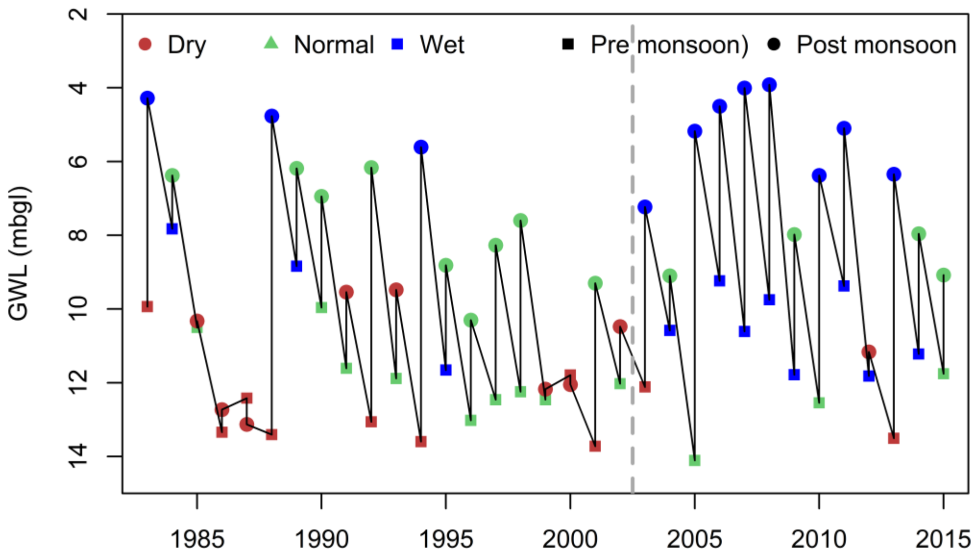

Figure 3.5: Catchment-averaged pre- and post-monsoon GWLs (GWL_{PrM} and GWL_{PM}). Number of observation wells, n=15. Color denotes SPI classified years. Symbols denote pre- (circle) [May] and post- monsoon (square) [November] levels. Blue vertical line divides the pre-and post-CD. Hydrological year in June-May.

3.5 Discussion

3.5.1 Dynamics of groundwater balance changes

Table 3.4 compares changes in observed (ΔGWS_o) and estimated (ΔGWS_E) groundwater storage, increase in recharge (ΔGWR_{CD}), changes in potential groundwater demand (ΔGWA_{Pot}) and actual groundwater abstraction (ΔGWA) for the Kamadhiya catchment between pre- and post-CD periods. The latter two are aggregated sums of cotton and wheat (Table 3.3). Results show that both

ΔGWA_{Pot} and supply via increased recharge (ΔGWR_{CD}) has increased in post-CD but the increase in GWA_{pot} has outpaced the increase in GWR_{CD}. Additionally, the increase is not uniform across the SPI classified years. ΔGWR_{CD} is highest in the wet years, whereas ΔGWA_{pot} is highest in the dry years and vice-versa. Thus, the deficit (demand-supply) is highest for dry years followed by normal and wet years, with ΔGWR_{CD} representing only 11% of the increased groundwater demand (ΔGWA_{Pot}) for dry years. With limited natural recharge in dry years combined with low groundwater storage at the start of the year (i.e., GWL_{PrM} of previous year) (Figure 3.5, Table 3.3) and low additional CD recharge (ΔGWR_{CD}) (Table 3.4), only ~30% of cotton GWA_{pot} is met in the post-CD period, whereas wheat cultivated area is significantly reduced (~10% of average wheat area in post-CD) (Table 3.3). Limited abstraction and recharge also mean that there is very limited change in estimated groundwater storage (ΔGWS_E = -2.5 MCM) from pre-CD to post-CD (Table 3.4). This matches with limited change observed in groundwater storage (ΔGWS_o = 2.4 MCM). This shows that groundwater storage remains low in dry years for both periods (Table 3.3) and is unable to meet irrigation demands. The high unmet demand reflects the limited efficacy of CDs in semi-arid regions with low storage aquifers for mitigating impact of droughts, which supports the findings of earlier studies (Kumar et al., 2008; Kumar and Perry, 2018; Boisson et al., 2015; Enfors et al., 2008; Ogilive et al., 2016; 2019). For example, Ogilive et al., (2016; 2019), in assessing rainwater storage structures in Tunisia, showed that their low storage capacity limits their ability to recharge groundwater sufficiently, thus having a limited impact on farmers' drought coping capacity. A similar conclusion was reached by Enfors and Gordon (2008) assessing MAR in Tanzania (locally termed Ndiva system). Thus, the hypothesis that sufficient runoff is available and remains available for planning recharge interventions may not hold in semi-arid areas, especially in dry years (Boisson et al., 2014; 2015).

Table 3.4: Average values of change in potential groundwater demand (ΔGWA_{pot}), groundwater abstraction (ΔGWA) [cotton + wheat], CD recharge (ΔGWR_{CD}), estimated (ΔGWS_E) and observed (ΔGWS_O) groundwater storage change for SPI classified years between pre-CD and post-CD period. All values are in MCM.

	Dry	**Normal**	**Wet**
ΔGWA_{pot} (MCM)	94.9	61.7	64.4
ΔGWA (MCM)	8.3	38.9	62.4
ΔGWR_{CD} (MCM)	10.7	21.2	37.2
ΔGWS_E (MCM)a	2.4	-17.7	-25.2
ΔGWS_O (MCM)	-2.5	-19.4	-31.1

[a] $\Delta GWR_{CD} - \Delta GWA$

For normal and wet years, the deficit is less pronounced relative to dry years (Table 3.4). However, ΔGWR_{CD} can only meet 34% and 58% of increased groundwater demand (ΔGWA_{Pot}) in normal and wet years, respectively (Table 3.4). In normal and wet years, in contrast to dry years, groundwater storage is recharged by rainfall (Figure 3.5, GWL_r in Table 3.3) and meets the irrigation demand in excess of increased recharge from CDs (ΔGWR_{CD}). This is reflected in the results indicating that most of the potential groundwater demand is met in normal and wet years for both major crops (Table 3.3). Thus, higher groundwater abstraction translates to decrease in ΔGWS_E in post period (Table 3.4) for both normal (-17.7 MCM) and wet years (-25.2 MCM). This matches well with ΔGWS_O of -19.3 MCM and -31.1 MCM in normal and wet years, respectively. This implies that increase in recharge by CDs can only partly support increased kharif irrigation and positive impact of GWR_{CD} on groundwater storage is overshadowed by the increase in demand.

The findings from this study related to no long-term increase in groundwater storage are contrary to findings of other studies (Patel et al., 2020; Shah et al., 2009; Bhanja et al., 2017) and we find that higher overall average storage in the post-CD period is primarily due to an increased number of wet years. The divergence between the findings could be attributed to differences in the temporal period considered and/or the spatial scale of analysis. For example, Shah et al., (2009) only compared two distinct years (2000 and 2008) but did not fully account for the variability of rainfall. Similarly, both Asoka et al., (2017) and Bjanja et al., (2017) have a different temporal period for analysis with data starting from 1996, thus having very limited data for the pre-CD period which may accentuate low groundwater levels during the 2000-2002 drought relative to post-CD period. Their analysis was also focused at the national scale thus discerning regional differences is more difficult. While Patel et al., (2020) do account for longer time series (starting from 1975), they only compare wet year periods during the pre-CD (1975-1984) and post-CD (2004-2009), and the analysis focuses on the larger spatial region (whole of Saurashtra), thus again making a direct comparison difficult. It is important to note that none of the above studies accounted for changes in water demand, without which dynamics of groundwater storage cannot be reliably derived.

3.5.2 Implication of MAR on kharif and rabi season cropping

Overall, our findings of increased cropping and irrigation water demand of mainly kharif cotton and additional recharge from CDs partly support the hypothesis of Shah et al., (2009) that kharif production has increased, with GWR_{CD} making good rainfall years (i.e., normal, and wet years) better. However, even in normal and wet years, increased recharge can only partially meet increased demand (Table 3.4) translating to lower groundwater storage in post-CD when compared with pre-CD across similar SPI years (Table 3.3 and 3.4). This further builds on the argument that CDs can only provide supplemental irrigation during good (normal or wet) rainfall years and cannot be expected to sustain intensive irrigation in dry years, as also evidenced in other regions (e.g. Ogilive et al., 2016; 2019).

Our results do not show any consistent and significant increase in wheat area which was also hypothesized by Shah et al., (2009), except in wet years (Table 3.3). In this respect, our findings also contrast with findings by Garg et al., (2020) carried out in Bundelkhand region of Uttar Pradesh state of India. Their results show that the impact of recharge interventions in terms of increasing area and production was more tangible during the rabi season.

The low impact on rabi area and production in our study could be attributed to extensive irrigated cotton area in the study catchment (Table 3.2), which utilizes much of recharge during the monsoon season thus leaving limited storage for rabi cultivation dependent on irrigation. This is supported by the observation that post-monsoon GWLs (GWL_{PM}) have been similar or slightly lower in post-CD relative to pre-CD (Figure 3.5 and Table 3.3). With no increases in groundwater storage at the end of the monsoon, (indicated by GWL_{PM}), there is limited increase in wheat area (Table 3.2) as it is highly dependent on GWL_{PM} signified by good correlation (R^2 of 0.64) of wheat area and GWL_{PM} (Figure 3.6a). This also suggests that farmers across the catchment consistently plan their wheat crop areas cognizant of the irrigation demand that the post monsoon storage can support. The correlation of pre-monsoon levels with cotton area is much less pronounced (R^2 of 0.01) (Figure 3.6b). This could be attributed to kharif cropping dependence on expected monsoon rainfall. The increase in wheat area for wet years (~21% increase in post-CD) couldn't be explained just from dynamics of GWLs, as GWL_{PM} are high and similar in both periods (Table 3.3). Thus, further research is needed to ascertain whether the increase in wheat area in wet years is a result of CD recharge or other dynamics.

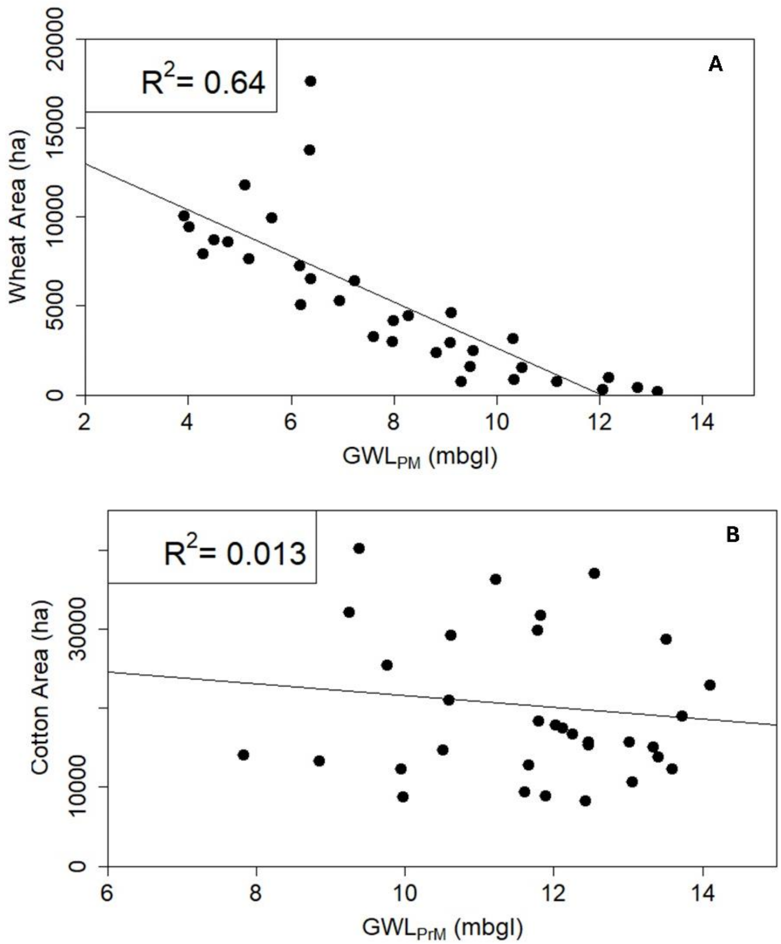

Figure 3.6: Relationship between A) wheat area (Y-axis) and spatially averaged post-monsoon groundwater levels (GWL_{PM}) (X-axis); and B) cotton area (Y-axis) and spatially averaged pre-monsoon groundwater levels (GWL_{PrM}) (X-axis).

3.5.3 Inter-annual groundwater storage

A commonly stated benefit of recharge interventions is that they create storage for dry years by recharging in years of good rainfall (Garg et al., 2020; Megdal et al., 2014; Singh et al., 2021). This may happen in situations where structures have larger storage capacity and are thus able to capture more and recharge over longer durations (Ogilive et al., 2016; 2019) or in areas where there is low demand due to low cropping and irrigation intensity thus recharged water in wet years is in excess to demand and remains available for irrigation in dry years (Garg et al., 2020; Singh et al., 2021).

The study catchment, underlain by hardrock aquifers (low porosity, limited thickness) with limited aquifer storage capacity, shows no clear evidence of this. As compared to post-monsoon GWLs (GWL_{PM}), pre-monsoon GWLs (GWL_{PrM}, representing end of year storage) are much less sensitive to yearly rainfall and is in the range of ~10-12 m for all years (section 4.4 and Table 3.3). We hypothesize that because of the wheat area's (post monsoon crop) strong dependence on GWL_{PM} (Figure 3.6a) and limited post monsoon storage due to high demand by the monsoon cotton crop, limited storage is available by the end of hydrological year (Figure 3.5). Very low wheat cultivated area in years with GWL_{PM} lower than 10 m bgl (Figure 3.6a) suggests that groundwater storage below 10 m bgl offers limited utility to support irrigation due to the low porosity and limited thickness of the underlying hardrock aquifers.

Direct evidence of limited impact of carry-over storage is indicated by the severe impact on crop area and production in the drought year of 2012, which followed a wet year of 2011 (Figure A.2). During 2011, wheat sown area was very high, resulting in limited storage at the end of the season (GWL of 11.8 m bgl) (Figure 3.5). Thus, without significant carry-over storage and low rainfall (thus low recharge and high demand), the impact of drought was severe in the catchment with cotton and wheat production in 2012 being only 27% and 6% of their respective production in 2011.

3.5.4 Vulnerability versus benefits and tradeoffs of MAR

Supply-demand dynamics in the catchment points to the case of Jevons paradox (Alcott, 2005) where increased water demand from increased production outweighs water savings (Scott et al., 2014; Glendenning et al., 2012), in this case the increased recharge from CDs. In the absence of any policy or quota on irrigation, irrigation expansion, and higher irrigation efficiency can aggravate scarcity, and reduce resilience (Scott et al., 2014). However, more research is required to ascertain if the increase in demand (increased crop area and irrigation water use) is resulting from perceived increase in supply through GWR_{CD}, increase in rainfall years or other market-related factors. A counter argument to this is that these small storage aquifers are self-regulating, because they cannot be continuously depleted over many years (Taylor et al., 2019). The silver lining to this is that the system will likely not collapse, and whenever there is a good rainfall, the aquifers will be filled up. In turn, irrigated areas will not expand continuously, and likely they will vary more in tune with rainfall but exhaust the groundwater storage every year.

The argument can be made that this increase in demand outpacing supply has increased agricultural vulnerability to drought in the catchment. For example, the percent of demand met was only ~30% in dry years for the post-CD period, whereas this was ~54% in pre-CD period dry years (Table 3.2). This is evident in the 2012 drought where reduction in cotton production is much higher (relative decrease of 300%) in post-CD compared to 2000 in pre-CD (relative decrease of 61%) (Figure A.2). This reiterates that CDs are not effective in a catchment with very low rainfall in dry years, little runoff to capture and low storage aquifers meaning limited carry-over storage.

However, on the other hand, an argument can be made that increased production in normal and wet years supported by CDs outweighs the losses in dry years. This suggest that rather than looking at productivity in individual years, the benefits of CDs or recharge interventions in the area should be assessed by combining good years with bad years. Good rainfall years allow farmers to make higher profits from increased capture of rainfall and address tide-over losses from dry years which remain as bad or worse as the pre-MAR situation. More research and analysis are needed to ascertain these aspects. The narrative also points towards the need for better understanding the benefits and tradeoffs of MAR in these environments. Our results suggests that though CD came up in response to a drought, they are not necessarily efficient in drought proofing.

3.5.5 Uncertainties in this analysis and future research needs

The simple method applied in this study, with clearly defined assumptions and accounting for major factors, is able to progress the assessment of the impact of high-density CD development on climate resilience of agriculture in Saurashtra with implications for similar regions elsewhere. There are two major sources of uncertainty in the analysis: (a) reliability and inherent errors in the data used, and (b) methodological assumptions and simplifications made.

Agricultural data (crop area, irrigated area, and irrigation source) in Gujarat (and in India more broadly) is primarily derived from government reported annual agricultural statistics which are collected bottom-up from the village scale (and then aggregated to higher administrative levels) through random sample surveys of 20% of the villages during each crop season in a state and is then further cross-checked through random sampling (Ministry of Statistics & Programme Implementation, 2018; Planning Commission, 2001). Similarly, crop yield data are collected through crop cutting experiments in randomly selected fields and then cross-checked. However, being a manual survey process errors can result from: (1) non-reporting of crops sown (predominant error); (2) incorrect area entered for the crop; or (3) non-reporting of the crop actually sown in the field (Ministry of Statistics & Programme Implementation, 2018). Data for 2015-16 at the national scale in India shows that the error (mismatch of information identified in cross-checking) was 9-25% in different seasons for crop area, 9% for irrigation data (annual) and 5-10% for yields (cotton and groundnut) (Ministry of Statistics & Programme Implementation, 2018). Despite these errors, the absence of other annually available and long-term collected data makes this the primary source of data used extensively in agricultural and water resources research (Sidhu et al., 2022) and contributes to data for many global datasets (e.g. Sibert et al., 2010).

Similarly, data on groundwater levels is collected by the Central Ground Water Board (CGWB) four times each year (January, May, August, and November) by field personnel covering an extensive national monitoring well network (CGWB, 2015). The CGWB data has again been used extensively by researchers over many years as this represents the main source of groundwater data in India (e.g. Hora et al., 2019; Asoka et al., 2017; Bhanja et al., 2017). However, this data has gaps, and outliers, and is often sparse. These issues are usually addressed by removing outliers and monitoring wells with missing data above a threshold (as was done in this study) (Asoka et al., 2017; Bhanja et al., 2017). However, Hora et al., (2019) found that this may lead to bias (so-called survivor bias) where dried wells (often missing data) may lead to better picture of the aquifer than is actually the case. Other sources of data such as GRACE satellite data couldn't be used due to the small spatial scale of the catchment. Daily rainfall is taken from IMD gridded datasets and again has been used extensively (Asoka et al., 2017; Kumar Singh et al., 2019). IMD gridded data is derived from using records of ~ 7,000 rain gauge stations (Pai et al., 2014). Multiple studies evaluating the performance of available rainfall products have shown that the IMD data performs satisfactorily over Indian monsoon conditions (Pai et al., 2014; Kumar Singh et al., 2019). Thus, while we have used the best available data (in some cases the only source) and published data sources (Table 3.1) which have been used extensively, they come with inherent uncertainties which have a bearing on the results.

This analysis required making certain methodological assumptions and simplifications as have been documented in section 3. One limitation is that the method applied assumes that changes in annual yields primarily results from changes in (ground)water availability, whereas moving average of yields captures changes resulting from improvement in inputs (e.g., better seeds, fertilizers, better wells and pumps, etc.). However, the other factors (e.g., heat waves, cold waves, pest attacks) can still add to yield variability and couldn't be accounted for. Also, we do not consider irrigation efficiency with the assumption that irrigation return flows are completely recyclable. Additionally, while we have considered potential recharge by check dams, there is a need for further research to ascertain plausible upstream-downstream tradeoffs due to the same, as effects of flows captured in upstream areas potentially negatively impacts downstream communities (Calder et al., 2008; Ribeiro Neto et al., 2022; Nune et al., 2014). Similarly, lumped catchment assessment ignores the distribution, both spatial and social, of impacts and there is a need to assess how socially equitable the benefits have been. For example, there are concerns that CD impacts are concentrated near structures in low lying areas (Shah et al., 2021) and that farmers with more financial and social capital benefit the most (Bouma et al., 2011; Calder et al., 2008). This requires setting up more comprehensive hydrological assessments capturing catchment water balance and more explicit inclusion of surface-groundwater dynamics along with socioeconomic field data. The latter is also critical to determine the drivers and impacts of increase in demand. Further research is also needed to assess how these structures will work under the realities of climate change where extreme events are expected to increase (Mukherjee et al., 2018).

3.6 Conclusions

Managed aquifer recharge (MAR) through various interventions (including CDs) is increasingly being promoted and adopted for sustainable groundwater use and resilience building to dry periods and droughts. Our study analyzed the case of high-density CD development in the Saurashtra region of Gujarat, India. Results considering rainfall variability and crop irrigation water demand show that counter to assumptions of CDs being a strong measure to alleviate the impacts of droughts, their capability is highly restricted in dry years, and especially under scenarios of, possibly accompanying, increasing water demand. This is because there is limited runoff to capture and recharge and the underlying aquifer has low storage capacity that is replenished and depleted annually with limited carry-over storage. The study shows that irrigation water demand has increased significantly and outstripped the increase in recharge from CDs. Thus, with limited runoff in dry years, low groundwater storage, and increasing demand, these interventions may not be very effective in securing irrigation water supplies and may not necessarily lead to long-term climate resilience. For good rainfall years, increased recharge via CDs does increase supply but can only partially compensate for the increased demand of the kharif season, indicating that overall reduction of irrigated areas and flexible annual adjustment to rainfall in the wet season and adjustment to groundwater storage in the dry season are required. These findings suggest that MAR, unless complemented by greater emphasis on water demand management and groundwater governance, may not suffice as a standalone solution to achieving sustainable groundwater and concurrently expanding food production in hydrogeological and climatic settings like in Gujarat, India. Additionally, Irrigated agriculture needs to be flexible and adaptable to prevailing climate and groundwater storage conditions. There is a need for clear communication and realistic assessment and expectation of the potential benefits of recharge interventions in regions with limited aquifer storage and highly variable runoff, while also ensuring that basic water needs are not sacrificed in the quest for increased food production.

4. Benefits, equity, and sustainability of community rainwater harvesting structures: An assessment based on farm scale social survey[4]

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4.1 Introduction

Agriculture accounts for 70% of total freshwater withdrawals globally, going up-to 90% in developing countries (FAO, 2022). As a result, it is highly vulnerable to water shortages resulting from unpredictable and unreliable availability of water. This is particularly a concern in arid and semi-arid regions that face high variability in the availability of water, which is characterized by short rainfall seasons, frequent dry periods, and droughts (Falkenmark et al., 1989; Ragab and Prudhomme, 2002). The climate change impacts manifested through increases in water extremes are already intensifying the existing risks (IPCC 2022, United Nations, 2019) posing concerns for water and food security in large parts of the world.

Asian adaptation measure and to bridge the frequent supply-demand gaps in semi-arid regions, ex-situ rainwater harvesting systems (RWHs) that collect rainwater in surface reservoirs or recharge groundwater (e.g., check dams, farm ponds, tanks, percolation tanks), have been one of the key interventions in agricultural areas (Garg et al., 2020; Alam and Pavelic, 2020; Sikka et al., 2022). The reported benefits from such RWHs include increased water availability, increased crop yields, increased groundwater storages, diversification of water uses and mitigation of droughts (Singh et al., 2018; Glendenning et al., 2012; Bouma et al., 2016; Garg et al., 2020; Patel et al., 2020; Parker et al., 2022).

In India, with large parts under arid and semi-arid climate, government and non-government organizations have also heavily invested in building RWHs under different water management programs (Sikka et al., 2022; Joshi et al., 2008). One such example is of Gujarat, a state in western India (Figure 4.1a) where it has invested heavily in RWHs, largely through the construction of check dams (small structures with low storage built across smaller streams) (Patel et al., 2020; Verma and Shah, 2019). In total, more than 90,000 check dams (hereafter referred as CDs) have been constructed with the financial support from government and non-government organizations (NWRWS, 2018).

Despite multiple studies that have documented positive impacts of CDs on groundwater and agriculture in the region (Shah et al., 2009; Jain, 2012; Patel et al. 2020), disagreements remain on the extent to which the positive impacts can be attributed to CDs (Alam et al., 2022b; Kumar et al., 2008). Additionally, concerns have also been raised that these RWHs may not always be effective or beneficial in arid and semi-arid regions (Kumar et al., 2008; Glendenning & Vervoort, 2011), may lead to inequitable benefits (Deora and Nanore; 2019; Alam et al., 2022a) and are not sustained due to the neglect of maintenance and lack of clear ownership (Singh, 2018, Sharma, 2007; Venot et al., 2012).

The concerns about the efficacy of benefits arise because semi-arid areas have low rainfall with high interannual variability and thus the runoff available for storage or recharge is very limited and often negligible in dry years (Kumar et al., 2008; Glendenning & Vervoort, 2011; Enfors et al., 2008; Oglivie et al., 2019; Alam et al., 2022b). Further, the benefits of RWHs may not be equitably distributed. The farmers nearby the streams where RWHs are built (Shah et al., 2021; Deora and Nanore; 2019), and rich and influential farmers with the capacity to invest in irrigation and agronomy measures benefit more from increased availability of water (Bouma et al., 2011; Calder et al., 2008; Alam et al., 2022a). The sustainability concerns arise from little or no maintenance of such structures once the project is over, representing the build-neglect-rebuild syndrome (Sharma, 2007; Venot et al., 2012; Singh, 2018). Additionally, there are concerns that increased perception of supply from RWHs may have led to more demand in the region, offsetting the benefits of increased supply (Alam et al., 2022b).

Most of the studies assessing the impacts of CDs in the region (Shah et al., 2009; Jain, 2012; Patel et al. 2020; Alam et al., 2022b) have been technical in nature either at a larger spatial scale (regional or catchment) (Patel et al., 2020; Shah et al., 2009; Alam et al., 2022b) or focus on standalone CD structures (Patel et al., 2002; Sharda et al., 2006; Mozzi et al., 2021). These studies do not shed light on how farmers, the ultimate beneficiaries of CDs, perceive the impacts of CDs and benefit from it. For example, Shah (2001) estimated that CDs benefited only 15-16 % of households in the villages of the region where CDs were constructed. Additionally, these studies do not account for the equitability of impacts and the sustainability of the investments.

Therefore, this study employs farmer's surveys to assess the benefits, equity, and sustainability of investments made in CDs to complement the existing studies and fill the abovementioned research gaps. The adoption of interventions, equated here with farmers' behavior towards the maintenance of RWHs critical for the sustainability of corresponding investments, is influenced by range of socio-economic, psychological, perceptual, and cultural factors (Daniel et al., 2020; Kaufmann et al., 2009). The RANAS (i.e., R-risk, A-attitude, N-norm, A-ability, and S-self-regulation) behaviour model has been used to consider such diverse set of factors on the behaviour of adoption (Mosler, 2012). The model was originally developed for the WaSH sector, which 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 model has been used previously to understand farmer behavior with respect to irrigation practices (Hatch et al., 2022), willingness to conserve groundwater (Klessens et al., 2022) and household water treatment behavior (Daniel et al., 2020, 21; Stockler and Mosler, 2015).

This study employs the RANAS model and descriptive analysis of a farmers survey to answer two research questions: 1) How do farmers perceive the benefits of RWHs and equitability of benefits? and 2) what are the contextual and socio-psychological factors that influence the sustainability of RWHs through the lens of farmers' behavior towards the maintenance of RWHs? With the progressive prioritization and increased investment being made in RWHs in India and globally, the research results will contribute to making investments in RWHs more effective, equitable, and sustainable.

4.2 Study area

The study is carried out in the Kamadhiya catchment (1,150 km^2), located in the Saurashtra region (~ 6,600 km^2) of the southwestern state of Gujarat, India (Figure 4.1a and 4.1b). Kamahdiya lies in the Bhadar basin, the main river basin of the area, and drains into the Bhadar dam (Figure 4.1b). Administratively, the Kamadhiya catchment is predominantly located in the Rajkot district of the Saurashtra region. The catchment has a semi-arid climate with an average annual rainfall of 638 mm year^{-1} (1983-2015), with more than 90% of the rainfall being concentrated in the four monsoon months of June to September (Pai et al., 2014). Agriculture is the predominant occupation in the district with the area under crop production covering ~ 70 % of the district area. The kharif (monsoon season starting from June to October) is the main cropping season with groundnut and cotton being the main crops The other growing season is Rabi (during the post-monsoon months of November to February) that has limited cropping area with chickpea and wheat as the main crops (DoA Gujarat, 2021).

The Groundwater is the main source of irrigation, accounting for 82% of the irrigated area (DoES Gujarat, 2018). It is found at shallow depths in unconfined aquifers of the region that are characterized by parent basalt rocks of the Deccan trap formation with little primary porosity (Mohapatra, 2013). It is largely accessed from the top 20-30 m of weathered upper parts of basaltic aquifer, by wide diameter open dug wells (Mohapatra, 2013; Patel, 2007). Its storage in the shallow aquifers is mostly depleted by the end of the hydrological year with little carry over storage from year to year (Alam et al., 2022b).

4.2.1 Check dam development

The Saurashtra region within Gujarat has been the focus region of intensive construction of CDs (Shah et al., 2009; Patel et al., 2020). An estimated 27,000 CDs were constructed across Saurashtra before 2018 (NWRWS, 2018). This has been part of a multi-decade long groundwater recharge movement in the region (Shah et al., 2009; Mudrakartha, 2012). Though the movement had been going since 1980s, the construction of CDs accelerated following the multi-year drought of 1999-2001 (Shah et al., 2009; Alam et al., 2022b). In the Bhadar basin, within which Kamdhiya catchment is located, the number of CDs increased from 484 in 1999 to 4385 by the end of 2010 (Alam et al., 2022b, Kamboj et al., 2011). In the Kamadhiya catchment, the total number of CDs till 2006 were estimated to be 576 with a total storage capacity of 12.7 MCM (Patel, 2007). This represents a CD density of approximately 1 check dam per 2 km^2.

The CDs were implemented with government financial support under the participatory scheme 'Sardar Patel Sahbhagi Jal Sanchay Yojana (Sardar Patel Participatory Water Conservation Program)' and by several non-government organizations and local leaders (Shah et al., 2009; NWRWS, 2018; Verma and Shah, 2019). Under the government scheme, 60 % subsidies were provided to construct the CDs. Any group of farmers or NGOs could apply for the subsidies and many individual farmers, who could afford 40% cost, took advantage by constructing CDs close to their farms (Mudrakartha, 2012). In the region, construction of CDs is primarily done for groundwater recharge (Shah et al., 2009; Mudrakartha, 2012), which is the main source of irrigation and accounts for 82% of the irrigated area (DoES Gujarat, 2018). Thus, most farmers do not directly use (lift) water from CDs.

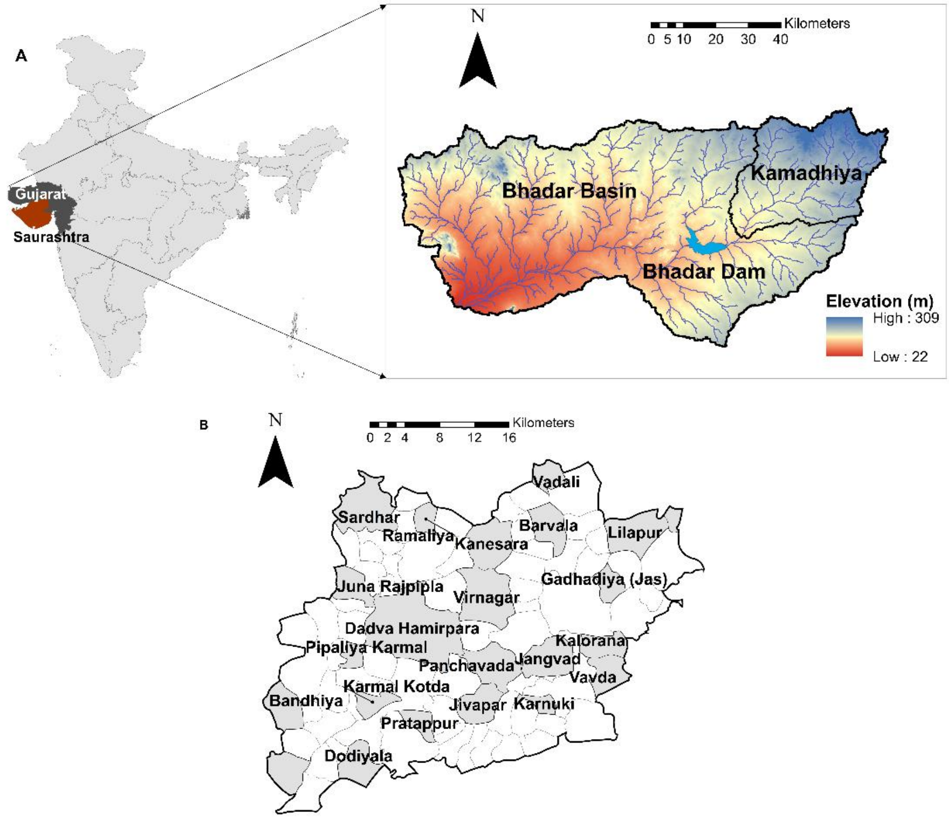

Figure 4.1: (A) Location of Kamdhiya catchment, Bhadar basin, Saurashtra region and Gujarat state in India, (B) Sampled villages for household survey in Kamadhiya catchment. In brackets are the number of check dams in each village (from the survey).

4.3 Methodology

4.3.1 Survey

During December 2021, 492 farmers distributed across 24 villages were interviewed in the Kamadhiya catchment. The study sample was selected through a multistage random sampling procedure. First, 24 villages from a total of 88 villages lying within the Kamadhiya catchment were selected (Figure 4.1b, Table B.1) using regularly distributed sampling. Thereafter, in each village, 20-22 farmers were selected for the survey using proportionate random sampling. This involves taking random samples from stratified groups in the same proportion as their proportion in the total population. Farmers were stratified into four groups: marginal (<1 ha), small (1 -2 ha), medium (2- 4 ha), and large farmers (>4 ha) based on farmers' land areas in the blocks where the villages are located (Table B.2).

Interviews were conducted, after obtaining consent, with the head of households responsible for managing agricultural farms. Each structured interview lasted approximately 45-50 minutes and was carried out by a trained team of 10 enumerators native to the region. The questionnaire was translated into the local language (Gujarati), which was the primary language used for collecting data.

4.3.2 Questionnaire

The survey questionnaire consisted of two parts, 1) farmers' socio-economic characteristics and 2) farmers' perception of CD impacts and sociopsychological questions regarding the maintenance of CDs. Farmer socio-economic information (e.g., age, wealth, land) was measured on binary, ordinal, and interval scales. The questions on CDs consisted of a mix of informative questions, farmers' perceptions of CD benefits, and their behavior towards the maintenance of CDs. The detailed questionnaire can be accessed from the link given in the data availability statement.

The farmers' perception of CDs benefits was elicited through multiple questions asking about the benefits of CDs in general, benefits to main crops grown in the region, and the intensity of benefits. The questions regarding the intensity of benefits were asked for different rainfall years (dry, normal, and wet) because of high inter-annual rainfall variability in the region (rainfall in dry years ~ 334 mm, normal years ~ 564 mm, wet years ~ 974 mm). Recent research has shown that this significantly impacted CDs functioning with recharge in dry years being very limited and insufficient to meet the irrigation demand in the catchment (Alam et al., 2022b). Mozzi et al. (2021) have reported similar dynamics with the number of fillings being lowest in the dry years, followed by normal and wet years. However, they did not account for CDs in series so this could even be lower, especially in dry years when runoff is limited (Alam et al., 2022b).

Information regarding the behavior of farmers towards the maintenance of CDs (equated to adoption) consisted of questions on sociopsychological factors (Table 4.1) and were elicited based on the RANAS model (Mosler, 2012). RANAS sociopsychological factors (i.e., R-risk, A-attitude, N-norm, A-ability, and S-self-regulation) were measured with 2 to 4 questions on five-point Likert scales.

Table 4.1: RANAS sociopsychological factors and questionnaire with descriptive statistics

RANAS factors		Question	Scale	Mean (SD)
	Behavior	Do you help maintain the check dam?	0 (never) – 4 (always)	0.43 (0.8)
Risk[a]	Perceived Vulnerability	How high is the risk of your groundwater wells going dry in the next 5 years?	0 (no risk) – 4 (a high risk)	2.11 (1.12)
		How high is the risk of drought in the coming 5 years?		1.78 (1.29)
	Perceived Severity	How severe will be the impact of drought on your crop production?	0 (Not severe) – 4 (very severe)	2.97 (0.99)
		How much GW decline will impact your crop production?		2.82 (0.98)
Attitude[b]	Benefits: response efficacy	How beneficial you think is check dam during dry rainfall year for crop production?	0 (Not beneficial) – 4 (Very high)	1.32 (1.44)
		How beneficial you think is check dam during normal rainfall year for crop production?		1.57 (1.15)
		How beneficial you think is check dam during wet rainfall year for crop production?		2.10 (1.30)
	Effort: Instrumental belief	How effortful is it to maintain a CD?	0 (Not effortful) – 4 (Very effortful) [b]	0.81 (0.93)
Norm[c]	Descriptive norm (Others behavior)	What proportion of people in your village thinks maintaining check dam is helpful?	0 (Almost nobody (<10 %) – 4	1.54 (1.04)

			(Almost all of them (> 90 %)	
	Injunctive norm (Others' (dis)approval)	Most people whose opinion I value think maintaining check dam is good?	0(Disapprove) – 4 (Approve)	1.86 (0.97)
	NGOs	How important are NGOs/government official opinions to you?	0 (Not important) – 4 (Very important)	1.47 (0.87)
Ability[d]	Maintenance self-efficacy	How confident are you in your financial capability to maintain the check dam alone?	0 (Not confident) – 4 (Very confident) [d]	0.37 (0.68)
	Ability: Govt	If you want to, how confident you are in your capability to get check dam maintained by a govt dept?		0.94 (0.92)
Self-Regulation[e]	CD attention (Action control)	How much attention do you pay to the check dam condition?	0 (Pay no attention) – 4 (Pay much attention)	1.11 (1.03)
	CD plan* (Action planning)	Do you have a plan on how to get the check dam maintained?	0 (no plan) – 1(moderate) – 2 (good) [e]	0.68 (0.67)

[a] represent a person's understanding and awareness of the risk

[b] measures a person's positive or negative stance towards a behavior. Answers to confidence questions where the response was NA (don't know) were equated to having no confidence (0.)

[c] measures the perceived social pressure towards a behavior

[d] measures a person's confidence in her or his ability to practice a behavior. Answers to effort questions where response was NA (don't know) were removed from analysis leaving 420 responses.

[e] measures a person's attempts to plan and self-monitor behavior. Action planning were measured for different options (No plan, know the govt dept, know the personnel number from govt, ask gram panchayat, we have a farmers group, will do myself) and then were classified into 3 (no plan, moderate (know the govt dept; will ask gram panchayat) and good (have a farmers group).

4.3.3 Data analysis

Descriptive analysis is carried out to interpret the socioeconomic profile of the farmers in the region and their perception of CD benefits and impacts. This is followed by a regression analysis to understand the main determinants of farmers' behavior. The regression analysis included a first stage forced-entry linear regression considering all potential contextual factors, socio-economic and biophysical factors (e.g., distance from CDs, location in the catchment), that have a bearing on farmers' behavior (outcome variable) towards CD maintenance (measured on Likert scale of 0 (never) – 4 (always)). This is carried out to select key (significant) socioeconomic variables that impact the behavior as input to the second step of a hierarchical linear regression (Lewis, 2007).

In the second step, a hierarchical linear regression is carried out. Here, selected contextual factors (predictor variables) were used after removing factors that were found to be insignificant in the forced entry regression in the first step and sociopsychological variables were further added as predictor variables. This method has been used by other RANAS studies (Stocker and Mosler, 2015; Friedrich et al., 2017; Daniel at al., 2021; 2020a). The regression brings out the contribution of contextual factors explicitly, which in behavioral theories is often considered to be indirectly influencing behavior through sociopsychological factors (Daniel et al., 2020b).

To carry out the regression, some of the contextual factors were reclassified. Farmers based on the land area were classified (on a 1 to 4 scale) into marginal (<1 ha), small (1- 2 ha), medium (2 – 4 ha), and large farmers (> 4 ha). Farmers' education was reclassified on a 1-4 scale with 1 (No schooling), 2 (till 8th Grade), 3 (till 12th Grade), and 4 (Bachelors or Masters). A wealth index (1-4) was created based on the assets owned with 1 (all other), 2 (owning Fridge and TV), 3 (owning TV, fridge, and 2-wheeler), and 4 (owning car or air conditioning). The participation of farmers at the time of CD construction was reclassified to 0 (no participation) and 1 (all other forms of participation including labor, and financial support). Additionally, based on the elevation of villages, 24 villages were reclassified as 1 (upstream), 2 (midstream), and 3 (downstream).

4.4 Results

4.4.1 Socio-economic descriptive statistics

The surveyed farmers were distributed across marginal (17.3%), small (31.5%), medium (27.8%), and large farmers (23.4%) (Table 4.2). This matches with the overall proportion of these farmers in the region (Table B.2), indicating that proportionate sampling was able to capture the diversity of farmers in the region. All the respondents were male. This also reflects the social context where questions are mostly answered by men unless women are specifically targeted. Since the information was collected on farming operations and on the perceived impact of CDs on agriculture, activities were primarily being done by men in this region and therefore women farmers were not explicitly sought. Farmers in the sample were relatively senior with an average age of 49 years and 62% were above the age of 40. Education was low among the farmers with 22% having no schooling and 61% of the farmers had 8 years or less of schooling.

The income from crop production contributes more than 75% of total income for 37% of the farmers. This shows that other sources exist for generating income such as livestock production (reported by 71.7% farmers), followed by non-agriculture-related business (20.9 %), non-agriculture wage labor (10.5%), salary (8.9%) and agricultural wage labor (8.5%). Most of the farmers that were interviewed had pucca (brick and plastered) or semi-pucca houses. In terms of wealth, most of the farmers owned a television (83.9%), 2-wheeler (89.2%), and a cooking gas connection (86.2%). However, only a few farmers owned a car (7.3%) or an air conditioner (1.8%).

Table 4.2: Socio-economic characteristics of farmers

Characteristics	Variable	Frequency (%)
Land	< 1ha	85 (17.3%)
	1-2 Ha	155 (31.5%)
	2-4 Ha	137 (27.8%)
	>4 Ha	115 (23.4%)
HH members	0 - 2	52 (10.6%)
	2-4	140 (28.4%)
	4-8	240 (48.8%)
	8	60 (12.2%)
Age	< 25	13 (2.6%)
	25 - 40	122 (24.8%)
	40 - 60	275 (55.9%)
	60- 85	82 (16.6%)
Education	No schooling	112 (22.8%)
	Till 5th Grade	158 (32.1%)
	Till 8th Grade	144 (29.3%)
	Till 12th Grade	64 (13%)
	Bachelor and above	14 (2.83%)
Income from Agriculture (%)	< 25 %	47 (9.6%)
	25 – 50 %	161 (32.7%)
	50 – 75 %	100 (20.3%)
	75 – 100 %	184 (37.4%)

Main sources of Income	Self-Employed in Agriculture	488 (99.2%)
	Agricultural wage labor	42 (8.5%)
	Livestock	353 (71.7%)
	Other non-agriculture related wage	52 (10.6%)
	Non-agriculture related business	103 (20.9%)
	Salary	44 (8.9%)
	Pension	3 (0.6%)
House type	Pucca (Brick and mortar)	322 (65.4%)
	Semi-puccaa	151 (30.6%)
	Kuccha	18 (0.04%)
Things owned	TV	413 (83.9%)
	Car	36 (7.3%)
	2-wheeler	439 (89.2%)
	Fridge	282 (57.3%)
	AC	9 (1.8%)
	Gas connection	424 (86.2%)
	none	17 (3.5%)

[a] Thatched roof with brick and mortar.

4.4.2 Farmer perception of check dams' benefits and impacts

Overall, there are on an average 12 CDs per village in the catchment (Table B.3). The median number of CDs reported in a village ranged from 3 to 40 with only 9 villages having less than 10 CDs. However, data shows that there is a large variation in the number of CDs reported by farmers within a village (Table B.3). This shows that farmers either do not know about all the CDs in their village or their answers do not relate to the village administrative area but to their knowledge of nearby areas (which may overlap with other villages).

Most CDs were reported to be built during the period 2000-2010 (44 %) (Table B.4), coinciding with the period following the multi-year drought (1999-2001) when CD construction accelerated. There has been a decline in the number of new CDs being built in recent years, with only 3.5 % of CDs reported being from the period 2015-2020. When asked about the participation of farmers in the construction of CDs, 91.2 % of farmers reported playing no role in the construction of CDs. Only 8.8 % reported contributing towards construction mainly through providing labor (5.2 %) followed by a financial contribution (2.8 %) and material contribution (0.8 %).

4.4.2.1 Farmers benefiting from CDs

Overall, 61 % of the farmers reported that they benefitted from CDs. The results also show that the proportion of farmers benefiting from CDs decreases with distance. Overall 87.3 %, 82.5 %, 70.7 %, and 49.5 % of farmers reported benefitting at a distance of < 250 m, 250 - 500 m, 500 - 1000 m, and > 1000 m, respectively from the closest CD. Of the sampled farmers, a majority of the farmers (~ 61 %) have farms at > 1000 m from CDs and only ~ 20 % reported nearest CD at a distance of less than 250 m. The relation of CD benefits with distance was found to be significant (chi-square test: $\chi^2 = 55.3$, p-value < 0.05). There was no significant difference in reported CD benefit with increasing land size of farmers in the sample. Also, there was no significant relation (using OLS) between proportion of farmers reporting benefits from CDs (Table B.3) and the median number of working CDs in a village.

4.4.2.2 Type of CD benefits

The farmers who reported benefitting from CDs, indicated that the main benefits were increased groundwater levels (93.3 % of the farmers) and water lasting longer in the wells (81.6 % of the farmers) (Figure 4.2a). This was followed by 40 % of the farmers (26 % in the rabi season, 13 % in the kharif season and 1 % in the summer season) reporting an increase in water availability for irrigation. Also, 24 % of the farmers reported increasing crop area (16 % in the rabi season, 7 % in the kharif season, and 1 % in the summer season). Only 16 % of the farmers directly reported protection against drought as a benefit of CD (Figure 4.2a). However, the top three benefits reported by the farmers are direclty linked to the increased capacity to mitigate the impacts of droughts. About 4 % of the farmers also reported spreading the silt from the CDs on their fields. Also, only 4 % of the farmers reported directly using water from the CDs which is in line with field evidence that these CDs are primarily for the purposes of groundwater recharge.

In response to the specific question of how CDs benefitted their main crops, results showed that increased water for irrigation (29-39 %), helped them achieve more yields (13-18%), and increased reliability of irrigation (8-15 %) were the most often reported answers (Figure 4.2b). This shows that farmers perceive the primary impact of CDs on groundwater which then translates to the secondary impacts of an increase in irrigation water availability (and reliability) and enhanced yields for crops. Protection against droughts was reported to be a direct benefit by only ~ 1-2 % of the farmers but the increase in availability (and reliability) of irrigation water can be considered as safegaurds against droughts. Further, 44-53 % of the farmers no benefits from CDs when asked about impact of CDs for each crop they grow.

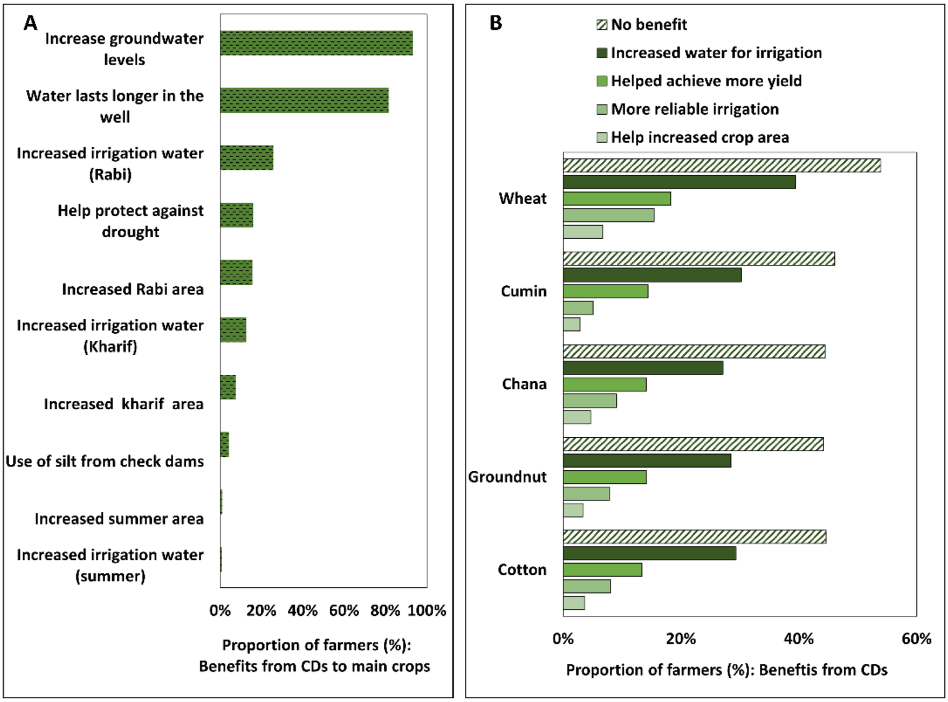

Figure 4.2: (A) Farmers proportion reported benefitting from CDs, elicited response to open questions on main benefits of CDs; (B) Farmer's proportion reported benefitting from CDs to main crops

4.4.2.3 CD benefits in dry, normal, and wet years

Of the farmers who reported benefits from CDs, Figure 4.3a shows the intensity of benefits (measured on Likert scale of 0 (not beneficial) – 4 (very high)) reported by them. The intensity of benefits reported was highest for the wet years, with 44% and 30 % of farmers reporting very high or high and moderate levels of benefits, respectively. For normal years, the intensity of benefits was relatively lower with most farmers reporting low (42.8 %) or moderate (33.3 %) levels of benefits and only 20 % of the farmers reported high or very high benefits. For dry years, intensity of benefits reported was lowest.

Most farmers (32.4%) reported no benefits in followed by 25 % reporting low benefits.

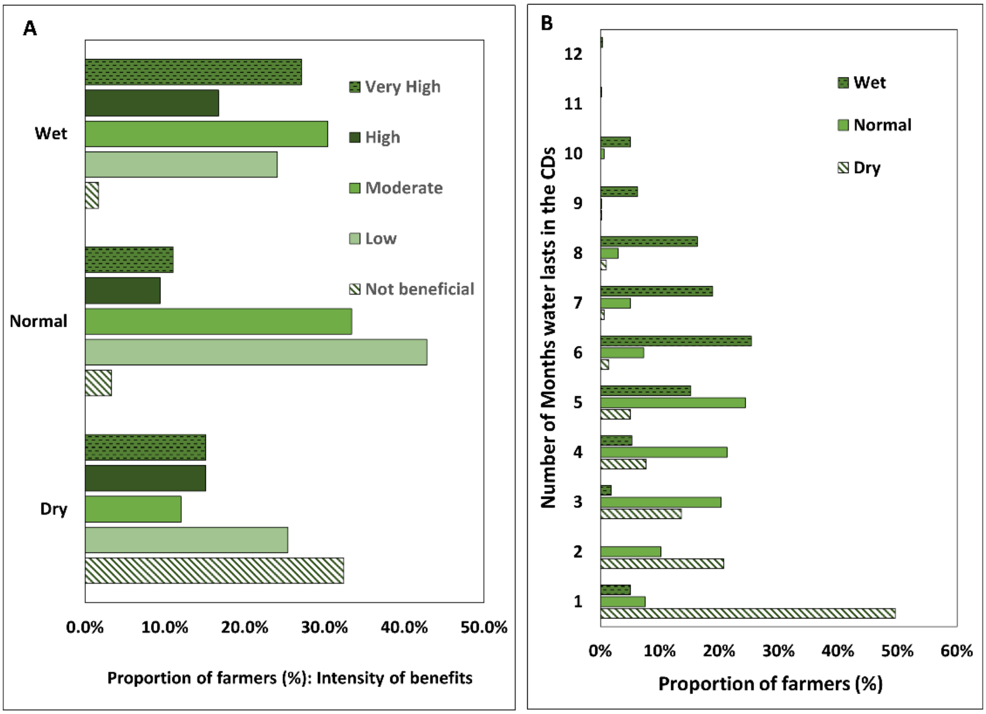

Figure 4.3: (A) Distribution (as a proportion of farmers) of the intensity of benefits reported for dry, normal, and wet years; (B) Distribution (as a proportion of farmers) of the number of months till which water lasts in CDs for dry, normal and wet years

The relatively low benefits in dry years and high benefits in wet years correlate well with reported availability of water in the CDs (visible on surface) by farmers. Since the farmers do not use the water directly from the CDs, the availability of water in CDs indicates the water that is available for recharge. Most of the farmers reported that in dry years water lasts only for less than 3 months (till June to August) with June being the start of the monsoon season. On the other hand, most farmers reported water availability for ~ 8 months (till January) for the wet years and for ~ 5 months (till October) for the normal rainfall years (Figure 4.3b). This reflects no or limited availability of water for recharge in dry years as the rainfall is scarce.

4.4.3 Maintenance of check dams

The sustainability of CDs requires regular maintenance to repair damages to structures from debris and de-siltation. Without maintenance, its performance decreases over time and ultimately, becomes dysfunctional. The results show that out of 12 CDs reported per village, only 6.9 CDs were working. This means that about 40 % of the CDs were not operational. Results also showed that farmer participation in the maintenance of the structures was quite low. Most farmers (72.8 %) reported never doing any activity to maintain the CD whereas 21 % reported doing it only sometimes. In the next sections, the contextual and sociopsychological factors that influence farmers' behavior toward the maintenance of CDs are discussed.

4.4.3.1 Contextual predictors impacting farmer's behavior towards CD maintenance

Table 4.3 shows the results of forced linear regression on contextual (socio-economic and biophysical factors) predictors of farmers' maintenance behavior. The model explains 28 % of the variance. Results show that education, wealth, participation in CD construction, proximity to CD, and direct water use from CD are the significant factors ($p \leq 0.05$) influencing farmers' behavior toward its maintenance. The participation in CD construction is the most influencing factor ($\boldsymbol{\beta} = 0.34$) followed by direct water use ($\boldsymbol{\beta} = 0.17$) and distance from CDs ($\boldsymbol{\beta} = -0.16$). The negative sign for the latter shows that farmer's behavior towards maintenance is negatively correlated with distance from CDs i.e., the larger the distance, the lower the participation in maintenance. Farmers land area ($\boldsymbol{\beta}$ =

0.14), proportion of income from farming (**β** = -0.15) and house type (**β** = 0.09) are significant socioeconomic factors. Farmers with more diversified incomes show more inclination toward maintenance as indicated by the negative sign for the proportion of income from farming in the regression (Table 4.3).

Table 4.3: Results of forced entry regression on contextual factors

	B	**SE B**	β
	R^2 = 0.28		
(Intercept)[a]	0.66	0.32	0.00*
Farmers land area	0.01	0.00	0.14**
Farming experience	0.00	0.00	-0.04
Agriculture income proportion	-0.01	0.00	-0.15***
CDs direct water use	-0.62	0.16	0.17***
Distance from CDs	0.00	0.00	-0.16***
Education	0.10	0.06	0.09
Wealth	0.07	0.04	0.07
Irrigation access	-0.10	0.20	-0.02
Location (Upstream – downstream)	0.07	0.04	0.07
House type	0.12	0.06	0.09*
Participation in CD construction	0.98	0.12	0.34***

[a] The point where the function crosses the y-axis.

*p ≤0.05, **p ≤ 0.01, ***p ≤ 0.001

[#] Variance inflation factor (VIF) was estimated to check for multicollinearity. All values were less than threshold of 5.

4.4.3.2 Sociopsychological predictors impacting farmers' behavior towards CD maintenance

Hierarchical regression was performed after incorporating important (significant) contextual factors identified in the forced regression in the first step and RANAS sociopsychological factors in the second step. The addition of sociopsychological factors increased the percentage of variance of the outcome variable explained by the model to 53 % (Table 4.4). The attitude towards effort (instrumental belief) and attention to the state of maintenance of CDs (self-regulation) are the only two sociopsychological factors that influence farmers' behavior towards the maintenance of CDs. Attitude (**β** = 0.34) and self-regulation (**β** = 0.23) were more influencing than the contextual factors. All other RANAS sociopsychological factors (Table 4.2) including farmers' risk perception, social norm, attitude towards CD benefits, and ability factors were found to be insignificant towards influencing farmers' behavior of maintaining CDs.

Table 4.4: Results of Hierarchical Regression with Contextual (model 1) and Sociopsychological factors (model 2) for farmers behavior towards CD maintenance

	Beta (B)	**Standard error (B)**	**Standardized beta (β)**
		Model 1 (R^2=0.26)	
(Intercept)[a]	0.90	0.22	0.00***
Farmers land area	0.01	0.00	0.15***
Agriculture income proportion	0.00	0.00	-0.15***
Direct water use from CDs	-0.73	0.16	0.20***
Distance from CDs	0.00	0.00	-0.17***
House type	0.20	0.06	0.14***
Participation in CD construction	0.99	0.12	0.34***

	Beta (B)	Standard error (B)	Standardized beta (β)
	Model 2 (R^2=0.53)		
(Intercept)	-0.24	0.22	0.00
Farmers land area	0.00	0.00	0.08*
Agriculture income proportion	0.00	0.00	-0.01
Direct water use from CDs	-0.40	0.14	0.11**
Distance from CDs	0.00	0.00	-0.09*
House type	0.14	0.05	0.10**
Participation in CD construction	0.55	0.11	0.19***
Perceived risk: GW depletion	-0.02	0.03	-0.03
Perceived risk: Drought	0.04	0.03	0.06
Perceived severity: Drought	0.05	0.03	0.06
Perceived severity: GW depletion	0.03	0.03	0.03
Descriptive norm (Others Behavior)	0.02	0.03	0.03
Injunctive norm (Others’	0.07	0.04	0.08
NGO’s opinion	-0.04	0.03	-0.04
Ability: Maintenance self-efficacy	-0.03	0.05	-0.03
Ability: Govt	0.04	0.04	0.05
Attitude effort (Instrumental belief)	0.29	0.04	0.34***
Attitude: Benefit dry year	-0.01	0.03	-0.02
Attitude: Benefit normal year	-0.04	0.05	-0.06
Attitude: Benefit wet year	-0.04	0.03	-0.07
CD attention (Action control)	0.18	0.04	0.23***
CD plan (Action planning)	0.07	0.05	0.06

[a] The point where the function crosses the y-axis.

*$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$

[#] Variance inflation factor (VIF) was estimated to check for multicollinearity. All values were less than threshold of 5.

4.5 Discussion

4.5.1 Check dam benefits

4.5.1.1 Drought impact mitigation

The results show that the main perceived benefits of CDs are enhanced water availability and reliability that helps farmers to expand their crop and irrigated area (Figure 4.2 and 4.3). However, these benefits are mostly accrued in wet years and are least in dry years (Figure 4.3a) when irrigation demand is the highest. This is due to limited rainfall and runoff in the dry years that limits inflows to the CDs (Alam et al., 2022b; Mozzi et al., 2021). Thus, the duration of water availability in CDs decreases from 8 months in wet years to only 3 months in dry years (Figure 4.3b). It is intuitive that most farmers do not perceive a CD as an intervention that directly mitigates the impacts of drought (Figure 4.2a and 2b). However, ~ 30 % of the farmers do report high or very high benefits even in dry years (Figure 4.3a). This shows that the presence of CDs does add, though little, to drought adaptation if compared to the villages with no CDs.

These results corroborate with the findings of water balance study in the catchment that showed that recharge from CDs was insignificant in dry years and crop demands remained unmet (Alam et al., 2022b). This is because in semi-arid regions with shallow basaltic hard rock aquifers having little primary porosity, CDs or water storage structures have limited capacity to recharge aquifers sufficiently to mitigate the impact of droughts (Kumar et al., 2008; Kumar and Perry, 2018; Enfors et al., 2008; Ogilive et al., 2016; 2019; Alam et al., 2022b). Similar conclusions have been drawn by for example, Enfors et al., (2008) and Ogilive et al. (2016; 2019) who assessed RWHs in Tanzania (locally termed Ndiva system) and Tunisia respectively. The authors showed that the low storage capacity of small reservoirs, often the case of RWH systems, limited their capacity to augment surface water supplies or recharge groundwater sufficiently to provide reliable irrigation supply and did not lead to significant increases in farmers' capacity to cope with droughts. Thus, in the situation of limited possibilities to increase water availability especially during dry years, these efforts need to be strengthened in tandem with other drought management strategies such as crop diversification, agriculture insurance, off-farm income and drought tolerant crops and varieties.

The results show that rather than drought mitigation, the main benefits of CDs are accrued in good rainfall years where additional water availability makes irrigation more reliable. This helps mitigate the impact of short dry spells and leads to increased crop cultivation in the post-monsoon dry season. This is in line with the hypothesis and results by Shah et al. (2009) for the study region and by Ogilive et al., (2019) in Northeast Brazil. This emphasises that small storage RWHs are more suitable to support supplemental irrigation and cannot be expected to sustain widespread intensive irrigation (Ogilive et al., 2016; 2019).

In certain situations, carryover benefits of CDs from good rainfall years to dry years may enhance RWHs capacity to mitigate water scarcity in dry years (Garg et al., 2020; Singh et al., 2021). This may happen in the case of RWHs with relatively larger storage capacity, enabling farmers to capture more and store longer (Ogilive et al., 2016; 2019). Additionally, in places where cropping and irrigation intensity is limited, recharged water in wet years may remain available for irrigation in dry years (Garg et al., 2020; Singh et al., 2021). For example, a study by Garg et al. (2020) in semi-arid central India showed that even in dry years with negligible runoff, groundwater storage (measured by the number of wells going dry) was much higher (low number of wells going dry) in the watershed with RWHs compared to control watersheds. Singh et al., (2021) in the same region showed that recharge in wet years can sustain for two years.

However, as observed by Alam et al. (2022b), in an intensively irrigated area like the one studied here where groundwater storage in shallow aquifers is mostly depleted by year end, any such carryover impact is less likely. This was also the finding of Enfors et al. (2008) who did not find any carryover effect from preceding seasons in Tanzania as the irrigation systems were substantially overused.

4.5.1.2 Equity of benefits

Previous studies focusing on CD benefits largely focused on regional or watershed scales relying on assessing the dynamics of groundwater levels and rainfall (Patel et al., 2020; Shah et al., 2009). This ignores the equitability of the distribution of benefits within the population. The results show that despite the high density of CDs in the region, 40 % of the farmers still reported no benefits from CDs. This percentage was higher (~ 50 %) when asked about specific benefits for the main crops grown. This is similar to the results from Shah (2001) who estimated that ~ 80 % of households in the villages where CDs were built did not benefit from CDs.

Also, a decrease in benefits with distance from CDs (section 4.2.1) reflects an inequitable distribution of benefits skewed towards farmers nearest to the streams where the structures are constructed. This skewed distribution was also reflected in a study by Shah et al. (2021) in Maharashtra where farmers' responses showed that benefits of lowland stream-course work (e.g., check dams) remained concentrated in nearby areas and were not achieved when located far away from CDs in upland areas. Deora and Nanore (2019) studying RWH systems in Maharashtra, India also showed that recharge structures' benefits on streams are limited to agriculture fields that are downstream and close to the streams, leaving a large portion of agriculture area with no benefits.

This skewed distribution of benefits is more pronounced in watershed development projects. A high proportion of works in watershed projects are concentrated on hard adaptation options such as water harvesting structures, which are also more costly structures relative to other watershed works (e.g., in-situ soil moisture conservation, land area treatment) (Shah et al., 2021; Sharma, 2007; Shah, 2001; Singh, 2018). Thus, a large proportion of project budgets may go on to benefit a small proportion of farmers. Hence, there is need for a more holistic and balanced approach, acknowledging biases towards RWHs in projects and emphasising adoption of a wider suite of area-based practices focusing on in-situ conservation (e.g., forestry, contour bunds, trenches) available for implementation. This will encourage more equitable distribution of benefits.

Additional concerns are that water harvesting and recharge interventions may benefit relatively influential and richer farmers who have the financial capacity to invest in irrigation infrastructures and other agronomy investments (Bouma et al., 2011; Calder et al., 2008; Shah et al., 2021). While our results do not find any significant correlation of reported benefits with land size, this does not exclude other socio-economic and political characteristics that wield social power and may skew benefits. For example, the distribution of land in villages is not random and land acquisition and settlement over time leads to marginalized communities occupying less favorable lands (low fertility, limited water) (Sharma et al., 2008; Shah et al., 2021). Thus, inequitable distribution of lands and groundwater rights bundled with land ownership (Sharma, 2007) may mean that landless or marginalized communities located away from drainage lines do not benefit from these interventions. More research is needed in the region to unravel this phenomenon.

4.5.2 Sustainability of investments

With a high proportion of project budgets allocated to hard adaptation measures such as CDs, it is critical to ensure their sustainability. This requires regular maintenance and desiltation to assure their structural integrity and optimum functioning. However, the sustainability of RWH structures after the withdrawal of project support has remained a challenge (Sharma, 2007; Singh, 2018; Deora and Nanore, 2019). Results also show that already 40 % of CDs are not working. This seems to arise from the ageing of these structures (40 % of CDs are over 20 years old) and lack of maintenance with 72.8 % of farmers reported no activity to maintain the CDs. The average life span of CDs (masonry ones) is expected to be ~ 20 years (Lee et al., 2022) but is dependent on regular maintenance. Dysfunctional CDs and limited construction of new CDs, threaten the long-term benefits that could be accrued from these investments. Yet the limited involvement of farmers in maintenance and neglect of infrastructure is not uncommon (Deora and Nanore, 2019; Agoramoorthy et al., 2009).

The regression analysis shows that the participation of farmers during the construction of CDs is a key determinant of farmers' behavior towards maintenance. Public participation as a key indicator of post project success has been well established in previous research and plays a key role in watershed program guidelines (Sharda et al., 2005; Sharma, 2007; Joshi et al., 2008; Deora and Nanore, 2019; Singh, 2018). Thus, low maintenance of structures by farmers aligns well with results that also show limited participation of farmers (~ 92 % did not participate in any way) during the construction of CDs. While many of the CDs are old, the results show that ~ 77 % of sampled farmers were >18 years old at the time CDs (ones nearest to them) were built. This is despite the participatory nature of government schemes where farmers were expected to contribute ~ 40 % of CD costs. Mudrakartha (2012) reflects that this largely happened because local contractors secured the work in the names of local farmers (subsidising the farmers contribution) and made profit. This also led to the weakening of the participatory nature of the programme where farmers viewed these structures as government structures and lost the sense of ownership (Mudrakartha, 2012). This heterogeneity in the implementation process and dynamics may explain variation in maintenance of CDs.

The significance of socio-economic factors including wealth (land area, house type) may indicate that CD maintenance is effortful and an expensive task that may be difficult for individual farmers to carry out. This is also highlighted by the fact the farmers with more diversified income have more tendency to maintain (Table 4.4). This could be because farmers with more diversified income can allocate a higher share of their total income to tasks requiring financial commitments such as CD maintenance. Other studies have also shown that a more diversified income is linked to higher adoption of new farm technologies such as drip irrigation (Nair and Thomas, 2022). To overcome the financial barrier, research has highlighted the role that community institutions such as farmers' groups can play in ensuring the sustainability of such investments (Singh, 2018, Agoramoorthy et al., 2009). While the survey data analysed here did not elicit any information on the existence of such groups in the region, none of the farmers reported being part of a farmers group in response to the question on "plan to maintain check dams." Other significant contextual (biophysical) factors include direct use of water from CDs and distance from CDs which are related to the benefits arising from CDs.

Limited community participation and non-existent farmer groups calls for a stronger emphasis and monitoring of post project exit protocols as already outlined in guidelines for watershed programs in India (DoLR, 2021; NRAA, 2011). This includes the formation of watershed committees and creation of watershed development funds for future maintenance, and its convergence with other development programs to pool resources for major repairs and maintenance (Sharda et al., 2005; Joshi et al., 2008).

In terms of sociopsychological factors, only instrumental belief towards the efforts that it takes to maintain CD and self-regulation (action control) reflecting attention paid by farmers towards CD state of repair comes out to be significant factors influencing the behaviour of farmers towards its maintenance. In terms of effort, the results are counter-intuitive because farmers that perceive CD maintenance as more effortful show higher participation in its maintenance. This is similar to what Stocker and Mosler (2015) found where the perceived increase in the effort was related to a stronger habit of cleaning with soap and water. This could be because of the reverse effect, where farmers who regularly contribute towards CD maintenance are more aware of how effortful the task of maintaining a CD is. Behavioral change techniques such as communication and visualization of CD state of repair and a more systematic recording of the maintenance behavior (increasing self-regulation) can lead to more farmers contributing to its maintenance. The formation of farmers groups can bring down the effort (perception associated with it) required for the maintenance of CDs.

4.5.3 Unintended consequences: Human-water dynamics

Annual crop area and irrigation data shows that cotton (main kharif irrigated crop in the region) area has increased by ~ 124 % in the years following 2002 (the period also coincides with accelerated construction of CDs) and the irrigation coverage has increased from 64.2 % to 85.4 % (DoA, 2021; Alam et al., 2022b). This translated to higher demand and in the case of limited increase in supply, as is the case for dry years, increased supply-demand deficits. This potentially led to higher vulnerability to droughts (Alam et al., 2022b). This study provides an indirect link between the increase in irrigation demand and increased (perception of) supply. The results show that the primary benefit to crops reported by farmers includes increased (perceived) availability of irrigation followed by a small set of farmers also reporting an increase in cropped area (Figure 4.3a and 3b). In the region where crop production is limited by water availability (especially in the post-monsoon season), this increased supply (and its reliability) of irrigation water directly links to increased intensity of irrigation in both pre and post monsoon seasons (leading to increased yields). This to an extent has led to increased cultivation of post monsoon crops which are completely dependent on water. Earlier research in the region (Shah, 2001) has also shown that additional water availability has led to an increased overall irrigated area under more water-intensive cotton crops. Studies in other semi-arid regions have also found that farmers have increased their cropping intensity and crop diversification in agriculture farms that were near such RWH structures (Deora and Nanore, 2019).

This shows the existence of supply-demand feedbacks where increased supply (from RWH or another supply measure) leads to more demand, offsetting the benefits from the increased supply (Glendenning et al., 2012; Scott et al., 2014 Di Baldassarre et al, 2018). The increase in demand, associated with increased irrigation and cropping intensity may lead to greater shocks in dry years when water availability remains low and CDs are less effective. However, the argument can be made that the additional benefits accrued from increased production in normal and wet years supported by CDs outweighs the losses in dry years. Additionally, there is a risk that farmers may acquire deep borewells, tapping deeper aquifers, to continue supporting increased irrigation (area) of good rainfall years. Survey results showed (not given in results) that already 25 % of farmers own deep borewells in addition to dug wells. Thus, to ensure the long-term sustainability of the systems, there is a need to supplement supply interventions with greater emphasis on water demand management interventions (e.g., more efficient irrigation, less water-intensive crops, improved water management practices) and groundwater governance. This is often lacking in such programs (Singh, 2018) and is reflected in our survey where only ~ 10 % of farmers reported using drip irrigation for irrigation.

Overall, this reflects two-way feedback that is endemic to human-water systems where both human and water systems feedback to each other and co-evolve. For example, Ribeiro Neto et al. (2022) showed how small man-made reservoirs in Northeast Brazil, made by the local population as a coping mechanism to drought, induce and modify drought events. These unintended consequences are necessarily not always negative. For example, Enfors et al. (2008) found that while RWHs in Tanzania did not directly change the coping capacity to drought but it incentivized nearby farmers to have better farmland management practices with more investment in nutrient management and soil conservation.

There is an inherent need to model these two-way human-water system feedbacks to understand and predict the impacts of RWH systems, without which investments can exacerbate and reinforce current inequalities and lead to long-term natural resource degradation. More recent interdisciplinary approaches such as sociohydrology can help to understand and disentangle the dynamics and help better plan these RWHs (Sivapalan et al., 2012; Pande and Sivapalan, 2017).

4.5.4 Recommendations

The findings of the study call for a more nuanced and site-specific approach towards the implementation of RWHs for effective, equitable, and sustainable implementation outcomes. First, there is a need for clear communication and realistic assessment and expectation of the potential benefits of RWHs. This is especially so for semi-arid regions with intensively irrigated areas and hard rock aquifers having little primary porosity, where drought mitigation potential of CDs remains limited. Second, the implementation of CDs should be complemented by greater emphasis on other drought management strategies (e.g., demand management, insurance, off-farm income). The special focus should be on water demand management for more effective use of stored/recharged water and to avoid unintended consequences of supply-demand feedbacks. Third, equitability concerns regarding the distribution of the benefits (spatially and among socio-economic groups) should be evaluated. For a more equitable distribution of benefits, a holistic suit of interventions should be implemented with equal emphasis on a wider suite of area-based practices focusing on in-situ conservation (e.g., forestry, contour bunds, trenches). Finally, to ensure the sustainability of projects through the maintenance of such structures, the participation of farmers (beyond consultations) should be encouraged to build a sense of ownership, and post-project exit protocols (forming water user groups, maintenance funds) should be strictly adhered to. Behavioral change techniques (communication, visualisation of the state of CDs) can assist in raising the awareness of farmers and make them more responsible towards maintenance.

4.6 Conclusion

RWHs through various interventions (including CDs) are increasingly being promoted and adopted as an adaptation measure to build resilience to cope with dry spells and droughts, especially in arid and semi-arid regions of the world. This study analysed the perception of the farmers' about the benefits of CDs, the equitability of such benefits, and the sustainability of CDs in the semi-arid Saurashtra region of Gujarat, India, where CDs have been extensively implemented for more than 30 years. The results of the study showed that the key perceived benefit of CDs is increased water availability for irrigation that is realised through increased groundwater levels and longer availability of water in wells. This helps farmers to achieve more yield and increase area under crops. However the benefits are mostly accrued in wet years, followed by normal years and least in dry years. CDs are therefore not perceived as a drought mitigating interventions. This is due to low runoff in dry years limiting the water inflow to the CDs and underlying hard rock aquifers having limited inter-annual carry over capacity. Also, the benefits of CDs are inequitably distributed and are concentrated to farmers who are near to the streams where CDs are built. Overall ~ 40-50 % of farmers reported accruing no benefits from CDs despite the high density of CDs. The results also reported that ~ 40 % of total CDs are not functional and most of the farmers (72.8 %) do not participate in any maintenance activity. The regression analysis showed that both contextual (e.g., participation during CD construction, farmers' land area) and sociopsychological factors (e.g., attitude towards CDs, attention they pay to the CDs condition) significantly influenced the behaviour of farmers. The perception of an increase in water supply from CDs, as seen in good rainfall years, may lead to increased irrigation and cropping intensity which increase the risk of greater shocks in dry years (when increase in water availability is limited). This could be worsened by the lack of maintenance of CDs and over the long-term may lead to unsustainable solution of overexploitation of deeper aquifers with more farmers drilling deep groundwater wells. The study therefore calls for a more holistic implementation of drought mitigating measures with balanced implementation of supply enhancing and demand management interventions.

5. Subsidies alone are not enough to increase adoption of agricultural water management interventions[5]

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5.1 Introduction

Agriculture with a strong dependence on weather is highly vulnerable to climate change (FAO, 2021; Sikka et al., 2022). With changing climate intensifying hydroclimatic extremes of floods and drought, adaptation in agriculture is extremely important (United Nations, 2019; IPCC 2022). Without adaptation, agricultural yields could decrease by 30% by 2050, impacting livelihoods and food security, especially in less developed countries where smallholder farmers have limited capacity to adapt (GCA and WRI, 2019). Given the centrality of water in climate change adaptation efforts, climate smart agriculture water management is critical to building water resilience and adapting to climate change (Sikka et al., 2022). The efficacy and benefits of a range of climate smart agriculture water interventions for adaptation have been widely reported and established (Evans and Giordano, 2012; Alam et al., 2021; Sikka et al., 2022).

The successful scaling of these interventions is needed to achieve transformational and visible impacts in building climate change adaptation (Sikka et al., 2022; Aggarval et al., 2018). However, the widespread adoption of agricultural water management interventions and technologies has been slow and limited (Shiferaw et al., 2009; Palanisami et al., 2015; Alam et al., 2021). Multiple studies over time and in different contexts have evaluated the factors influencing the uptake of different adaptation strategies and technologies in agriculture (Balasubramanya et al.,2023; Pathak et al., 2019; Palanisami et al., 2011; Reddy, 2016). Several factors including socio-economic (e.g., land size, experience), biophysical (e.g., soil), technology (e.g., cost, availability), and institutional (e.g., capacity building, subsidies) have been identified (Pathak et al., 2019; Nair and Thomas, 2022; Balasubramanya et al., 2023).

However, psychological factors have been often overlooked in many studies (Nair and Thomas, 2022; Balasubramanya et al., 2023; Namara et al., 2007). This is a gap as several studies have shown that psychological factors significantly influence the adoption of interventions (Alam et al., 2022a; Daniel et al., 2020; Hatch et al., 2022). For instance, farmers' perceived behavioral control, belief about cost and benefits, and risk perception have been shown to significantly influence their adoption decisions (Arunrat et al., 2017; Yazdanpanah et al., 2014; Alam et al., 2022a,b). Thus, neglecting psychological factors can lead to a lack of understanding of why some farmers adopt interventions while others do not, despite similar socio-economic and environmental conditions.

Several behavioral theories, grounded in social science, exist to evaluate the influence of psychological factors on farmers' adoption behaviors (Schlüter et al., 2017; An, 2012; Alam et al., 2022b). The risk, Attitude, Norms, Abilities, and Self-regulation (RANAS) model (Mosler, 2012) is one among them. The RANAS model assumes that multiple socio-psychological factors (i.e., risk, attitude, norm, ability, and self-regulation) impact behavioral outcomes (i.e., behavior, intention, use, and habit). Although initially developed for the WASH sector, the RANAS model is being increasingly used to understand farmer irrigation behavior or adoption of water management interventions (Alam et al., 2022a; Hatch et al., 2022; Klessens et al., 2022; Daniel et al., 2020; Stockler and Mosler, 2015). RANAS's strength is that it combines important socio-psychological factors from other important behavioral theories, can be adapted for a range of behaviors, and provides a systematic approach with a standardized questionnaire (Callejas Moncaleano et al., 2021).

This study, using the RANAS behavioral model, examines the factors that influence the adoption of agricultural water interventions in a semi-arid region (Saurashtra) in India. Specifically, adoption of two dominant and contrasting agricultural water interventions in the region: drip irrigation and borewells are analyzed. Drip irrigation, increasing efficiency of on farm water application, is a demand management strategy and is extensively promoted by the government with enabling policies and subsidies (Sikka et al., 2022; Nair and Thomas, 2022). While micro irrigation generally consists of both drip and sprinkler irrigation, in the studied region, drip irrigation is the dominant form, and therefore, we have used the terms "drip" and "micro irrigation" interchangeably in the paper. On the other hand, drilling borewells to tap deeper aquifers is a supply-augmenting intervention that farmers adopt in response to the drying of wells or depletion of aquifers (Patil et al., 2019; Kattumuri et al., 2017). Access to groundwater has played a crucial role in expanding irrigation and production globally, especially in South Asia (Mukherji, 2020) and now increasingly in Africa (Cobbing and Hiller, 2019). However, over time, this has led to the depletion of aquifers (Mukherji, 2020).

This paper evaluates the factors that govern the adoption of drip irrigation and borewells in the Saurashtra region. The findings of this study provide insights into the key factors that need to be addressed to promote the adoption of water interventions among farmers. It informs the development of effective policies and programs to improve water management in the region and elsewhere.

5.2 Study area

The study area is the Kamadhiya catchment located in the Saurashtra region of Gujarat state in India (Figure 5.1a). The region is characterized by a semi-arid climate, low rainfall (average of 638 mm year−1 (1983–2015)) with high evaporation and high-water demand. There is large intra- and inter-year rainfall variability that impacts the agriculture in the region, which covers ~70 % of the catchment area (Alam et al., 2022c). More than 90% of the rainfall is concentrated in the four monsoon months of June to September (Pai et al., 2014). The main crops grown in the region are cotton and groundnut during the Kharif season (the monsoon season, starting in June and ending in October) and chickpea and wheat during the Rabi season (the post-monsoon season, starting in November and ending in February/March). The lack of water during the post-monsoon season limits crop intensity (Alam et al., 2022c).

Groundwater is the main source of irrigation in the region, covering ~82 % of the irrigated area. Aquifers of the region are represented by parent basalt rocks of the deccan trap with low primary porosity and hydraulic conductivity (Mohapatra, 2013; Kulkarni et al., 2000). The storage of these aquifers is primarily limited to water-bearing zones mostly confined to upper shallow (15 – 30 m) weathered and fractured zones of hard rock (Mohapatra, 2013; Kulkarni et al., 2000). Groundwater from the top 15–30 m of weathered upper parts is tapped by open large diameter (4-8 m) dug wells usually 15-30 m deep (Mohapatra, 2013, Kulkarni et al., 2000). The groundwater availability in upper weathered zone remains limited in the post-monsoon season and is mostly depleted by the end of the year because of the limited extent and storage of aquifers (Alam et al., 2022c; Foster, 2012) thus limiting cultivated area in post monsoon seasons (Alam et al., 2022c). Groundwater availability in deeper aquifers is limited and dependent on nature and the degree of vertical and horizontal joints and fractures (Kulkarni et al., 2000; Foster, 2012). The deeper aquifer is tapped by deep (~ 100 – 300 m) borewells.

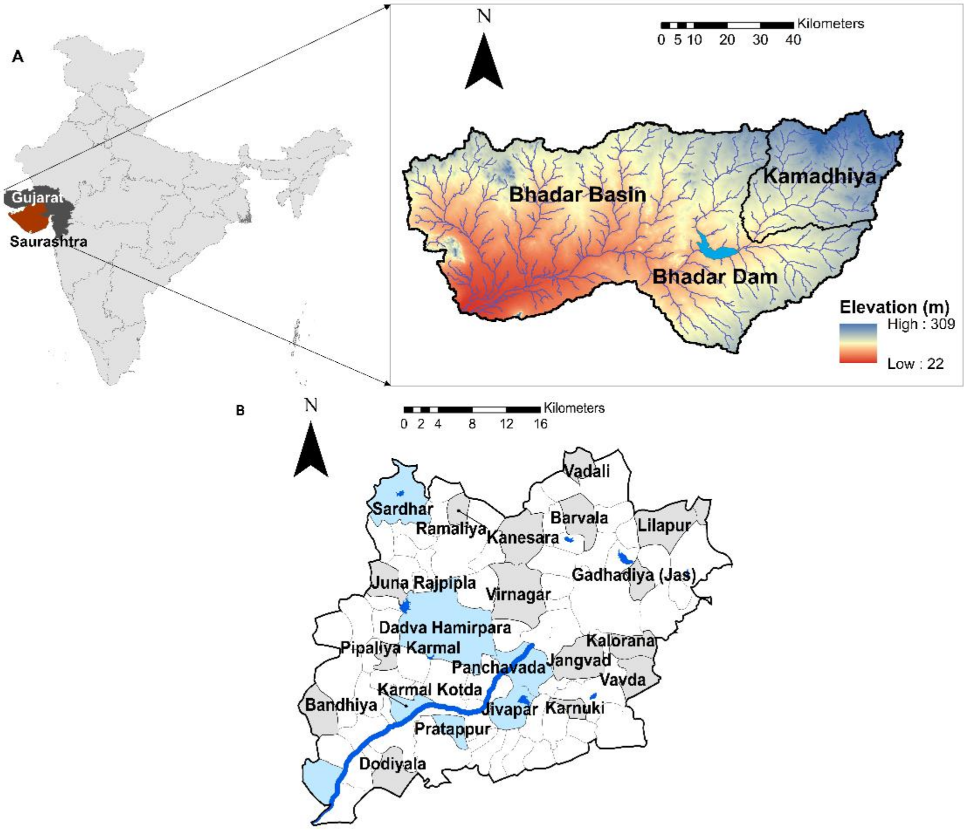


Figure 5.1: (A) Location of Kamdhiya catchment, Bhadar basin, Saurashtra region and Gujarat state in India, (B) Sampled villages for household survey in Kamadhiya catchment. In light blue color are the villages that lie downstream of dams (shown in dark blue) or near to the main stem of the river (stream order > = 4).

5.2.1 Agricultural water management interventions in the region

The vulnerability of the agriculture sector is high in India with large part of the country under arid and semi-arid climate and half of the cropped area being rainfed (Sikka et al., 2022; Alam et al., 2021). Saurashtra region with low and highly variable rainfall faces frequent droughts and associated production losses (Alam et al., 2022c). Governmental and non-governmental organizations have been promoting a range of interventions in the area to mitigate the impact of short and unpredictable monsoons. The key interventions in the region include supply augmentation through check dams, which are community water harvesting structures largely built on common land through state resources (Alam et al., 2022a) and increasing the efficiency of water use through drip irrigation (Namara et al., 2007; GGRC, 2023). The impact of check dams and farmers' perception on check dams has been evaluated earlier (Alam et al., 2022a, c). On other hand, field visits have shown that farmers increasingly are drilling deeper borewells to supplement water from shallow dugwells.

5.2.1.1 Drip irrigation

Drip irrigation involves applying water and nutrients directly to the crop root zone. Multiple studies have evaluated the benefits of drip irrigation, which includes water savings, yield enhancement, labor savings, efficient fertilizer use, and reduced weed and pest infestation among others (Palanisami et al., 2011; Namara et al., 2007; Singh, 2013; Reddy 2016). In India, the government has been running capital subsidy programs for more than a decade to increase the adoption of micro-irrigation (including drip), starting with the national mission on micro-irrigation and currently continuing with Pradhan Mantri Krishi Sinchai Yojana (PMKSY - Prime minister Farm Irrigation scheme) (Nair and Thomas, 2022; DAC&FW, 2017). Additionally, non-governmental organizations have also invested (funds, knowledge transfer, training) to increase the uptake of micro-irrigation (Panda, 2003). In the region, Gujarat state government has set up a special purpose vehicle, Gujarat Green Revolution Company (GGRC) limited in 2004–05, to expand the area under micro irrigation in the state (GGRC, 2023). A subsidy of 50 % is provided (limited to ~ $ 750/per hectare) with an additional subsidy of 25 % for tribal and scheduled caste farmers (GGRC, 2023).

However, despite being subsidized and with widely reported benefits, multiple studies over time have shown that the adoption of micro-irrigation has remained low (Palanisami et al., 2011; Namara et al., 2007; Nair and Thomas, 2022). The micro-irrigation has been adopted in less than 15 % of the potential area in India (Suresh and Samuel, 2020). The question then becomes why?

5.2.1.2 Borewells

Borewells are narrow, deep wells drilled into the ground using a tube (Steinhübel et al., 2020) to tap deeper aquifers (~ 100 – 300 m), in contrast to large diameter shallow (~ 15-30 m) dug wells. Although dugwells remain the primary source of irrigation, farmers in the study region have increasingly been using borewells to supplement their shallow dugwells. Unlike drip irrigation, borewell drilling in the region is not supported by government subsidies but is being taken up by farmers as a supply augmentation strategy (Mudrakartha, 2012; Kulkarni et al., 2000).

Farmers drill borewells to hedge against production risks associated with low rainfall years, particularly during the dry seasons after the monsoon when the shallow weathered aquifer (15-30 m) in the region dries out (Steinhübel et al., 2020). The drilling of borewells or digging deeper wells as an adaptation strategy in response to droughts or declining groundwater levels has been observed in other parts of the country as well (Jain et al., 2015; Singh et al., 2018;

van Steenbergen, 2006; Steinhübel et al., 2020; Mudrakartha., 2007). However, the hard rock aquifers of the region are characterized by low primary porosity and a heterogeneous and low-density fracture network thus leading to high borewell drilling failure rates (Robert et al., 2018; Foster, 2012). Even if borewells are successfully drilled, their yields are low and can only supplement the water supply from dug wells.

5.3 Methodology

5.3.1 Household survey

The primary data were collected through a household surveys in December 2021. A total of 492 farmers were interviewed across 24 villages (20-22 farmers in each village) in the Kamadhiya catchment (Figure 5.1b). More information on survey sampling and procedures can be found in Alam et al. (2022a). The farmers were stratified into four groups: marginal (<1 ha), small (1 -2 ha), medium (2-4 ha) and large farmers (>4 ha) based on farmers' land area in the administrative blocks where villages are located. The structured interviews, translated into the local language (Gujarati), lasted approximately 45-50 minutes and were carried out by a trained team of 10 enumerators native to the region.

5.3.2 Questionnaire

The structured survey questionnaire consisted of two parts, 1) farmers' socio-economic factors and 2) farmers' perception of drip irrigation and borewells and RANAS related questions regarding the adoption of the irrigation technologies. Farmer socio-economic data included information on farmer's age, gender, number of household members, farming experience, area of land owned, main income sources, livestock, house type, and ownership of material assets (e.g., TV, scooter, car). In addition, data on farmers' cropping practices were also collected.

The questions on drip irrigation and borewells consisted of a mix of informative questions (e.g., cost, subsidy, benefits) and farmers' perceptions about the benefits of each. Questions on RANAS sociopsychological factors (i.e., R-risk, A-attitude, N-norm, A-ability, and S-self-regulation) towards the adoption of drip and bore wells were measured with two to four questions on a five-point Likert scale (Table C.1). Risk factors represent a person's understanding and awareness of the health risk; Attitude factors represent a person's positive or negative stance towards a behavior; Norm factors represent the perceived social pressure towards a behavior; Ability factors represent a person's confidence in her or his ability to practice a behavior and self-regulation factors represent a person's attempts to plan and self-monitor behavior and to manage conflicting goals and distracting cues (Mosler, 2012).

5.3.3 Data analysis

A descriptive analysis is carried out to understand farmers' socioeconomic profile in the region and their perception of the benefits and impacts of drip irrigation and borewells. This is followed by a binary logistic regression analysis to understand the main determinants of farmers' behavior toward the adoption of drip irrigation and borewells. Separate logistic regression is carried out for both drip and borewells considering their contrasting roles and assuming that adoption of one technology does not necessarily influence adoption of the other. This is supported by field observations indicating farmers consider them as individual technologies catering to separate goals.

Binary logistic regression is a statistical method that estimates the probability of one of two possible outcomes, based on a set of predictor variables and is appropriate when the dependent variable has only two outcomes (e.g., such as yes/no or adopters/non-adopters) (Tranmer and Elliot, 2008; Harris, 2021). To account for variations in village size, sampling weights (farmers interviewed in each village divided by the village population) were derived and used in the analysis. The effects (coefficients) estimated by a logistic regression are interpreted as changes in the log-odds of the outcome variable for one-unit change in the predictor variables, with other variables held constant. A positive and significant coefficient indicates an increased likelihood of the outcome, while a negative and significant coefficient indicates a decreased likelihood. The magnitude of the coefficient indicates the strength of the association (Tranmer and Elliot, 2008; Harris, 2021). Binary logistic regression has been used widely across fields and in a range of studies to evaluate the adoption of water management technologies (Patil et al., 2019; Raut et al., 2021; Yifru et al., 2022; Singh, 2013; Namara et al., 2007).

5.3.4 Definition and Selection of variables

The dependent variable was whether a farmer has adopted drip irrigation (or borewells) or not. A value of 1 was assigned to all the farmers who use drip irrigation and 0 to those who use other irrigation methods. The use of sprinkler irrigation was negligible in the area. For borewells, a value of 1 was assigned to all the farmers who have installed a borewell in addition to dugwell(s) and 0 to those who only have dugwells. The farmers that only had borewells as their primary source of irrigation were excluded from the logistic regression of borewell adoption.

The selection of explanatory variables, in addition to RANAS psychological variables, was done based on previous studies that have shown that the adoption of practices is influenced by a range of socio-economic factors including farmers' economic, social, and demographic factors (Yifru et al., 2022; Nair and Thomas, 2022; Namara et al., 2007). This included farmer owned land, age, farming experience, education, income from agriculture and wealth (defined by ownership of assets). Additionally, based on field visit observations, number of livestock, distance from check dam and proximity to river or dams (Shown in Figure 5.1B) were identified as important factors and were added. The location of the administrative block in which farmers are located was added to account for other unobserved factors. A multi-collinearity analysis was carried out among the socioeconomic variables and any variables with a high degree of correlations (threshold of 0.6) were removed. Final socioeconomic and biophysical variables retained for the binary logistic regression are presented in Table 5.1.

Table 5.1: Description and summary statistics (mean and percentage) of the variables used in the binary logistics model. T-test and chi-square tests are done to assess if the differences between adopters and non-adopters are significant. Superscript s represents a significant difference ($p < 0.05$) of mean or proportion between adopters and non-adopters.

Variable	Description	Adopters	Non-adopters	Adopters	Non-adopters
		Drip		Borewell	
Dependent variable					
Drip/borewell adoption	Have adopted drip irrigation/borewell (count)	79	399	122	286
Psychological variables (RANAS) (mean)					
Risk (Perceived	Farmers' perception of risk (drought, groundwater)?	1.78^{s}	2.03^{s}	1.79	2.04
Risk (Perceived	Impact of drought and groundwater decline on crop production?	2.92	2.83	2.82	2.88
Attitude (Reliability, benefits) *	How beneficial and reliable drip irrigation/borewell is for crop production?	2.94^{s}	2.28^{s}	2.24^{s}	1.75^{s}

Attitude (Time)	How time-consuming is it to get a drip irrigation/borewell set up?	2.19	1.65	2.74 [s]	1.27 [s]
Ability (drip irrigation) *	How confident are you in your financial and knowledge to own, operate and maintain the drip?	2.18[s]	1.47[s]	-	-
Financial ability (borewell)	How confident are/were you in your financial capability to afford the drilling of a BW?	-	-	1.28	1.07
Technical ability (borewell)	How confident are/were you in your capacity/knowledge to install a BW?	-	-	1.75	1.49
Societal norm*	What proportion of people in your village have drip/borewell and people whose opinion you value think having drip /borewell is good?	2.03[s]	1.56 [s]	1.99 [s]	2.18 [s]
Norm (NGOs)	How important are NGOs/government official opinions to you?	1.64	1.47	1.58	1.48
Drip Self-regulation	How much do you pay attention to how much water you use for irrigation?	3.43	2.97	-	-
BW Self-regulation (Action planning)	Do you have the plan to acquire the required personnel and material it takes to drill a borewell?	-	-	1.89	1.05
	Do you have a plan if your borewell does not yield water or stop giving water?	-	-	1.30	1.15
Socio-economic					
Land[a] (Total area cultivated)	Marginal (%)	6.3[s]	17.8[s]	8.3	15.6
	Small (%)	24.1	33.1	28.9	31.6
	Medium (%)	26.6	28.8	29.8	28.7
	Large (%)	43.0[s]	20.3[s]	33.1	24.1
Experience	Years of farming experience	29.8	26.7	27.9	26.88

Education[a] (Years)	No education (%)	17.7	23.8	24.8	22.3
	Primary (%)	36.7	31.3	29.8	33.3
	Secondary (%)	44.3	41.6	40.5	41.8
	Higher (%)	1.3	3.3	5.0	2.5
HH	Number of Household members	5.2	5.5	5.04	5.65
Income	Percent of income coming from	68.2[s]	60.5[s]	65.1	62.62
Livestock	Number of livestock owned by the	2.17[s]	2.82[s]	3.38	2.45
Biophysical					
CD distance	Distance (m) from nearest check dam in meters (mean)	1317.5	1314.4	1449.1	1311.6
Block[a]	Gondal (%)	26.6	21.3	28.9	19.5
	Babra (%)	5.1[s]	14.0[s]	13.2	9.2
	Jasdan (%)	51.9	48.1	43.8	51.4
	Kotda (%)	5.1	9.0	9.1	8.5
	Rajkot (%)	7.6	3.5	4.1	5.0
	Chotila (%)	3.8	4.0	0.8[s]	6.4[s]

*Taking average of individual RANAS questions (Table C.1) before PCA.

[a] Dummy variable.

[b] Wealth derived as score from ownership of assets. Wealth = 1*gas connection + 2*fridge + 2*tv + 2*two-wheeler + 3*ac + 4*car + 1*kuccha house + 2*semi-pucca + 3*pucca

To address multicollinearity caused by RANAS questions measuring common latent variables, principal component analysis (PCA) for factors with three or more questions (Table C.1) was used (Daniel et al., 2020). Detailed results of the PCA and redefined psychological factors for all questions under each RANAS factor are presented in Tables A4.1 and A4.2. For instance, the three questions on perceived ability (financial, knowledge, operate) (Table C.1) to adopt drip irrigation were renamed as "ability" since they all loaded on the first principal component (Table C.2, Table 5.1). Likewise, the five questions related to risk (Table C.1) were renamed as perceived vulnerability and severity, which loaded on the first two principal components, separating risk and impact factors (Table C.2, Table 5.1). Table 5.1 lists the final RANAS factors retained for the binary logistic regression.

5.4 Results and discussion

5.4.1 Descriptive statistics

The average landholding in the catchment was reported to be 2.9 hectares (median = 2.0 hectares). Small farmers (1-2 ha) represented the highest share of sample farmers (31.7 %) followed by medium (2- 4 ha) (27.8%) and large (> 4 ha) (23.4 %) and marginal (< 1 ha) (17.5 %) farmers. More than 60 % of farmers were above the age of 40 and had 8 years or less of schooling. Agricultural income from crop production (99.2 % of farmers) and livestock rearing (71.7 %) were the main sources of income. Further description of socioeconomic statistics can be found in Table 4.2 (chapter 4).

Table 5.2 gives a summary of agriculture and irrigation characteristics in the region. Cotton and groundnut are the main Kharif crops (~ 98 % area) covering 44 % and 54 % of the Kharif cultivated area, respectively. Rabi cultivated area is limited (~ 46 % of Kharif cultivated area), with chickpea (49 %), cumin (24 %), and wheat (15 %) being the main crops. Cultivation is negligible in the area from March to May. Overall ~ 97 % of the farmers reported having access to irrigation, with groundwater (~ 96 %) being the main source of irrigation.

Table 5.2: Agriculture and Irrigation characteristics for the main crops

		Kharif (Jun –		Rabi (Nov – Feb)		
		Cotton	**Groundnut**	**Chick-pea**	**Cumin**	**Wheat**
Season area	Area (%)	44.1	53.9	49.2	24.3	14.9
Irrigation (%)	Always	84	80.0	93.5	100	100
	Never	2	1.4	0.00	0	0
	Only in a dry year	11	13.7	3.7	0	0
	In dry spell	3	4.8	2.8	0	0
Irrigation source sufficiency in dry year (%)	Not	24.5	23.5	19.9	22.5	19.2
	a little	40.1	40.1	41.7	42.3	51.9
	Sufficient	29.9	29.9	31.0	27.0	24.0
	Quite	5.1	5.9	5.6	5.4	4.8
	Very	0.3	0.98	1.9	2.7	0.0
Irrigation method (%)	Flood	8.0	6.7	6.40	7.21	7.4
	Furrow	16.7	46.9	13.8	11.7	14.7
	Drip	10.4	2.7	0.5	0.9	0.0
	Sprinkler	0.3	3.0	1.5	0.0	0.0
	Bed	64.4	40.6	77.8	80.2	77.9
Irrigation schedule (%)	no plan	6.7	7.3	10.2	9.0	6.7
	Crop calendar	0	0	0.0	0.0	0.0
	Moisture probe	3.8	4.4	8.8	4.5	4.8
	Examine soil visual	5.4	5.6	5.6	5.4	2.9
	Irrigate when need	82.5	81.9	68.1	74.8	78.8
	Irrigate every day	1.6	0.7	7.4	6.3	6.7

For the Kharif crops, ~ 80 % of farmers indicated that they irrigate always (every year) whereas ~ 10 % indicated that irrigation is needed only in dry years. On the other hand, almost all farmers indicated that they irrigate their crop always (every year) in the post-monsoon Rabi season reflecting the lack of rainfall. About two-thirds of the farmers indicated that their irrigation source is not sufficient (not sufficient or only a little sufficient) in dry years, which shows limited groundwater storage in the region. Regarding the irrigation schedule, most farmers indicated they irrigated when they felt the need.

5.4.2 Adoption of drip irrigation and borewells

5.4.2.1 Drip irrigation

Overall adoption of drip irrigation is low in the catchment with only 16.5 % of the farmers using drip irrigation systems. The use of drip irrigation is mainly for the cotton crop (10.4 %) followed by small areas under groundnut cultivation (2.7 %) (Table 5.2). This is despite the subsidy program by the government with farmers reporting an average of ~ 50 % subsidy for drip irrigation systems. Also, both cotton and groundnut, dominating the cropping area are cash crops and are suitable for drip irrigation. Studies have shown that adopting drip irrigation has technical and economic benefits, including water savings and increased physical and economic water productivity for both crops (Namara et al., 2017; Singh, 2013). For Rabi crops, the use of drip irrigation remains negligible. Micro irrigation remains less suitable for cereals and pulses (Namara et al., 2017; Singh 2013), which could explain negligible use in the Rabi season. The main irrigation method reported was conventional flood irrigation for all crops except groundnut where both furrow and flood irrigation are used (Table 5.2).

The statistical tests (t-test and chi-square) (Table 5.1) showed that adopters were significantly ($p < 0.05$) wealthier and earned a higher percentage of their income from agriculture. Similarly, adopters' have higher landholdings, with significantly more large farmers being adopters and significantly fewer marginal farmers being non-adopters. With respect to the psychological factors, adopters show significantly higher ability, positive belief about the utility of the drip irrigation technology, and societal norms towards drip irrigation systems.

5.4.2.2 Borewells

In the catchment, 57.3 %, 12.8 %, and 24.6 % of farmers reported owning only a dugwell, a borewell and a borewell in addition to a dug well, respectively. The latter group of farmers who own a borewell in addition to a dugwell (24.6 % of farmers) are referred to as adopters and those who own only a dugwell are referred to as non-adopters.

The average depth of borewells was reported to be ~ 115 meters (ranging from 45 to 300 meters) against the average depth of ~ 20 m for dugwells. This shows that borewells are accessing deeper groundwater. The average age of borewells is ~12 years against ~25 years for dugwells, which shows that the drilling of borewells has started more recently. The drilling of borewells is capital intensive. The average cost of drilling a borewell and associated pump (~ 6 HP) was reported to be ~ 120000 INR (~ 1450 USD). The drilling of borewells was also associated with high failure rates. The farmers who owned a borewell reported drilling on average 2.3 bore wells (range 1-12) to get a successful bore. This was also reflected in farmers' reported reason for not owing a borewell, with 42 % saying that it is too expensive and 35 % saying it is too difficult to drill one. Additionally, 10 % of farmers reported trying for one but not having success.

The main benefits of borewells as reported by farmers, both adopters and non-adopters, was the protection against drought (86 %), followed by an increase in the Rabi (post-monsoon) cropping area (53.3 %). This corroborates observations from the field studies that demonstrate that borewells are primarily adoption measures against low water availability in the dry or post-monsoon season (Birkenholtz, 2009). This is also reflected in the crop data reported by the farmers. On average, borewell owners reported cultivating 53.7 % of their Kharif area in the Rabi season as opposed to 40.9 % by non-adopters.

The statistical tests (t-test and chi-square) showed that adopters were significantly wealthier ($p < 0.05$). However, no significant difference in landholdings between the adopters and non-adopters was found. Also, the adopters have a higher perceived ability and more positive belief toward borewells than non-adopters.

5.4.3 Factors influencing the adoption

Table 5.3 and 5.4 presents the results of binary logistic regression for drip irrigation and borewells, respectively, with two regression models implemented for each technology. Model 1 included both socio-economic and psychological factors, while Model 2 considered only socio-economic factors. The results revealed that incorporating psychological factors improved the model's explanatory power by almost threefold for adopting both drip and borewells.

For drip irrigation (Table 5.3), Model 1 yielded a pseudo-R^2 of 0.31, with an overall accuracy of 88.4% and an area under the ROC Curve (AUC) of 87.1%, indicating satisfactory model performance. In contrast, Model 2 (only socio-economic factors) produced a lower pseudo-R^2 of 0.12, with corresponding reductions in overall accuracy (84.2%) and AUC (75.9%). Similarly, for borewells (Table 5.4), Model 1 generated a pseudo-R^2 of 0.21, with an overall accuracy of 76.9% and an AUC of 78.9%. Model 2 had a lower pseudo-R^2 of 0.07, with corresponding reductions in overall accuracy (69.6%) and AUC (69.7%).

These findings underscore the significance of psychological factors in explaining farmers' adoption decisions, as they influence their attitudes, beliefs, perceptions, and motivations towards new technologies or practices. While previous studies on adoption have often overlooked the role of psychological factors (Nair and Thomas, 2022; Namara et al., 2007), our results demonstrate that considering these factors can facilitate a better understanding of farmers' adoption decisions. This can help extension workers, researchers, and policymakers develop effective strategies to promote the adoption of new technologies among farmers. In the following section, we have discussed results from the model 1 which combines both socio-economic and psychological factors.

Table 5.3: Results of binary logistic regression of farmer's decision to adopt drip irrigation. Model 1 includes both socio-economic and psychological factors, while Model 2 consideres only socio-economic factors.

	Model 1		**Model 2**	
	Estimate	**Odds**	**Estimate**	**Odds**
(Intercept)	-5.26***	0.01	-4.47***	0.01
Experience	0.04**	1.04	0.01	1.01
Higher education#	-2.49**	0.08	-1.42	0.24
Primary education#	0.28	1.32	0.29	1.34
Secondary education#	-0.51	0.60	-0.26	0.77
Income from farming	0.01	1.01	0.01	1.01
Household members	-0.08	0.92	-0.09	0.91
Livestock count	-0.08	0.92	-0.07	0.93
Distance from Check dam	0	1.00	0	1.00
Proximity to dam and river #	-1.64***	0.19	-1.48***	0.23

Wealth	0.15**	1.16	0.24***	1.27
Small farmer#	0.55	1.73	0.88	2.41
Medium farmer#	0.19	1.21	1.01	2.75
Large farmer#	1.07	2.92	1.52**	4.57
Babra block#	-0.96	0.38	-1.21*	0.30
Jasdan block#	-0.22	0.80	-0.25	0.78
Kotda block#	-1.75**	0.17	-1.29*	0.28
Rajkot block#	1.29*	3.63	1.4**	4.06
Chotila block#	-1	0.37	-0.73	0.48
Gondal block#		-	-	-
Ability	0.81***	2.25	-	-
Perceived risk: Vulnerability	-0.75***	0.47	-	-
Perceived risk: Severity	-0.48*	0.62	-	-
Attitude (benefits, reliability)	0.73***	2.08	-	-
Attitude (time)	0.33	1.39	-	-
Society norm	0.29	1.34	-	-
NGO norm	0.19	1.21	-	-
Self-regulation application)	0.29	1.34	-	-
Psedu-R2	0.307		0.116	
Accuracy	88.4%		84.3 %	
AUC	87.1		75.9	

[a] odds ration = exp(estimate)

***, **, * Significant at < = 1%, 5%, and 10% probability level, respectively

* All VIF < 10

dummy variable

Table 5.4: Results of binary logistic regression of farmer's decision to adopt drip irrigation. Model 1 includes both socio-economic and psychological factors, while Model 2 considered only socio-economic factors.

	Model 1		Model 2	
	Estimate	**Odds**	**Estimate**	**Odds**
(Intercept)	-3.09***	0.05	-2.6**	0.07
Experience	0.01	1.01	0.01	1.01
Higher education#	1.2	3.32	0.59	1.80
Primary education#	-0.73*	0.48	-0.71*	0.49
Secondary education#	-0.49	0.61	-0.56	0.57
Income from farming	-0.01	0.99	0	1.00
Household members	-0.09	0.91	-0.12**	0.89
Livestock count	0.09**	1.09	0.1**	1.11
Distance from Check dam	0**	1.00	0	1.00
Proximity to dam and river #	1.23**	3.42	0.93**	2.53
Wealth	0.02	1.02	0.09	1.09
Small farmer#	1.24**	3.46	0.83*	2.29
Medium farmer#	1.06*	2.89	0.97*	2.64
Large farmer#	1.54***	4.66	1.21**	3.35
Babra block#	0.12	1.13	0.81	2.25
Jasdan block#	-0.33	0.72	-0.01	0.99
Kotda block#	0.41	1.51	0.4	1.49
Rajkot block#	-1.33**	0.26	-0.84	0.43
Chotila block#	-1.48	0.23	-1.86*	0.16
Gondal block#			-	-
Ability (Financial)	-0.08	0.92	-	-

Ability (Technical)	-0.06	0.94	-	-
Perceived risk: Vulnerability	0.02	1.02	-	-
Perceived risk: Severity	0.04	1.04	-	-
Attitude (benefits, reliability)	0.77***	2.16	-	-
Attitude (time)	0.01	1.01	-	-
Society norm	0.45**	1.57	-	-
NGO norm	0.05	1.05	-	-
BW Self-regulation (1)	0.46***	1.58	-	-
BW Self-regulation (2)	0.33**	1.39	-	-
Psedu-R2	0.214		0.075	
Accuracy	76.9 %		69.6 %	
AUC	78.6		69.7	

***, **, * Significant at < = 1%, 5%, and 10% probability level, respectively

* All VIF < 10

dummy variable

5.4.3.1 Land size and wealth

Earlier studies have widely reported that larger or wealthier farmers are more likely to adopt both drip irrigation and bore well technologies, as both require significant capital investments (Nair and Thomas 2022; Namara et al., 2007; Singh et al., 2018; Patil et al., 2019). This is reflected in results which show that small, medium, and large farmers are 246 % ([odds ratio - 1]*100), 189 % (at 10% significance level) and 366 % more likely to adopt borewells as compared to marginal farmers, respectively. The influence of land size is not visible for drip irrigation. However, wealth (an indicator of capital) shows significant positive but small (~ 16 %) positive influence on drip irrigation adoption. Additionally, the ownership of more livestock significantly increases the adoption of borewells by 9 % and could be explained by the need to fulfill the water needs of livestock.

5.4.3.2 Proximity to water (River, dam and check dams)

The impact of proximity to water sources, such as the main river and dam, on the adoption of drip and borewell irrigation is significant, but in opposite directions. In contrast to a 242% increase in the adoption of borewells, the likelihood of adopting drip irrigation decreases by approximately 81% in villages with proximity to rivers or dams. This could be due to the increased recharge in downstream villages near rivers and dams, which increases the success rate of borewell drilling and the availability of groundwater, prompting more farmers to adopt borewell irrigation. However, this also suggests that the increased availability of water (absence of water scarcity) may make farmers less inclined to adopt drip irrigation. This observation reflects the presence of supply-demand feedback, where increased water supply leads to an increase in demand (Scott et al., 2014; Di Baldassarre et al., 2018) and less adoption of demand management measures. The impact of check dams' proximity on adoption is negligible, indicating their limited and short-lived storage (Alam et al., 2022a).

5.4.3.3 Perceived ability

A strong perception of one's ability to practice (operate, maintain, and financially afford) drip irrigation translates to a 125 % greater likelihood of its adoption. With lack of technical knowledge and support after adoption along with high cost of maintenance (e.g., replacement of parts) being major constraints for adoption (Nair and Thomas, 2022), it is natural that those who have more confidence in their ability to do so adopt more. Low adoption in the region is also due to farmers' perceived financial inability to afford drip irrigation systems, as reflected in the low score (mean score = 1.28) on the perceived financial ability data. In comparison, farmers reported higher capacity to install (mean score = 1.65) and operate and maintain (mean score = 1.89) the systems.

Farmers reported the average cost of drip installation to be ~ 65000 INR (~ 790 USD) /hectare and after an average subsidy of 50 %, this would translate to a farmer share of ~ 32500 INR (~ 395USD) /hectare. This upfront investment in combination with a lack of belief in benefits may be limiting farmers' adoption of drip irrigation systems. However, it could also be due to institutional and operational issues in the subsidy programs (e.g., delay in subsidy disbursement, the requirement to pay full cost upfront, and cumbersome paperwork) that have been highlighted by several studies (Nair and Thomas, 2022; Chandran and Surendran, 2016; Misquitta and Birkenholtz, 2021; Malik et al., 2018). While the Gujarat state special purpose vehicle, Gujarat Green Revolution Company (GGRC), to increase adoption has been highlighted as a relatively successful model with good institutional mechanism (Pullabhotla et al., 2012), the case of institutional issues needs to be further investigated.

Other than financial ability, limited capacity to operate and maintain drip irrigation has been highlighted as a key barrier to adoption (Cremades et al., 2015; Nair and Thomas, 2022; Palanisami et al., 2011). Thus, farmers who have higher perception of their capability to operate and maintain also adopt more (Table 5.3). For drip irrigation, the lack of capacity has been related with a lack of extension services and post-adoption support with frequent issues of clogging of filters and drippers in drip irrigation systems (Nair and Thomas, 2022; Palanisami et al., 2011). Field visits have shown that issues associated with clogging along with challenges for storing drip systems due to damage caused by rodents that gnaw the drip irrigation tubings creating holes were reiterated by farmers and hinders adoption.

In contrast to drip irrigation, perceived ability (financial and knowledge to install) did not significantly influence the adoption of borewells. This could be as with high uncertainty of successful borewell drilling, higher perceived financial and capacity/knowledge to install a borewell does not necessarily lead to higher adoption. This is similar to findings from Ethiopia where a reduction in ambiguities related to well drilling was found to be one of the main factors influencing the adoption of groundwater irrigation (Balasubramanya et al., 2023).

5.4.3.4 Attitude towards technology

Results show that for drip irrigation and borewells, positive belief about the reliability and benefits of the technology translates to a 108 % and 116 % increase in the likelihood of adoption, respectively. This corroborates the observation from earlier studies that have also shown the importance of positive belief in increasing the adoption of micro-irrigation in India (Hatch et al., 2022), China (Wang et al., 2021) and Iran (Nejadrezaei et al., 2018). Nair and Thomas (2022), based on their review of micro-irrigation adoption in India, also observed that awareness regarding the benefits of drip irrigation is central to increasing adoption. Similarly, Reddy (2016), evaluating the Andhra Pradesh Micro Irrigation Project program, also found that awareness activities (television and radio programs, live demonstrations) played a key role in the success of the program. Interestingly, higher education negatively influences the adoption of drip irrigation (Table 5.3) showing that more years of education does not necessarily lead to more awareness about drip irrigation benefits and higher adoption.

5.4.3.5 Perceived risk and impact

The results show that for drip irrigation, interestingly, an increase in perceived vulnerability and associated impact severity translates to a 53 % and 38 % decrease (at 10 % significance level) in the likelihood of drip irrigation adoption, respectively. Whereas for borewells, the impact of perception of risk and vulnerability on adoption is not significant. Theoretically, both drip irrigation and borewells may act as risk-reducing strategies under conditions of water scarcity by using water more efficiently and augmenting the supply of water from deeper aquifers, respectively. Thus, intuition may suggest that an increase in perceived vulnerability and associated impacts should be associated with an increase in adoption of both. This has been observed in other studies where farmers choose to adopt the new technology/practices (e.g., crop insurance, efficient irrigation) to hedge/reduce the risk (Saqib et al., 2016; Koundouri et al., 2006).

The contrasting impact of perceived risk and vulnerability on the adoption of drip irrigation and borewell technologies reveals the differing nature of these technologies as perceived by farmers. Field observations indicate that farmers do not see drip irrigation as a solution for water scarcity as in times of water scarcity (as in dry years), drip irrigation is considered redundant (without any irrigation water). Thus, while the perceived threat of water scarcity is higher, adoption of drip irrigation remains low due to farmers' perception of the technology's benefits and costs. This suggests a lack of awareness about the benefits of drip irrigation as a risk-reducing strategy, as well as a perceived imbalance between the cost of adoption and the benefits it provides. Additionally, frequent climate threats, such as drought in the region, can lead to losses in crop yields and revenue, reducing farmers' financial capacity to invest in risk-reducing strategies (Alam et al., 2022c).

Additionally, the common pool nature of groundwater where the same aquifer is accessed by multiple users creates challenges for adoption of demand management strategies such as drip irrigation (Gardner et al., 1990; Asprilla-Echeverria, 2021). This is because saving water in one's well using drip irrigation does not necessarily translate to actual savings for the farmer if other farmers continue to abstract without drip irrigation.

5.4.3.6 Societal norm

The societal norms, perceived social pressure towards a behavior, have a positive influence on farmers' adoption behavior by affecting their perception of confidence, the benefits of adoption, norm conformity, learning, and perceived risk reduction (Daxini et al., 2019; Hatch et al., 2020; Qiu et al., 2021; Streletskaya et al., 2020). The results suggest that an increase in societal norms leads to a 57% increase in the likelihood of adopting borewell irrigation but has no significant impact on drip irrigation adoption. The positive impact of societal norms on borewell adoption may be due to farmers' perception of the success of borewells in nearby farms. However, the study was not able to determine why the same impact does not hold for drip irrigation adoption.

In addition, the study found that the opinions of government and NGOs do not significantly influence the adoption of drip or borewell irrigation. This may be because most farmers rely on neighboring farmers (71.8%), agro-dealers and private companies (56.9%), and lead farmers (39.1%) for information, while less than a quarter of farmers reported government or NGOs as their source of information. This finding highlights the importance of considering these channels while designing awareness and extension activities for promoting technology adoption.

5.4.3.7 Other factors

Action planning significantly increases borewell adoption by farmers. Access to information on external factors such as drilling contractors, engineers, and technicians is a key determinant of adoption. However, the observed association may be explained by reverse causality, as borewell owners are more knowledgeable about the necessary resources for drilling. (Daniel et al., 2020). For drip irrigation, farming experience shows a slightly positive (4% increase for each unit increase in farming experience) impact on adoption. Household size and income from farming did not have any influence on the adoption of both drip irrigation and borewell irrigation.

5.4.4 Recommendations

Our findings show that although subsidies (50-70%) are available for drip irrigation systems, adoption rates remain low (approximately 16% adoption rate). In contrast, the adoption rate for borewells, which require more capital investment and have no subsidies, is higher (approximately 24.5%). This suggests that farmers prioritize augmenting their water supply and view borewells as a more effective means of mitigating water scarcity or intensifying cultivation. This trend is consistent with observations from Patil et al. (2019) in another water-stressed area of Southern India, where the uptake of water-saving technologies was low, and farmers chose water-intensive crops and unregulated pumping, which exacerbates water stress.

The results indicate that the availability of water (proximity to dam and river) and higher perception of risk negatively affect the adoption of drip irrigation. This reflects that farmers may not necessarily perceive drip technology as a risk-reducing strategy, thereby hindering adoption. Furthermore, limited financial and technical capacity is another obstacle to adoption. Thus, a multi-pronged approach is necessary to build farmers' capacity to adopt drip irrigation (including alternative financial mechanisms and capacity building) and to raise awareness of its benefits.

Although subsidies have a positive impact on adoption (Cremades et al., 2015; Heumesser et al., 2012), our results indicate that in the region, subsidies alone are not enough to promote the adoption of drip irrigation. Alternative financial mechanisms may be required, such as increasing subsidies or providing low-interest or interest-free loans to cover the unsubsidized cost (Nair and Thomas, 2022; Palanisami et al., 2011). An example of this is the Aga Khan Rural Support Programme (AKSRP) in the region which provided added subsidies and interest-free loans (with delayed repayment) to cover the unsubsidized cost (Panda, 2003). Similarly, other studies have shown the positive impact of easy access and low-interest loans on adoption (Abate et al., 2016; Balasubramanya et al., 2023). For example, Abate et al. (2016) showed the positive impact of microfinance institutions and member-owned financial cooperatives on the adoption of agricultural technologies by alleviating credit constraints. Alternative financial mechanisms should be accompanied by supporting farmers to easily access the subsidy schemes by making the process faster and more flexible in terms of meeting farmers' requirements (Singh, 2013; Malik et al., 2018).

Additionally, capacity building efforts should prioritize building farmers' confidence in operating and maintaining drip irrigation systems. Research has shown that capacity building for farmers is an effective strategy for technology adoption across various countries and technologies (Cremades et al. 2015; Nair and Thomas, 2022; Zakaria et al., 2020; Arslan et al., 2014). This can be achieved through various means such as training programs, community-based approaches like farmer field schools, access to replacement parts, and post-adoption extension services. The government's operational guidelines for the micro-irrigation subsidy scheme also emphasize the need for capacity building, including organizing training programs and exposure visits (DAC&FW, 2017). In the study region, farmers have expressed concerns about dripper clogging and rodent damage to drip systems, which underscores the need for targeted training on these issues. Capacity building can also involve creating a network of local professionals who can provide on-site training and technical assistance to farmers.

In addition to the aforementioned capacity building efforts, it is essential to provide farmers with information on the benefits of drip irrigation, including increased crop yield and reduced water usage, to reinforce and strengthen positive attitudes and societal norms towards drip irrigation. This is crucial as farmers with higher risk perception are less likely to adopt drip irrigation due to lack of trust in the technology's ability to mitigate risk. Studies have shown that increasing awareness through training, demo farms, and social learning can positively influence adoption rates (Genius et al., 2014; Hunecke et al., 2017; Nejadrezaei et al., 2018; Wang et al., 2021). Ways to achieve this could include increasing access to information through local government institutions, education campaigns, workshops, and field visits. Government guidelines also recommend awareness raising through print and electronic media and publicity campaigns at block/ district/state level (DAC&FW, 2017).

To enhance the influence of extension services such as capacity building and awareness raising, it is important to have a presence and build trust in social, formal, or informal networks (targeting and influencing social norm) such as cooperative organizations and farmers' user groups, rather than focusing solely on individuals (Genius et al., 2014; Hunecke et al., 2017). While the government's official guidelines for promoting micro-irrigation recommend both capacity building and awareness raising (DAC&FW, 2017), low capacity and awareness in the region indicates a need to intensify efforts.

However, the increasing adoption of borewells in the region is a cause for concern. While access to borewells may lead to higher availability of water, it comes with social costs. Borewell drilling is capital-intensive and risky in the region, with no guarantee of success. This means that smaller and marginal farmers may not be able to tap the resource, thus exacerbating socioeconomic disparities in the region, as discussed in studies by Patil et al. (2019) and Birkenholtz (2009). The financial risks associated with borewells mean that farmers may fall into severe indebtedness with no access to low-interest loans or other safety nets, as observed by Reddy (2012). Our data also show that farmers drill an average of 2.3 borewells (range 1-12) to get a successful borewell. To mitigate the risks and uncertainties associated with borewells, it is essential to provide farmers with information on the underlying hydrogeology, as the hydrogeology in the region is complex.

Additionally, over-extraction of groundwater through borewells can lead to severe depletion and degradation of deeper aquifers. It is not clear whether shallow and deeper aquifers are connected and if connected, tapping deeper aquifers may have a negative influence on shallow water sources. Also, over-extraction of groundwater through borewells can lead to a decline in water levels, making it more difficult and expensive to extract water in the future. Moreover, this strategy may become maladaptive in the long run, as noted in the study by Jain et al. (2015). Also, depletion of groundwater can increase energy consumption for pumping leading to a vicious cycle of increased energy demand, higher costs, and further depletion of groundwater resources. Further research is required to understand the hydrogeology of deeper aquifers in the region.

Finally, the common pool nature of groundwater may hinder adoption at the individual level of demand management interventions (Gardner et al., 1990; Asprilla-Echeverria, 2021). Given that farmers tap into a shared resource, cooperation at the village level and incentivization may be required to realize the benefits of drip adoption at the individual level. This is necessary to avoid the free rider problem. Also, while including psychological factors in the analysis enhances understanding, RANAS theory may not account for all psychological factors that hinder adoption, such as perceived fairness and technology acceptance (Contzen et al., 2023). Future studies could consider adding more factors to RANAS theory or testing alternative psychological theories to gain a deeper understanding of adoption barriers.

5.5 Conclusion

Increasing the adoption of agricultural water interventions by farmers is critical to adapting to water scarcity and ensuring the food and economic security of millions of farmers. However, despite the availability of a range of interventions and successful pilots, adoption remains low. This study assessed socioeconomic, biophysical and psychological factors influencing the adoption of two contrasting adaptation strategies, drip irrigation (demand management) and borewells (supply augmentation), in a semi-arid catchment in India. While drip irrigation is being promoted with government subsidies, borewells are being taken up by farmers using their own resources. The results show that psychological factors play a significant role in the adoption of both technologies, and incorporating these factors improved model explanatory power by almost threefold. The findings show that despite subsidies, drip irrigation adoption lags behind borewells, suggesting farmers' preference for supply augmentation measures. Farmers' perceived ability and positive beliefs about the benefits of drip systems are significant factors in adoption. Based on the results, the study suggests that a multi-pronged approach is necessary to increase the adoption of drip irrigation, including augmenting subsidies with efforts on extension services, post-adoption services, training, and awareness campaigns to build farmers' capacity and raise awareness. On the other hand, the increasing adoption of borewells is concerning, with implications for increasing socioeconomic inequality, indebtedness, and threatening deeper aquifers. Overall, it is critical to devise strategies that look beyond the socioeconomic factors to increase fair access to water resources while safeguarding against the overexploitation of groundwater.

6. Development and application of Agent Based Model for unraveling supply-demand feedback from agricultural water interventions[6]

[6] This chapter has been submitted to Nature Sustainability and is under review. The chapter has been reformatted from the submitted version to fit the thesis format.

6.1 Introduction

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

However, there is a risk that poor implementation of the interventions may lead to unintended consequences leading to inequitable and unsustainable outcomes (Alam et al., 2022a; Adla et al., 2023). Examples include an increase in water use as farmers adopt more efficient irrigation methods to intensify production (Alam et al., 2022a; Birkenholtz, 2017). Of particular concern 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., 2018; Shah et al., 2021). This is because a significant portion of AWM interventions pertain to the supply side, such as the construction of small storages 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 (Shah et al., 2021; Alam et al., 2022b). 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 arise from bidirectional feedback and dynamics between human and water systems (Adla et al., 2023; Sivapalan et al., 2012). These are often not the focus of hydrological models used to simulate and assess the impacts of agricultural water interventions (Alam et al., 2022a; Adla et al., 2023; 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 (Alam et al., 2022a; Adla et al., 2023).

Within sociohydrology studies, Agent-Based Models (ABMs) stand out for their unique ability to consider human-water feedback while addressing the heterogeneity of farmers that is crucial for capturing inequitable outcomes (Alam et al., 2022a). Despite its versatility, application of ABMs for AWM have shown several limitations (Alam et al., 2022a), including the absence of spatially explicit hydrological models, the use of aggregated agents instead of individual farmers (Farhadi et al., 2016; Hu & Beattie, 2019), and notably, the absence of grounded behavioral rules, with most models assuming simplistic rational behavior (Schreinemachers et al., 2011) or heuristics rules derived from empirical data (Castilla-Rho et al., 2015).

This highlights the need for further advancements in the integration of human and hydrological dynamics to critically understand the human-water feedback related to agricultural water interventions. This paper therefore develops and applies an open-source modular agent-based model for AWM interventions (ABM-AWM) in order to unpack the emergent phenomenon of supply-demand feedback. It does so by integrating a spatially explicitly hydrological model with human behavior rules based on RANAS (Risks-Attitudes-Norms-Abilities-Self-regulation) behavioral theory (Mosler, 2012) and observed data.

6.2 Case study catchment

The ABM-AWM is applied to a case study area of Kamadhiya catchment (~ 1100 Km2) in the western state of Gujarat in India (Figure 6.1). This area has a semi–arid climate, characterized by low average annual rainfall of 438 mm per year (1983–2015) with more 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). The Kamadhiya catchment has seen intensive construction of check dams (CDs) supported by a broader movement to increase groundwater recharge and gained momentum in response to a severe drought from 1999 to 2001 (Alam et al., 2022b; Shah et al., 2009). In the catchment, the CD count reached 575 by 2006, contributing to a density of approximately one CD per 2 km^2 (Patel, 2007).

The farmers do not directly use (lift) water from CDs, but indirectly with additional recharge from CDs feeding their wells (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, and are confined to water-bearing zones in the upper 15-30 m of weathered and fractured rock (Kulkarni et al., 2000; Alam et al., 2022c). Farmers access this shallow groundwater through large-diameter open dugwells (Alam et al., 2022b; Mohapatra, 2013). In addition to publicly funded CDs, drip irrigation and borewells are other major agricultural water interventions where farmers invest individually (Chapter 5). Drip irrigation is a demand management intervention to increase the efficiency of irrigation water applied supported by a government capital subsidy program (Nair and Thomas, 2022). 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).

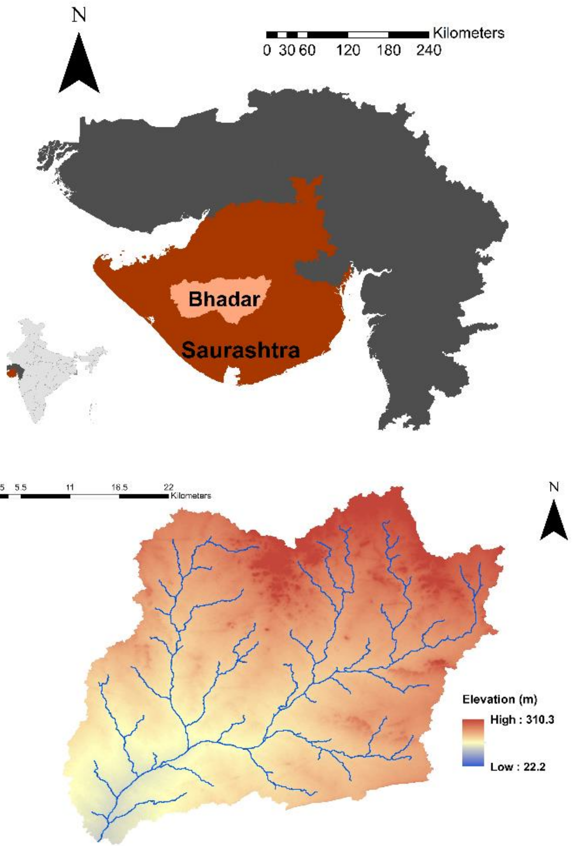


Figure 6.1: Location of the case study area showing Saurashtra region in Western India and Kamadhiya catchment in the Saurashtra region

The development of CDs at the catchment scale has shown signs that it has correspondingly fueled greater irrigation demand from groundwater (Alam et al., 2022b, c), indicative of the phenomenon of supply-demand feedback, which the ABM-AWM model aims to unpack. In addition, ABM-AWM assesses any impact, unintended, on the adoption of drip and borewell by the farmers.

6.3 Method

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. Further expanding the previous model (Pande and Savenije, 2016), the ABM-AWM model's modular structure allows for adapting model codes and altering model resolution and farmer characteristics. The core modules, which are exhaustive to unravel emergent dynamics such as the phenomenon of supply-demand feedback, are hydrological, crop growth, and farmer behavior dynamics.

6.3.1 Hydrological module

The hydrological module is adapted from the open-source Spatial Processes in Hydrology (SPHY) model (Terink et al., 2015) and simulates spatially distributed daily water flows. It is a three-layered leaky bucket model, including two soil layers (rootzone and subzone) and a groundwater layer. Figure 6.2 gives the conceptual workflow of the hydrological module. The spatially distributed hydrological module operates at 1 km^2 resolution with 1319 such grid grids within the study area. Please refer to SPHY model (Terink et al., 2015) and Appendix D.1 for more information on the hydrological model.

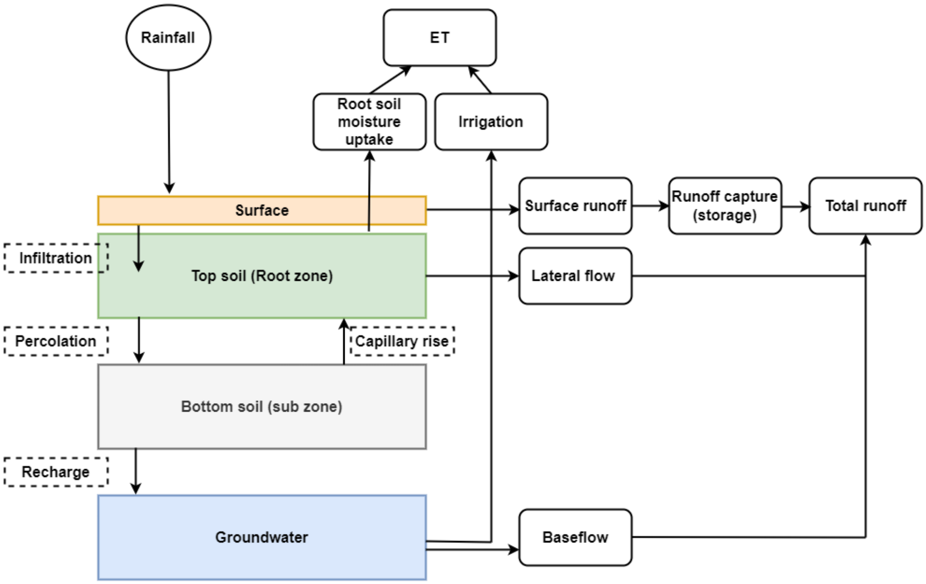


Figure 6.2: Conceptual workflow of the hydrological module

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 check dams). 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 check dams takes place Recharge and runoff capture from check dams were simulated using recharge empirical equations (Bouwer, 2002), that were refined for the study region (Mozzi et al., 2021). 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. Table 6.1 summarizes the climate and biophysical data employed in the model.

Table 6.1: Summary of data and parameters used and its sources in the hydrological module

Data/parameters	Unit	Average	Source
Rainfall	mm	478	SWRD, 2021
Temperature	^{0}C	27°C	IMD (Pai et al.,2014)
Slope	%	0.56	SRTM (Jarvis et al., 2008)
Runoff recession	-	0.05	Calibrated.
Baseflow recession	-	0.53	Calibrated.
Baseflow threshold	mm	300.00	Calibrated.
Topsoil depth (D_1)	mm	650.00	Calibrated. Initial values based from the pedo-transfer function (Saxton et al., 2006)
Bottom soil depth (D_2)	mm	400.00	
Soil Field capacity (FC)	$m^3\,m^{-3}$	0.30	
Soil Wilting Point (WP)	$m^3\,m^{-3}$	0.18	
Soil Saturation capacity	$m^3\,m^{-3}$	0.41	
Soil hydraulic conductivity	m day^{-1}	0.08	
Rootdrain velocity (v_{lat})	mm	0.88	Derived based on soil parameters (Terink et al., 2015)
Root lateral flow travel	d	0.49	
Root wilting point (RWP)	fractio	0.70	Calibrated.
Capillary rise (Cap)	mm	0.05	Calibrated.
Aquifer Depth (D_{GW})	m	20.00	Calibrated. Alam et al., (2022b)
Aquifer specific yield (S_y)	%	0.35	Calibrated. Initial values from GEC (MoWR, RD & GR, 2017)
Aquifer conductivity (K_{gw})	m day^{-1}	0.10	GEC (MoWR, RD & GR, 2017) and CGWB (Mohapatra, 2013)
Check dam number (&	#	453	Secondary data and social surveys (Alam et al., 2022b; Patel, 2007)
Check dam location,	MCM	12.90	
Check dam width	m	15.00	

6.3.2 Crop module

The crop module calculates crop water requirements, irrigation needs, and yields. It employs the FAO four-stage crop coefficient approach to estimate crop potential evapotranspiration (ETc) (Allen et al., 1998), with reference evapotranspiration (ETo) determined via the Hargreaves method (Hargreaves and 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 et al., 2022c). The kharif crops were modeled separately, whereas the rabi crops were simulated as one crop, i.e. wheat, for which long-term time series data are available.

Crop water needs (ETc) are first met by root soil water uptake from the rootzone soil layer. Soil water uptake reduces as a function of available moisture in the rootzone soil layer following a linear equation as used in SPHY (Terink et al., 2015) based on the Feddes equation (Feddes et al., 1978). The difference between ETc and root-soil water uptake is considered as the net irrigation water requirement (NIR), and gross irrigation requirements (GIR) are estimated based on irrigation efficiency (NIR/ irrigation efficiency). Irrigation efficiency is taken as 0.6 unless a farmer has adopted drip irrigation, in which case the irrigation efficiency is set to 0.9 (Rogers et al., 1997; Howell, 2003). For rainfed farmers, crop water needs are met solely through root water uptake, while irrigated farmers can also access groundwater.

To meet irrigation needs, which is groundwater-dependent, farmers access shallow groundwater through large-diameter open dugwells. The percentage of farmers having access to irrigation is set equal to the proportion of cotton area irrigated (Alam et al., 2022c; DoA, 2021), and this increases over the years

(Figure D.1). 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. The daily abstraction is limited by the maximum possible abstraction (GWD(max) = 525 m3 day-1) constrained by the pump and well capacities (Table D.1) . Also, farmers can access deeper groundwater, if they have invested in borewells, and again daily abstraction is limited by maximum possible abstraction (GWB(max) = 80 m3 day-1, Table D.1). A part of the applied irrigation water recharges groundwater based on a return flow coefficient.

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 et al., 2022c) 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).

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, i.e. 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 6.1). For estimating crop evapotranspiration and yields, crop-specific data on sowing day, growing period, crop coefficients (Kc), and crop yield reduction factor (Ky) are given in Table D.2. This is multiplied by crop price and then the cost of cultivation (Table D.3) is subtracted from it to estimate profit that is accumulated as capital over time.

$$\frac{Y}{Y_p} = \prod_{j=1}^{J} \sum_{i \in s_j}^{I_{s_j}} [1 - K_Y \left(1 - \frac{AET}{ET_c}\right)] \qquad \text{....Equation 6.1}$$

Where, K_Y is crop yield reduction factor, AET_i, ET_{ci} 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.

The net cultivated area in each grid cell was based on the land use land cover (LULC) map from 2015, which gives the percentage of agricultural land in each grid cell22. The net cultivated area (NCA) from the LULC map (summed over the Kamadhiya catchment) was compared with NCA for each year from reported administrative data15,23,24 and a correction factor (Actual NCA/LULC NCA) was applied uniformly across the grid. The distribution of net cultivated area between crops in the model is based on farmer decisions.

6.3.3 Farmers module

The farmers module models the daily, seasonal, and annual behavior of the farmers. The farmer behavior is based on the combination 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 (Chapter 5) and data-driven rules based on the analysis of crop and hydrological data in the catchment (Alam et al., 2022b). The farmer decision-making module captures their responses and feedback amongst them and the environment.

Each farmer is characterized by her socio-economic characteristics (land area, financial resources, access to irrigation) and assigned a location (i.e. a grid cell). The farmer co-occupies the space with other farmers in the specific grid cell and bi-directionally interacts with the biophysical resources (as modeled by the hydrological module) through decisions on crop choices and methods of irrigation. The farmers also interact with each other through norms, from the RANAS model. Farmer locations within the watershed determine their access to amenities such as check dams. Additionally, farmers are characterized by their access to drip irrigation and borewells, which are simulated based on behavioral rules.

In the model, farmers are differentiated based on socio-economic characteristics and biophysical endowments. They are stratified by land size into four categories: marginal (<1 ha), small (1-2 ha), medium (2-4 ha), and large (>4 ha) (Alam et al., 2022c). The proportions of these groups in the region and the average area per type (total area/number of holdings) are derived from the agricultural census data (Table 6.2). Subsequently, the number of each type of farmer in each grid cell is derived based on the total cultivated area in each cell (see crop module), the proportion of each farmer group, and the average area of each group (Table 6.2). Overall, this results in a simulation of 38,447 farmers in the watershed.

Table 6.2: Distribution, number and area of each category of farmers in the blocks covering Kamadhiya catchment

	%age of farmers [a]	Total holdings [a]	Total area (ha) [a]	Average area (ha)
Marginal	7.8%	40173	27350	0.68
Small	28.6%	68673	99690	1.45
Medium	35.1%	45162	121395	2.69
Large	28.5%	15320	95491	6.23

[a] Agricultural census 2015-16 (DoAC&FW., 2019)

While farmers make numerous decisions, the model focuses on a subset of these. These include: 1) allocating crop areas between kharif crops like cotton and groundnut; 2) deciding on the cultivated area for post-monsoon crops, and 3) making investments in drip irrigation and borewells.

6.3.3.1 Decision rules for the distribution of Kharif crop areas

All farmers are assumed to cultivate two kharif crops: groundnut and cotton. This is based on a household survey (Alam et al., 2022c), which indicates that the majority of farmers cultivate both the crops. Catchment-level analysis (Alam et al., 2022b), comparing the periods before (1983-2002; pre-CD) and after (2003-2015; post-CD) the implementation of CDs, showed a 124% increase in cotton cultivation in the watershed in the post-CD period. Additionally, the area under irrigation rose from 64% to 85% in the post-CD period. This increase has been attributed to the phenomenon of supply-demand feedback, where the perceived increase in water availability led to a rise in crop water demand, primarily through expanded cotton cultivation (Alam et al., 2022b). The survey confirmed that the primary benefits perceived by farmers from CDs include increased availability and reliability of water for irrigation (Alam et al., 2022c). The comparison of farmers' cotton area fraction (cotton area/total kharif area) from the survey (Alam et al., 2022c) shows that the farmers who are near CDs (<=250 m) devote 4.5% (cotton area/total kharif area = 0.55) more cotton area than the farmers who are away from CDs (cotton area/total kharif area = 0.50). Thus, the enhanced supply and reliability of irrigation water directly correlate with an increased area under the more water-intensive crop, cotton.

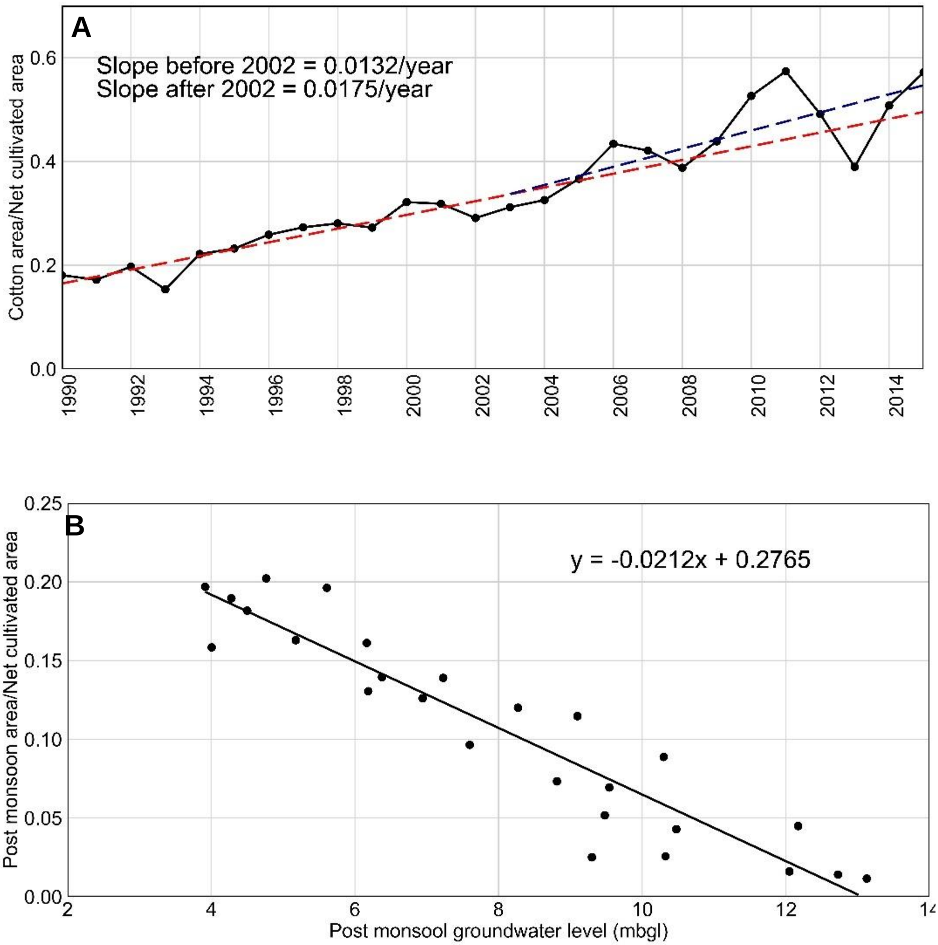


Figure 6.3: A) Fitted line showing cotton area per unit net cultivated area before and after 2002 (i.e. pre-CD and post-CD periods respectively); B) Relationship between wheat area per unit net cultivated area (post monsoon area) and spatially averaged post-monsoon groundwater levels

This was further analyzed by estimating the rate of change of the cotton area as a proportion of the net cultivated area over the modeling period (Figure 6.3a). The analysis of time series (1990 - 2015) of cotton area (as a proportion of the net cultivated area) identified a significant breakpoint in 2002 (matching pre and post-CD period), estimated using the R 'strucchange' package (Zeileis et al., 2002) which uses Bayesian Information Criterion (BIC) to identify breakpoints. The slope representing the rate of change in cotton area as a proportion of the net cultivated area before and after the breakpoint (2002) were estimated. The slope increased in the post-CD period (0.0175 $year^{-1}$) when compared with pre-CD period (0.0132 year-1) (Figure 6.3a).

This finding was integrated into the model as a rule (Equation 6.2). For farmers without CDs and irrigation, the slope (cotton area as a proportion of the net cultivated area) of the equation was kept 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 6.2). 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. A similar increase of 3.3% was observed in the household survey conducted (Alam et al., 2022c). The area dedicated to groundnut is calculated as the total area minus the area used for cotton.

$$Area_{cotton} = (-26.151 + slope * year) * Area_{farmer} \qquad \text{Equation 6.2}$$

where slope (cotton area/net cultivated area) before 2002 (pre-CD period) = 0.0132/year; slope after 2002, i.e. 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. $Area_{farmer}$ is farmer-owned cultivated land.

6.3.3.2 Decision rules for the cultivated area of post-monsoon crops

The availability of groundwater in dugwells remains limited during the post-monsoon season, often depleted by the year-end due to the limited extent and storage capacity of the aquifers (Mohapatra, 2013; Kulkarni et al., 2000; Alam et al., 2022c). This scarcity constrains the cultivated area in the post-monsoon (Alam et al., 2022b). The catchment water balance analysis demonstrated that the area cultivated with post-monsoon crops is highly dependent on the groundwater levels after the monsoon (Figure 6.3b). This finding indicates that farmers across the catchment 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 6.3b). This correlation was incorporated into the model for each farmer (Equation 6.3). 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.

$$Area_{wheat} = \left(0.2765 + -0.0212 * GWL_{post-monsoon}\right) * Area_{farmer}$$

Equation 6.3

Where, $GWL_{post-monsoon}$ is the groundwater level below the surface at the sowing date of wheat and $Area_{farmer}$ is the farmer-owned cultivated land.

6.3.3.3 Decision rules of investments in drip and borewell

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 et al., 2022c). 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 the psychological factors play a significant role in the adoption of both the technologies (Chapter 5). The authors showed that the inclusion of psychological factors in addition to the socio-economic factors improved the explanation power of the adoption behavior by threefold.

The binary logistic regression used to interpret the adoption behavior (Chapter 5) is used to generate farmer decision rules of the adoption of drip irrigation and borewells. First, based on the earlier results (Chapter 5), 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 (Table D.4 and D.5). Using the regression coefficient estimates (α) of the variables, farmer decision-making of the adoption of drip irrigation and borewells was formalized using equations 6.4 and 6.5. The probability of adoption was estimated using equation 6.6. Similar approaches, i.e. using regression equations to define rules, have been employed by others (Pouladi et al., 2019; Kaufmann et al., 2009). The probability thresholds (Probdrip/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 D.4 and D.5).

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

Equation 6.4

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

Equation 6.5

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

Equation 6.6

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 (Table D.4 and D.5).

The variables in regression equations 6.4 and 6.5 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 (Figure 6.4). The latter included all RANAS factors (risk (perceived and severity), norm, ability, impact self-regulation). The constant variables included proximity to water ($water\_proximity$) based on the village nearness to the dams and the main river stem (Alam et al., 2022c) livestock ownership ($livestock$) based on the household survey which showed 70% farmers owning livestock and farmer area ($area$) based on the farmers' type and their average area (constant in the model).

Dynamically simulated RANAS variables were linked with model variables (Figure 6.4). This linking involved estimating RANAS variables in equations 6.4 and 6.5 based on the simulated model variables for each year. Risk(perceived) was linked to drought occurrence, risk(severity) was linked to impact of drought on crop yields, ability and self-regulation was linked to farmers' accumulated capital, attitude was linked to incremental yield benefits achieved by neighboring adopters along with training and norm was linked to the percent of adopters in the grid cell where the farmer is located. All RANAS variables were then updated annually for each farmer based on the simulated values of the linked modeled variables. The responses to RANAS related questions were on a likert scale ranging from 0 to 4 and the regression coefficients in equation in 6.4 and 6.5 were derived based on this scaling. Therefore, the modeled variables that the RANAS variables link up with were also scaled between 0 to 4. This was done using min-max scaling ((variable – min)/(max-min)) and multiplying it by 4. The scaled modeled variable was then assigned to the corresponding RANAS variable.

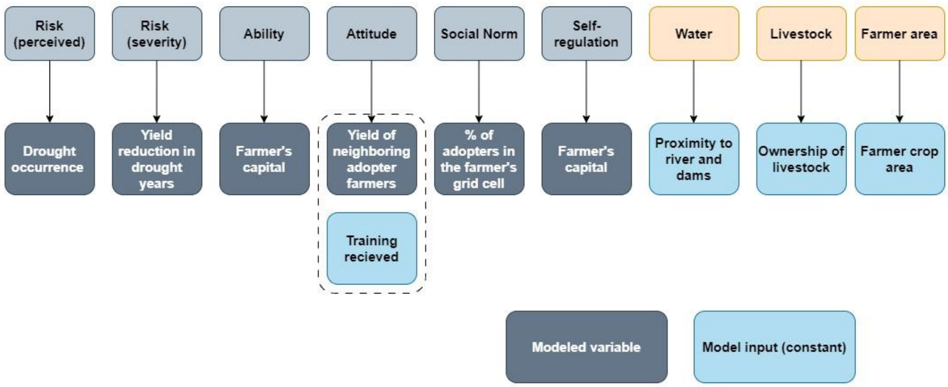


Figure 6.4: Linking of RANAS and socio-economic variable with the model variables and inputs

For example, Household survey (Alam et al., 2022c) measured perceived risk with the question "How high is the risk of drought in the coming 5 years?" and the risk severity with the question "How severe will be the impact of drought on your crop production?" on a scale of 0 to 4. Thus, the RANAS variable risk (perceived) was estimated based on a modeled variable occurrence of a drought year (annual rainfall < 400 mm) and RANAS variable risk (severity) was based on the modeled effect of drought on crop yields. For both risks, the model uses the principle of drought memory which considers the accumulative nature of farmers' experience and accounts for memory decreasing over time in non-drought (non-disaster) years (Wens et al., 2019; Di Baldassarre et al., 2019). For every drought year, a farmer's risk (perceived) memory was updated (starting with 0, each drought year adds 1 to it) and risk (severity) memory by adding a decrease in yield relative to potential yield (starting with 0, each drought year adds a decrease in yield to the farmers' memory) (Equation 6.7 and 6.8). Both drought and impact memory reduce over time with memory decay of 20% each year. This is based on the household survey (Alam et al., 2022c), which showed that on average farmers report 1.25 drought years (23% reported 0 drought years and 40% reported 1 drought year) in the last 10 years as compared to the observed three drought years (the year 2012, 2014, and 2018). Applying decay rate of 20% (per year) for the population (over 10 years) gives drought memory value at the end of the simulation period (year 2021) of 1.2 (shown in Table D.6). This is close to the average reported value of 1.25 drought years. At the end of a simulation year, risk and impact values were scaled from 0 to 4 and given as input to equation 4.

$$risk(p)_{(f,t)} = drought_{(f,t)} + risk(p)_{(f,t-1)} - d*risk(p)_{(f,t-1)} \quad \text{....Equation 6.6}$$

$$risk(s)_{(f,t)} = drought_{(f,t)}*(Yield(p)_t - Yield(f)_t)/Yield(p)_t) + risk(s)_{(f,t-1)} - d*risk(s)_{(f,t-1)} \quad \text{....Equation 6.7}$$

Where risk(p) and risk(s) is the risk (perceived) and risk (severity) for a farmer f in year t; $drought_{(f,t)}$ is the occurrence of drought (1 if rainfall < 400 mm else 0) at the farmer's location; $Yield(p)_t$ is the potential yield of crops and $Yield(f)_t$ is the actual yield of the farmer in year t and d is the memory decay rate. Potential and farmer yields are derived by taking the corresponding averages of all the crops farmer grows.

Similarly, the ability was linked to farmers' accumulated capital in the model as this was measured in the household survey (Alam et al., 2022c) with the answer to the question "How confident are you in your financial capability to afford the drip system/borewell?". Attitude in the survey was measured with the answer to the question "How beneficial drip/borewell is for crop production?" and in the model it was assumed to be influenced by incremental yield benefits achieved by neighboring farmers (living within the same grid) who have adopted drip irrigation or borewell (Equation 6.8). For drip irrigation, the effect of the drip subsidy scheme after 2005 is also added through the training and awareness component with an assumption that 5% of the farmers randomly received the training at the start of each year. This is based on the survey data (Alam et al., 2022c) which showed that, though in total 21% of the farmers have received information from the government or NGOs, they give less importance to their opinion. With training an important factor in shaping attitudes (Gautam et al., 2017; Nankano et al., 2018), after 2005 it was assumed that the attitudes were influenced in equal proportions by yield benefits achieved by neighboring farmers and training.

$$Yield\_benefit_{f,t} = \left[\frac{Yield(a)_{f(g),t}}{Yield(p)_t} - \frac{Yield(na)_{f(g),t}}{Yield(p)_t}\right] * 100 \qquad \text{.... Equation 6.8}$$

where $Yield(a)_{f(g),t}$ and $Yield(na)_{f(g),t}$ is the yield of adopters and non-adopters, respectively living in the same grid (g) as the farmer (f) in year t and $Yield(p)_t$ is the potential yield of crops.

Norm was measured with the answer to the question "What proportion of people in your village have a drip?". This was directly linked in the model to the percent of adopters in the grid cell where the farmer is located. This was estimated at the end of each year for each grid cell by dividing number of adopters by the total number of farmers living in the grid cell. Self-regulation was measured in the household survey[19] with the answer to the question "Do you have a plan to acquire the required personnel and material it takes to drill a BW?", and there was no direct model variable associated with it. We assume that action planning reflects intention to adopt which is related to farmers capital (Wens et al., 2020; Nguyen and Drakou, 2021) and thus self-regulation was linked to the farmers accumulated capital.

The farmer survey indicated that ~60 % of farmers encountered borewell failures before a successful borewell and on average, farmers drilled ~ 2.1 failed borewells before they succeeded with a working borewell. This information was integrated using a random function, where only one-third of farmers adopting borewell (based on equation 6.5) achieve a functional well, while the remaining two-thirds experienced non-functional borewell despite the utilization of capital. This is similar to earlier results in hard rock areas, which showed high failure rates of borewells (Anantha, 2013).

The costs of drip irrigation (INR 60000/hectare) and borewells were determined based on the household survey analysis (Chapter 5). For drip irrigation, the cost was set to 50% of the reported cost starting in 2005 when the government subsidy scheme came into effect that subsidized half of the cost (Nair and Thomas, 2022). Before 2005, the cost of drip was higher due to limited penetration. For example, drip cost (without subsidy) in 2005 was reported at INR 20000-55000/hectare (Narayanamoorthy,2009) , which after accounting for inflation rate of ~7% per annum results in the present cost of INR 70000 – 190000/hectare (1.2 – 3.2 times the current cost). This higher cost is accounted for by assuming that a drip system costs 1.5 times the current cost in years before 2005. Similarly, borewell adoption has been a recent phenomenon in the catchment with the farmer survey (Chapter 5) showing that only 8% of total borewells were drilled before 2000. This reflects the lack of access to cheaper technology before 2000 and was accounted in the model by setting its cost before 2000 at two times the current cost.

6.3.4 Overall workflow

In brief, the farmers, based on behavioral rules make decisions on crop choices and cultivation areas at the season's start. Thereafter, daily crop ETc, and irrigation needs for these crops are calculated for each grid cell and mapped to the farmers based on their locations. 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 ETC 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). Figure 6.5 gives the overall conceptual workflow of the ABM-AWM mode.

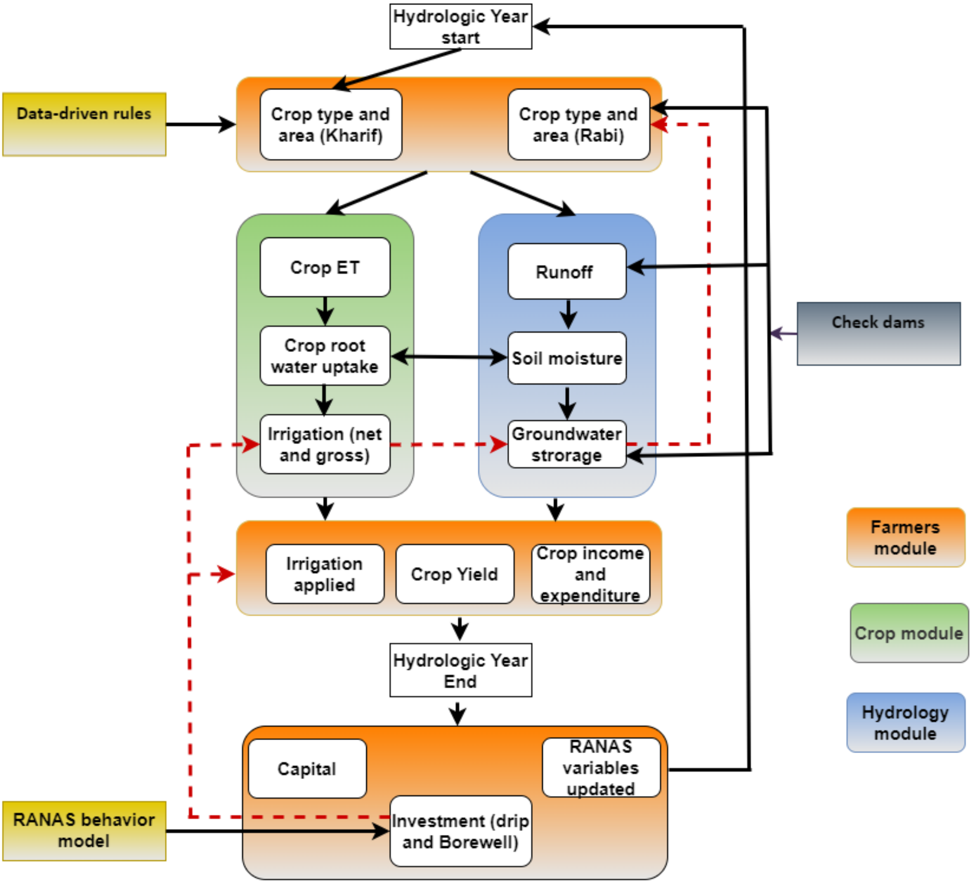


Figure 6.5: Conceptual workflow of the ABM-AWM model. Dotted lines show the feedback between the modules.

6.3.5 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 watershed average groundwater levels available for pre- monsoon (month of May) and post-monsoon (month of November) months (Alam et al., 2022b). The model was calibrated for the period 1991-2008 and validated for the period 2009-2015.

The model was calibrated for two versions: HB_{on} and HB_{off}. In both the versions, CDs were incorporated and differed only in the presence of human behavior rules. HB_{on} integrated all human behavior rules into the model, while HB_{off} excluded them. This 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. A manually calibrated HB_{on} served as the baseline model for both the versions. The HB_{off} model configuration involved deactivating the investment behavior module (drip and borewell), maintaining the rate of change of cotton (slope in equation 6.2) 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 check dams). 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 6.3). 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.

6.3.6 Uncertainty analysis

For the uncertainty analysis, the confidence intervals (5-95%) of the most sensitive model parameters (Table 6.1) were estimated based on the computation of the Jacobian matrix in the PEST search algorithm (Dohery et al.,2010). Additionally, the confidence intervals of regression estimates (in equations 6.2, 6.3, 6.4, 6.5) were derived from the corresponding regression models. Thereafter, based on the calibrated parameters and its confidence intervals (Table D.7), 500 parameter sets were sampled using Latin Hypercube Sampling (LHS) (Mishra, 2009). LHS combines Simple Random Sampling (SRS) as in Monte Carlo analysis and stratified sampling techniques, yielding statistically significant results with considerably fewer realizations beneficial for computationally demanding models. This was used to compute the 5% and 95% interquantile ranges of the model outputs of simulations where the NSE of runoff and groundwater was > 0.5.

6.4 Results

6.4.1 Model performance

Figures 6.6a and 6.6b 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 Nash-Sutcliffe Efficiency (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 (2009-15), 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.

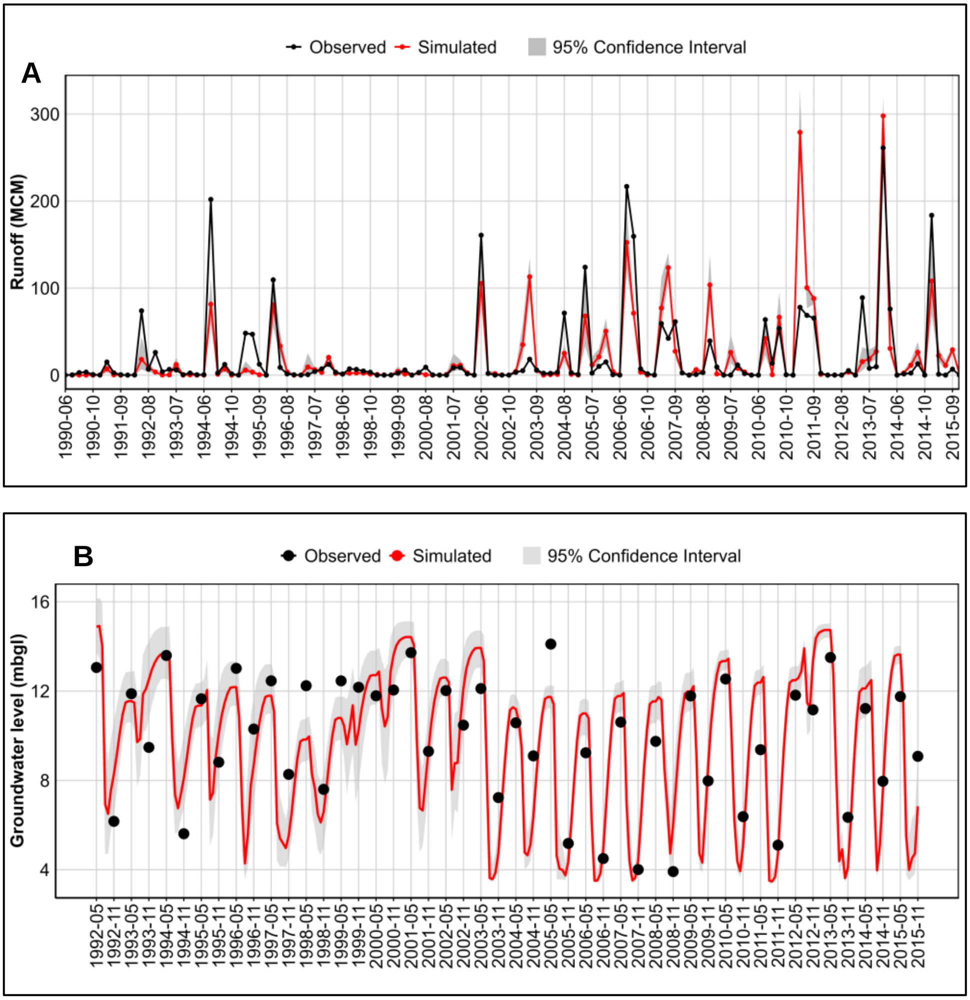


Figure 6.6: Simulated (HB_{on}) and observed runoff (A) and groundwater levels (B).

A comparison between the calibrated version of the model with embedded human behavior (HB_{on}) and the version without (HB_{Off}) revealed better performance 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) (Table 6.3). 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 A1).

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}).

Table 6.3: Calibrated model statistics and parameters with human behavior on (HB_{on}) and off (HB_{off}).

		Units	**Model HB_{on}**	**Model HB_{off}**
	NSE (runoff)	-	0.59	0.54
	PBIAS (runoff)	%	2.76	-1.19
	NSE (groundwater)	-	0.65	0.55
	Parameter	**Units**	**Value HB_{on} (Calibrated)**	**Value HB_{off} (Calibrated)**
Aquifer	Aquifer Depth	m	22.47	23.07
	Aquifer specific yield	%	0.012	0.011
	Baseflow threshold	mm	300.00	300.00
	Runoff recession coefficient	-	0.04	0.06
	Return flow fraction	-	0.10	0.15
Top soil layer	Soil Field capacity	$m^3 m^-$	0.24	0.29
	Wilting point	$m^3 m^-$	0.16	0.22
	Saturation capacity	$m^3 m^-$	0.37	0.42

	Hydraulic conductivity	m	0.16	0.16
Bottom soil layer	Soil Field capacity	m³ m-	0.27	0.28
	Wilting point	m³ m-	0.17	0.18
	Saturation capacity	m³ m-	0.29	0.30
	Hydraulic conductivity	m	0.08	0.10
	Root wilting point fraction	-	0.87	0.86
	Groundnut irrigation	-	0.70	0.59
	Capillary rise (Cap)	mm	0.016	0.05

Figure 6.7a 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 overall R^2 of 0.71 (Figure 6.7a). 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 D.2). 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 6.3). Also, the model only accounts for the effect of water stress on yields (whether water demands are met), 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 (Qiaozhen et al.,

2014) (Figure 6.7b) . The comparison of model-simulated ET for the years MODIS ET was available (2000-2013) shows a good correlation (R2 = 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.

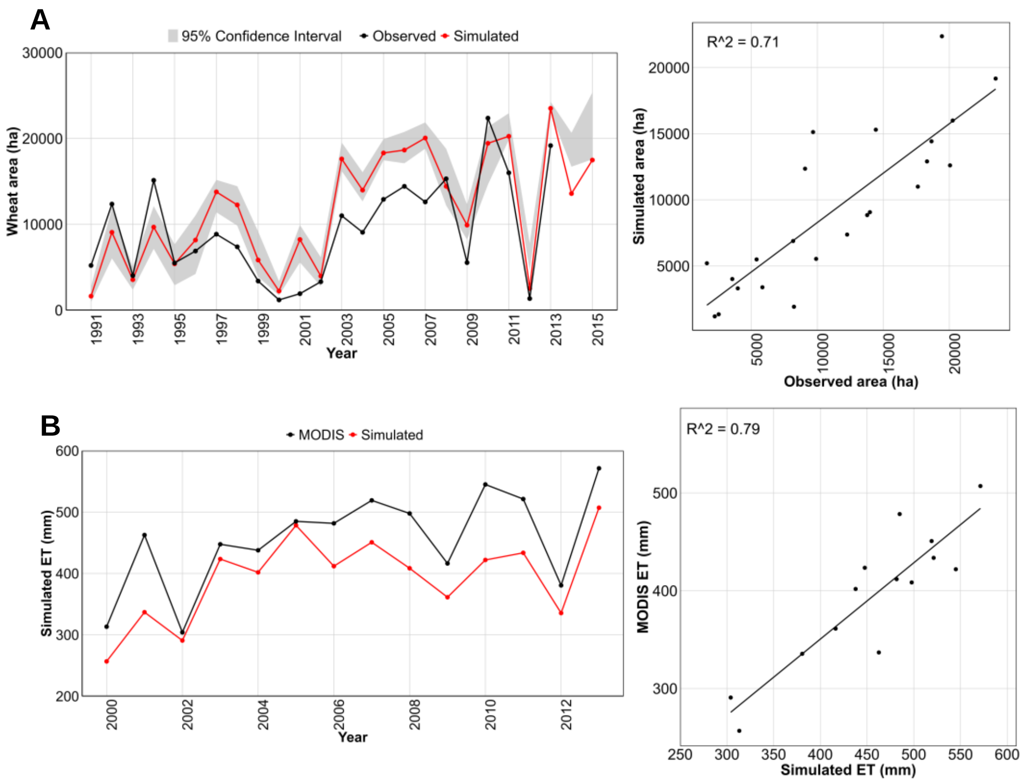


Figure 6.7: (A) Simulated and observed post-monsoon wheat area (ha); (B) Comparison of modelled ET with remote sensing-based MODIS ET, averaged over the catchment.

6.4.2 Increase in supply (recharge) from check dams

Figure 6.8 shows the increase in supply through recharge by CDs in the grid cells where CDs are located (453 grid cells out of 1319). On average, each year

CDs capture 18.5 million cubic meters (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 2005-08 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 mitigate drought impacts. This is especially so because groundwater is depleted annually and there is no transfer over the years or recharge from good years to bad. In grid cells with no CD storage, there is no increase in supply.

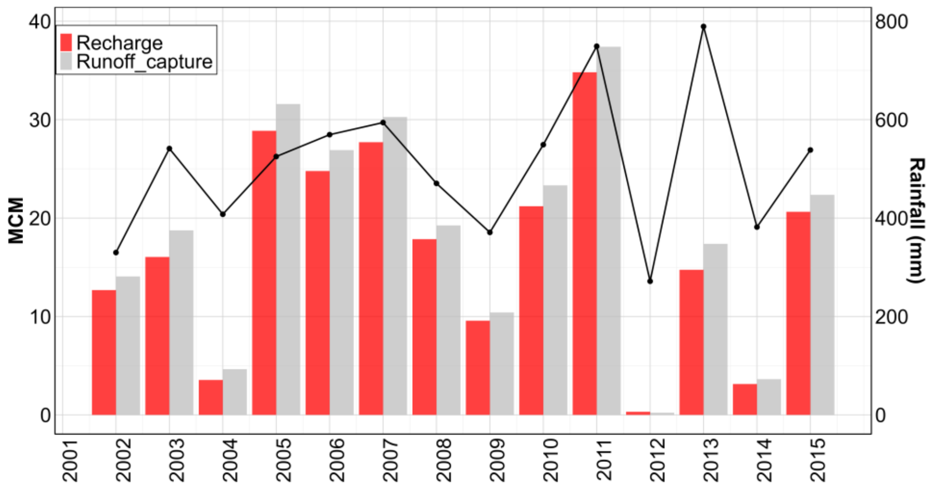


Figure 6.8: Runoff capture (MCM) and recharge (MCM) by check dams in the catchment in comparison with rainfall.

6.4.3 Increase in cotton and wheat area in response to increase in recharge

Figure 6.9 shows the increases in the areas of cotton (6.9a and 6.9b) and wheat (6.9c and 6.9d) in the catchment after the introduction of check dams in 2002 (post-CD period). The comparison is made for the whole catchment area (6.9a and 6.9c) and for farmers living in grid cells with CDs (6.9c and 6.9d) between models with human behavior (HB_{on}) and without human behavior (HB_{off}). The figures show the average crop area (cotton or wheat) per grid cell. 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 end of the simulation (in the year 2015), the cotton area (36.5 ha/grid cell) is higher by 4.3% (Figure 6.9a), and the wheat area (13.3 ha /grid cell) is higher by 15.5% (Figure 6.9c) 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. Since only one-third of grids have CDs, the impact of CDs between the HB_{on} and HB_{off} models becomes more discernable when comparing the cotton areas farmed only in the grid cells with CDs. The average area per grid cell of cotton (41.3 ha/grid cell) is 11.9% higher in the HB_{on} model as compared to the HB_{off} model (36.9 ha/grid cell) (Figure 6.9b). Similarly, the average area per grid cell of wheat (16.2 ha/grid cell) in the HB_{on} model is higher by 36.1 % as compared to the average wheat area per grid cell (11.9 ha/grid cell) in the HB_{off} model (Figure 6.9d).

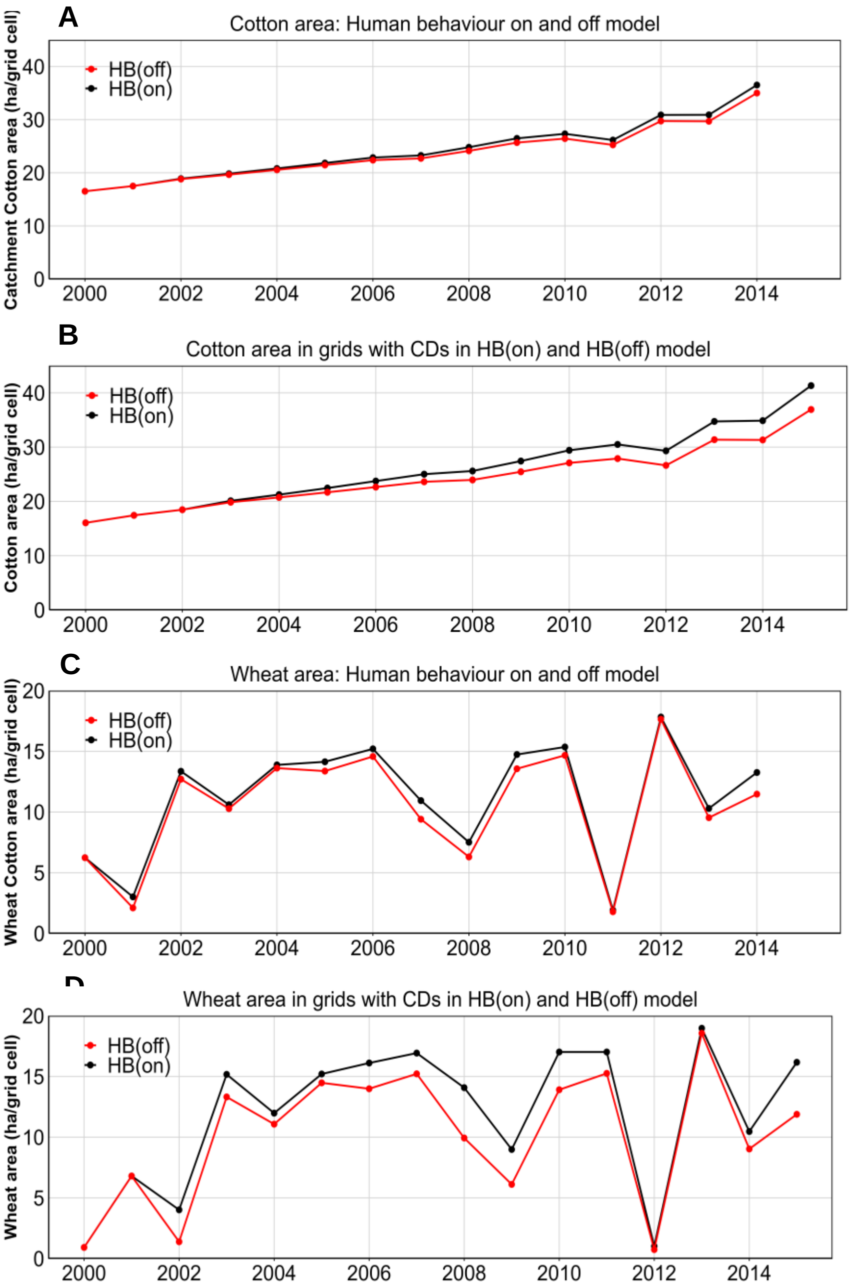
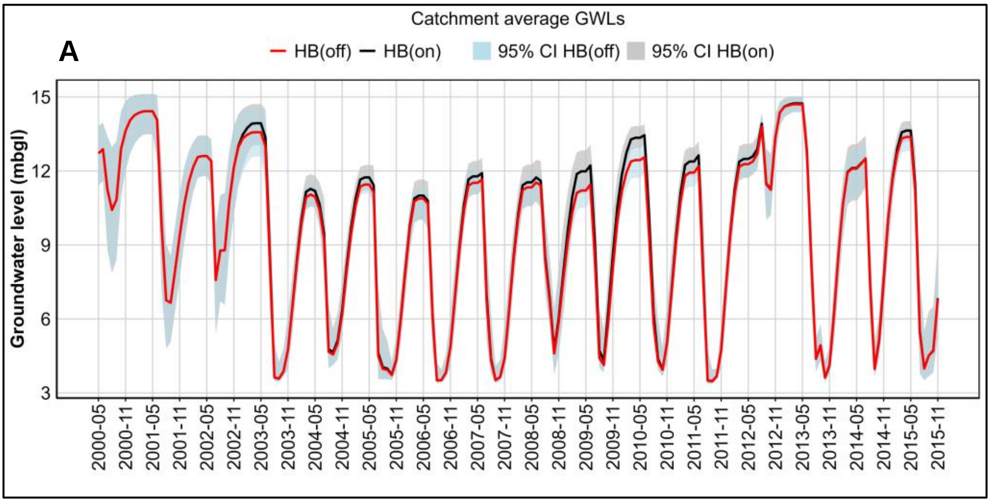


Figure 6.9: Total catchment A) cotton area and C) wheat area in the HB_{on} and HB_{off} model. Mean B) cotton area and D) wheat area in the grids with CD in the HB_{on} and HB_{off} models. The figures show the period starting from 2000 because there is no difference in crop areas in the pre-CD period (1991-2001).

6.4.4 Impact of increased crop area on groundwater levels

The expansion of cotton and wheat cultivated area (Figure 6.9) results in an increased demand for groundwater irrigation and reflected in the deeper groundwater levels. When assessing groundwater levels across the entire catchment, the difference is subtle but discernible. In the post-CD period, the HB_{on} model shows slightly deeper groundwater levels over the years on average (by 0.18 m) and in the pre-monsoon seasons (by 0.32 m) (after the end of the cropping season) than HB_{off} model due to increased irrigation abstractions to support the expanded areas of cotton and wheat (Figure 6.10a). However, the differences become more pronounced when comparing grid cells with CDs in both the HB_{On} and HB_{Off} models (Figure 6.10b). In the grid cells with CDs, where the expansion of crop areas occur, groundwater levels over the year are on average 0.62 m deeper (Figure 6.10b). 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 in the HB_{on} model when compared to the HB_{off} model. This indicates that the additional recharge due to CDs may have raised the groundwater levels by average 1.03 meters at the end of the (hydrological) year. However farmer, in response to increased water supply through CDs, utilize this surplus for expanding irrigation.

Over the years, on average 54% of additional recharge is used for expanding irrigation for cotton and wheat (Figure 6.11). 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).



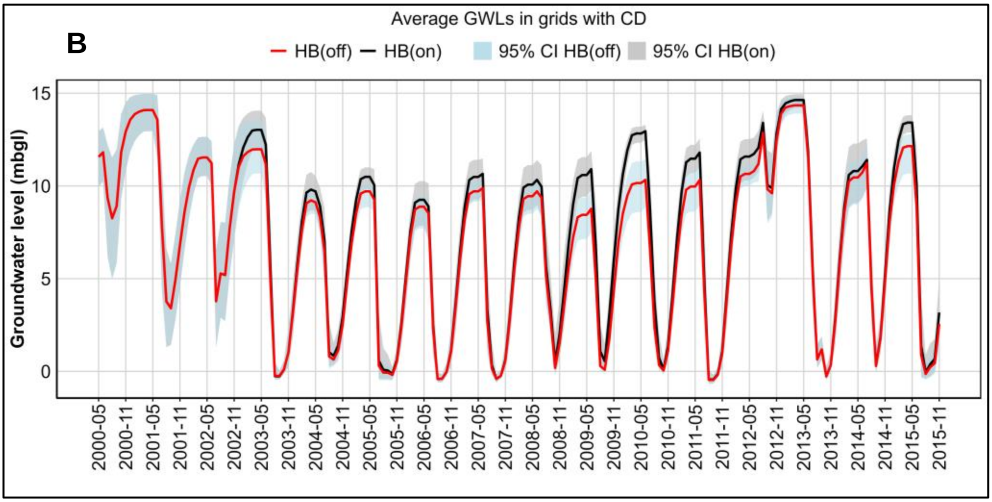


Figure 6.10: A) Overall catchment groundwater level and B) Groundwater level in grids with check dams in the HB_{on} and HB_{off} models

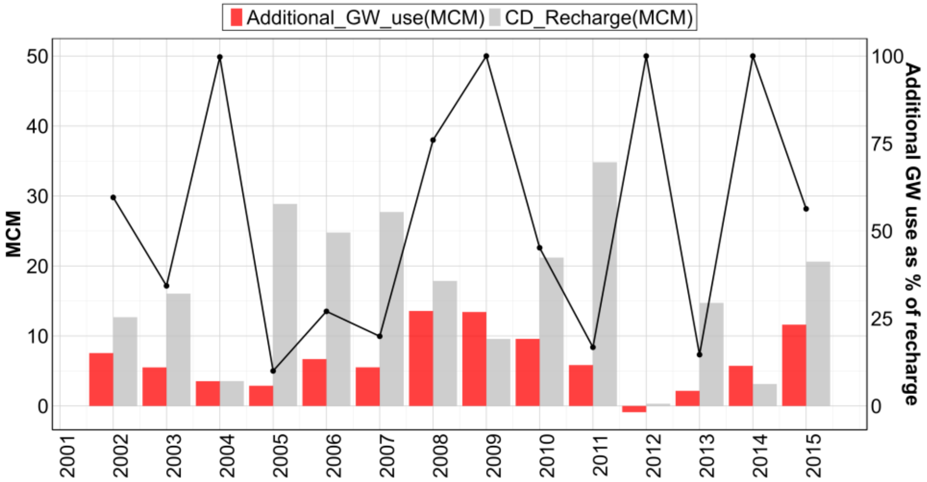


Figure 6.11: Additional GW use in model HB_{on} (compared to HB_{off} with no human behavior) relative to check dam recharge

6.4.5 Unintended impact on income and adoption

Figure 6.12 shows the effect of 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 6.12a), in line with the expansion of crop area (Figure 6.9). 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 year^{-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 year^{-1}).

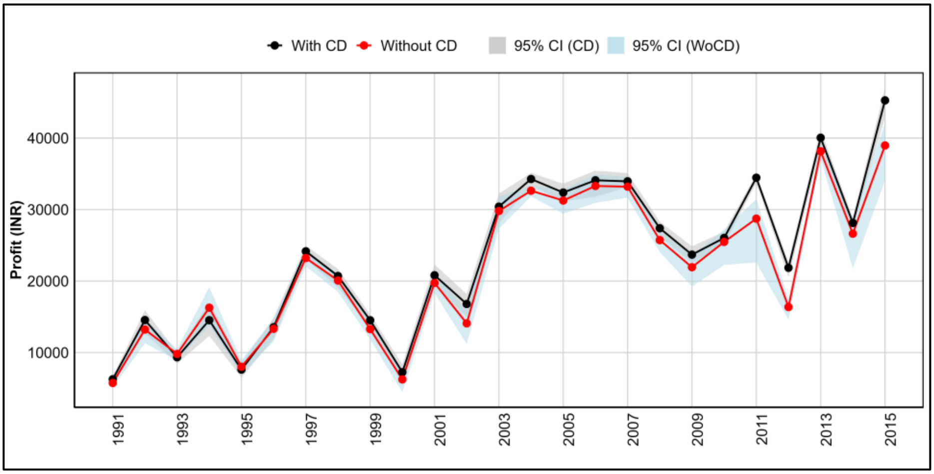
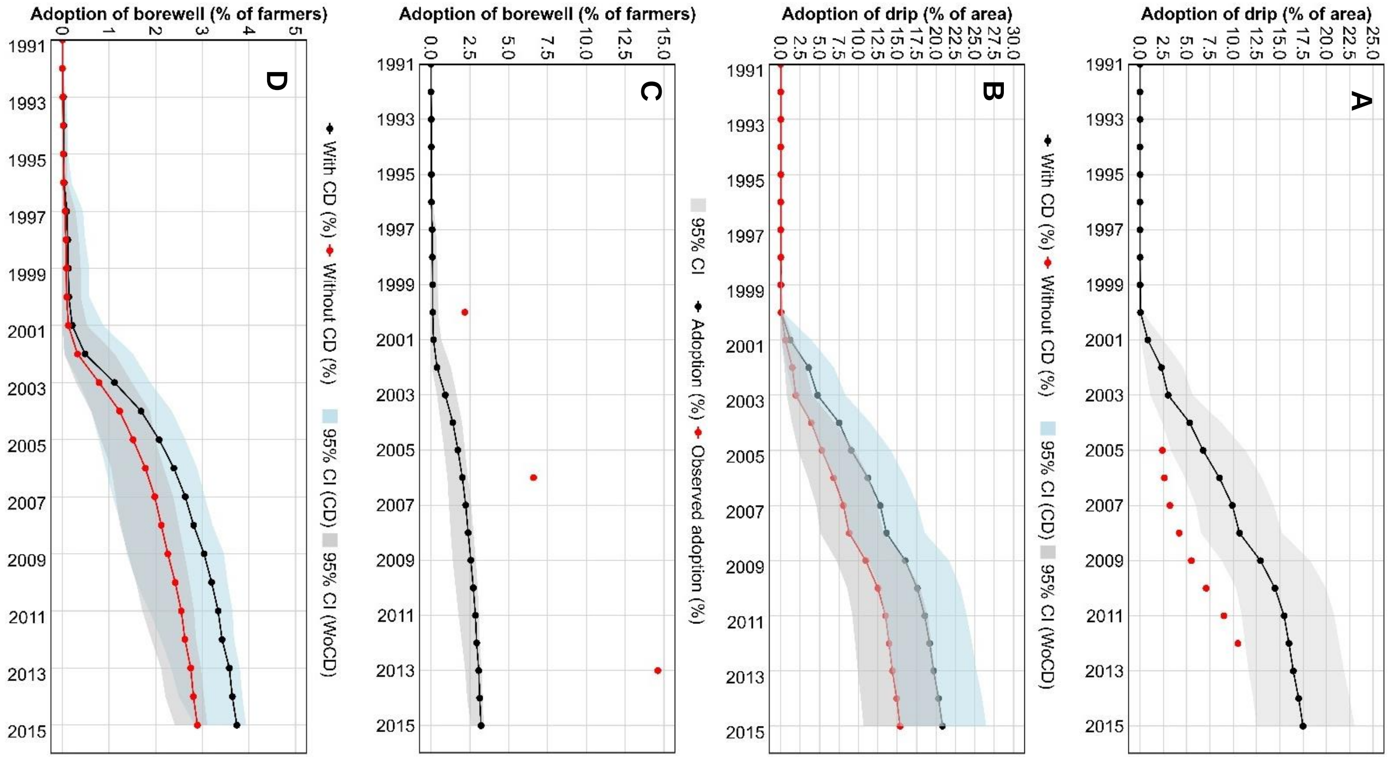


Figure 6.12: Average profit (INR) from crop production for farmers with and without a CD

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 6.13a 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 (Chapter 5), 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.



6.13: A) overall adoption (% of area) of drip in the catchment and B) in grids with (CD) and without a CD (WoCD); C) overall Adoption (% of farmers) of borewell in the catchment and D) in grids with (CD) and without a CD (WoCD) [Source: Observed drip adoption (GAPL, 2014) and Borewell adoption (MoWR, RD & GR, 2024)]

The impact of increased profit on adoption is evident when comparing the farmers living in grid cells with and without CDs (Figure 6.13b). 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 6.12a), 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 farmer survey conducted in the region (Chapter 5). 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 squared test).

In contrast to the adoption of drip irrigation, the model underestimates the observed borewell adoption (percent of farmers) patterns (Figure 6.13c). 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 6.13d). The adoption of both drip irrigation and borewells contributes to higher cotton yields among the adopters, as depicted in Figure D.3, further enhancing farmers' benefits.

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). 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.

6.5 Discussion

The results show that in response to the (perceived) increase in supply brought by recharge from CDs, farmers increase their crop areas, mostly irrigated by groundwater, leading to increased groundwater abstractions. The crop area increments are relatively small (4-10 %) for the whole catchment, which is in line with earlier results (Alam et al., 2022b, c) showing that the impact of CDs have been limited in the area. Nonetheless, this translates to higher groundwater use, subsequently leading to deeper groundwater levels.

Typically, recharge efforts are marked by conflicting assertions. These commonly strive to boost groundwater storage while concurrently asserting improvements in crop production due to increased availability of irrigation water (Alam et al., 2022b; Patel et al., 2020; Shah et al., 2009). The former may not happen if the latter is the case and vice-versa. However, neglecting the unfolding of the phenomenon of supply-demand feedback poses a deterrent to achieving either of the objectives. For example, if the objective of introducing recharge measures such as CDs was to augment groundwater storage, then the unfolding of the phenomenon of supply-demand feedback suggests that this approach may not yield the desired results. This is because farmers adapt their behavior based on perceived increase in water availability and increase their irrigation water use. This is reflected in the reduced groundwater storage with groundwater levels 1.03 m deeper in the pre-monsoon season when compared with the counterfactual of when the farmers do not change their behavior. This nullifies the increase in the groundwater levels expected from additional recharge from the CDs. This was also the finding from a catchment scale water balance study (Alam et l., 2022b) that showed that the implementation of CDs did not lead to any long-term increase in groundwater storage. Similar results have been reported elsewhere (Adla et al., 2023; Di Baldassarre et al., 2019; Kallis, 2010), which show that as the availability increases, demand increases leading to increasing water use.

On the other hand, if the goal is to enhance irrigation supply, the system seems to operate as designed, with increased recharge primarily dedicated to irrigation and leading to increasing area under cultivation, enhancing farmer's income. Nonetheless, this may not be sustainable. First, in the case study region and similar semi-arid regions with high inter-annual variation in rainfall, the augmented supply is constrained and negligible in dry years, when it is most needed, showing that CDs may not be effective drought mitigation measures. Also, the expansion of water-intensive crops may heighten vulnerability. This is because the increased irrigation water needs of water-intensive crops (that are often riskier crops to grow) may not be supported in drought years, leading to increased vulnerability (Alam et al., 2022b). Over time, under a lack of demand management and regulation measures, this would warrant even more drastic supply measures. This in turn would again accentuate demand to exhaust the new quantum of supply (i.e. another cycle of supply demand feedback). The region shows evidence of it with farmers investing in deeper borewells and government investments in scheme such as "Sauni" (WRD, 2024), that aims to transfer flood water from >1000 km through an underground pipeline to fill 115 reservoirs in the Saurashtra region. While increased supply measures may be required, focusing alone on supply and neglecting demand side management measures will lead to a self-reinforcing supply-demand cycles (Di Baldassarre et al., 2018in the region, and consequently to increased vulnerability. Thus, there should be equal focus on demand side management to avoid such self-reinforcing supply-demand cycle and sustain supply side measures.

Yet another consequence of the supply driven interventions with lack of demand side management is on farmers' investments. The introduction of CDs resulted in increased profits for the farmers living near the CDs, which led to higher adoption of drip irrigation and borewells among them. The increased profit leading to higher investment in both demand and supply measures reflects the unraveling of unintended consequences of the human-water feedback. The increase in supply led to more adoption of efficient irrigation via drip irrigation practices because of higher income realized and therefore improved ability to adopt efficient irrigation practices. However, this led to more efficient exhaustion of potential water savings from CDs, and even larger areas being cropped than would have happened under less efficient irrigation practices. This pattern is synonymous to the emergent patterns of Jevon's paradox, where adoption of efficient irrigation practices have led to further agricultural intensification (Birkenholtz, 2017; Ghoreishi et al., 2021a,b).

Further, this also leads to higher investments in borewells. While simulated results underestimate the actual adoption, the increase is concerning because it is leading to the unintended consequence of deep groundwater overexploitation. This means that the investments to augment shallow groundwater storage resulting in higher profits are increasing investments in deeper borewells that tap non-renewable groundwater. This may deplete deeper groundwater sources, which contrasts with the original investment made in CDs to augment groundwater storage.

These findings underscore the need to critically understand human-water feedbacks, informed by empirically grounded behavioral rules, that lead to unintended consequences. This knowledge is essential for planning long-term sustainable and equitable water resource investments.

7.

Success to the successful: the distribution of benefits from agricultural water interventions is skewed in favor of the wealthier farmers

7.1 Introduction

Agricultural water interventions are critical for adapting to the impacts of climate change and building the resilience of farmers. This necessity is particularly pronounced for approximately 500 million small and marginal farmers who are most vulnerable to climate change (GCA and WRI, 2019; Lowder et al., 2016). In Asia and Africa, smallholder farmers predominate, yet their capacity to adapt to climate change is constrained by low and fragmented land holdings, lack of capital, and inadequate access to financing, irrigation, and inputs, among other factors (Sikka et al., 2022; Tesfaye et al., 2021; Giordano et al., 2012).

To build farmers' resilience and capacity, governments and donors invest significantly in agricultural water interventions, exemplified by large-scale watershed management programs in India (Sharad et al., 2012), climate-smart villages (Alam and Sikka, 2019; CRIDA, 2019), and promotion/upscaling of agricultural water management (AWM) solutions (Giordano et al., 2012). However, implementing the interventions without proper planning can yield unintended consequences and externalities, leading to unsustainable and inequitable outcomes (Alam et al., 2022a). These externalities include supply-demand feedback, where increased supply interventions lead to increased demand and nullify or reduce the expected benefits (Alam et al., 2022a; Adla et al., 2023). For instance, the introduction of check dams (CDs) has resulted in increased groundwater demand, reducing anticipated benefits such as increased groundwater storage in the Kamadhiya catchment in India (Chapter 6).

Moreover, the resulting impacts from unintended consequences like supply-demand feedback may not be equitable, both socially and geographically. The advantages of water harvesting, and recharge, are often concentrated in farms situated in low-lying areas (Alam et al., 2022a; Shah et al., 2021). In the

Kamadhiya catchment in India, farmer surveys showed that showed that benefits of CDs were limited to nearby farmers (Alam et al., 2022c) and further modeling results indicate that increased storage led to increased income and subsequent higher adoption of the interventions of the farmers near to CDs. (Chapter 6). The results underscored the unequal geographical distribution of benefits, particularly around check dams.

Furthermore, existing inequalities in socio-economic status and power dynamics also determine the distribution of benefits from agricultural water interventions. These impacts are often exacerbated by disparities in financial capital, knowledge accessibility, and gender and power relations (Sharma et al., 2008; Namara et al., 2010; Linton and Budds, 2014). Often, affluent or influential farmers, endowed with greater access to social, financial, and biophysical resources, reap more substantial advantages, subsidies, and benefits from the interventions (Namara et al., 2010; Kafle et al., 2020). This represents the symptoms of the success to the successful archetype (Biella et al., 2024), where individuals or groups who are already advantaged are more likely to benefit from new opportunities or interventions. For instance, studies have shown that women farmers frequently encounter barriers in accessing support services, exacerbating existing disparities between male and female farmers (Namara et al., 2010). Similarly, research in Ethiopia highlights how high-value crop cultivators and wealthier farmers derive the greatest benefits from investments in farmer-led irrigation projects (Kafle et al., 2020). In this paper, the ABM-AWM model (Chapter 6) is used to explore how externalities and resulting impacts from the introduction of CDs in the case study area of Kamadhiya vary based on farmers' land size. Land size often serves as an indicator of wealth and social power in the region (Deininger et al.,2009; Chakravorty et al., 2019).

7.2 Methodology

The paper applies the ABM-AWM developed (see chapter 6) to simulate the impact of CDs and the resulting effects on farmers' capital, income, and adoption, differentiated by their land size. The model categorizes farmers into four types based on their land size (Table 7.1), which is derived from agricultural census data (DoAC&FW., 2019). In the region, marginal (< 1 ha) and small farmers (1- 2 ha) dominate, having 23.8 % and 40.6 % of total land holdings, respectively. However, in terms of area, they hold only 7.8 % and 28.6 % of total land with medium (2 – 4 ha) and large farmers (> 4 ha) holding 35.1 % and 28.5 % of total land, respectively.

The ABM-AWM model combines a spatially distributed hydrological model with farmers' decision-making based on RANAS (Risks, Attitudes, Norms, Abilities, and Self-regulation) behavioral theory and observed data (see Chapter 6). Overall, the model simulates the decisions of 38,447 farmers in the Kamadhiya catchment regarding their cropping decisions and investment strategies. In the model, farmers' decisions regarding the allocation of cultivated area to cotton and groundnut in the Kharif season, cultivated area for post-monsoon wheat crops, and investments in drip irrigation and borewells are simulated. Farmers' capital and income are estimated based on crop area, crop yields, prices, and cost of cultivation.

7.2.1 Access to groundwater

In the catchment, farmers irrigate their crops primarily through dugwells, which are recharged by rainfall and CDs (Alam et al., 2022b). The ownership of wells results in differential access to groundwater (Prabhakar and Olivia, 2009; Nagaraj and Chandrakanth, 1997). The survey results (Table 7.1) showed that large farmers own on average 2.1 wells followed by medium (1.6), small (1.3) and marginal farmers (0.9). This also reflects the land size holding of farmers; larger area requiring a greater number of wells or higher capacity pumps. To account for water access based on the ownership of wells, the model proportionately distributes groundwater in a grid based on average number of wells owned by a farmer type (marginal, small, medium and large; see Equation 7.1).

$$GWA_{f,i(g)} = (\frac{Well_f}{Total\_wells_g}) * GWA_{i,g} \qquad \text{.... Equation 7.1}$$

Where $GWA_{f,i(g)}$ is the groundwater available to a farmer type (f) living in a grid cell (g) on day i and $GWA_{i,g}$ is the total groundwater availability in grid cell g on day i; $Total\_wells_g$ is the total number of wells in the grid cell g and $Well_f$ is the average number of wells a farmer type, f, has (Table 7.1).

Table 7.1: Characteristics of marginal, small, medium and large farmers in the area

	%age holdings [a]	%age area [a]	Modelled area (ha)	% of area in grid cells with CD	No of Wells	Average of DW depth	Cotton area Slope[b]
Marginal	23.7%	7.8%	5952	38.70%	0.9	68.9	0.0156
Small	40.6%	28.6%	22447	38.70%	1.3	54.8	0.0167
Medium	26.7%	35.1%	27018	38.70%	1.6	62.98	0.0175
Large	9.0%	28.5%	20827	39.00%	2.1	63.05	0.0189

[a] Agricultural census 2015-16 (DoAC&FW, 2019)

[b] (2302*s1 + 8681*(1.3/0.9)s1+ 10457*(1.6/0.9)+8116*2.33(2.1/0.9)/ (29556) = (0.0175-0.0132)/0.0132

7.2.2 Allocation of cultivated area to cotton

In the catchment, cotton area has increased significantly after the introduction of CDs (after 2002; post-CD) (Alam et al., 2022b) and farmers' perception of increased availability of water has played a key role (Alam et al., 2022c). This is due to cotton providing a higher average return of 50,000 INR per hectare compared to groundnut's 41,000 INR per hectare since 2002, based on prevailing domestic prices. In the developed ABM-AWM model (Chapter 6), this was accounted for by using Equation 7.2, which gives farmers annual cotton area with slope (cotton area/net cultivated area) accounting for increase in cotton area proportion over the years. Based on the time series of analysis of cotton area, all farmers were given the same slope (0.0132 year^{-1}) before the introduction of CDs (till 2001). After 2002 (post-CD), the farmers in grid cells with a CD were given a higher slope (0.0175 year^{-1}) whereas the farmers in a grid cell without CD continue to have the same slope (0.0132 year^{-1}). The higher slope in grid cells with CDs reflects higher (perceived) availability of the water from introduction of CDs.

However, Equation 7.2 assumes that all farmers have equal access to water and perceive water availability uniformly, without considering the differences in well ownership (Table 7.1). To address this, Equation 7.3 modifies the model by incorporating the differences in well ownership and assuming that the increase in cotton area (slope) is directly influenced by these disparities in water access. In Equation 7.3, the slope for each type of farmer varies according to the number of wells they own (Table 7.1), while ensuring that average slope weighted by the proportion of different farmer types is equal to 0.0175 year^{-1}.

$$Area_{cotton(f)} = (-26.151 + slope\ (t) * year) * Area_{farmer} \qquad \text{.... Equation 7.2}$$

$$Area_{cottonf(t)} = (-26.151 + slope(f,t) * year) * Area_{farmer} \qquad \text{.... Equation 7.3}$$

In Equation 7.2, slope before 2002 (pre-CD period) = 0.0132 year^{-1}; slope after 2002, i.e. post-CD period (for farmers with irrigation and in grid cells with check dams) = 0.0175 year^{-1}. In equation 7.3, slope(f,t) before 2002 (pre-CD period) is same 0.0132 year^{-1} and after 2002, varies for different type of farmers (Table 7.1). $Area_{farmer}$ is farmer-owned cultivated land.

The model is run in two versions: HB_{on} and HB_{off}. Both versions incorporate CDs, but they differ in the inclusion of human behavioral rules. HB_{on} integrates all human behavior rules into the model, while HB_{off} excludes them. This approach allows for the assessment of how the integration of human-water feedback and behavior impacts the resulting benefits.

7.3 Results

7.3.1 Difference in capital and profit among farmer types

Figures 7.1a and 7.1b show the changes in accumulated capital and annual income for the model HB_{off} (without behavior) over the simulation period for marginal, small, medium, and large farmers. The results indicate that even without behavioral rules that account for the impact of differential water access, the size of the farmers' land significantly influences their accumulated capital and annual income. Capital increases over the years for all farmers, with the highest rate observed for large farmers (41,000 INR/year) and the lowest for marginal farmers (4,200 INR/year). By the end of the simulation period, the accumulated capital varies by almost an order of magnitude between large and small/marginal farmers.

This disparity in accumulated capital stems from differences in the farmers' annual income (Figure 7.1b) over the years. The average annual income of large farmers (269,000 INR/year) is 3.9 times higher than that of small farmers (68,000 INR/year) and 8.5 times higher than that of marginal farmers (31,600

INR/year). However, income for all farmers depends on rainfall, with lower incomes in years of low rainfall (Figure 7.1c). This dependence on rainfall reflects the limited storage capacity of underlying aquifers, which cannot sustain crops without adequate rainfall. The impact of rainfall is consistent across all farmers, as they rely on the same aquifer. Though large farmers have more access to water, they also have larger areas to irrigate.

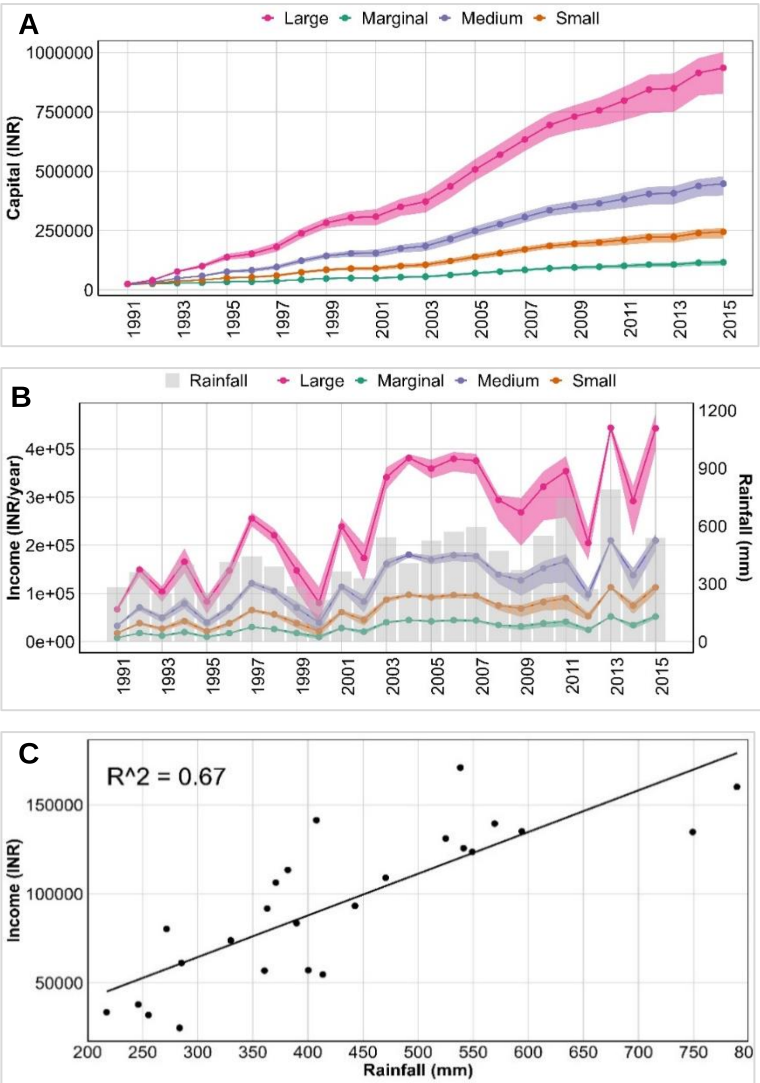


Figure 7.1: a) Capital and b) income of different types of farmers and c) relation between average income (all farmers) and rainfall

7.3.2 Impact of CD and farmers behavior

7.3.2.1 Cotton area

Figure 7.2 shows the impact of perceived increases in water availability, and differential access to it, on farmers' cotton cultivation areas. The implementation of CDs results in a notable rise in cotton areas for all farmers (HB_{on} compared to HB_{off}). However, with a greater number of wells providing more water access, the increase in cotton area is most significant for large farmers (15.4%) and least for marginal farmers (6.6%). Similarly, the wheat area expands for all farmers due to more recharge due to increased post-monsoon groundwater levels (Figure E.1). However, unlike cotton, there is no disparity among farmers in wheat areas, as this expansion depends on groundwater levels that are common to all farmers within a given grid cell.

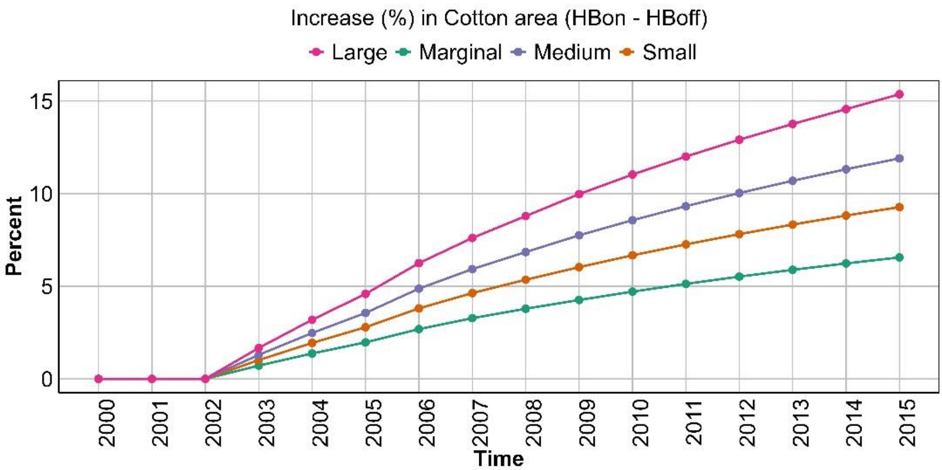


Figure 7.2: Increase in cotton area in HB_{on} model compared to HB_{off} model

7.3.2.2 Differential adoption of drip and borewell

The differences in capital and income between farmers (Figure 7.1) are also reflected in the varying adoption rates of drip irrigation and borewells among them (Figures 7.3a and 7.3c). Figure 7.3a shows that drip irrigation adoption at the end of the simulation period (year 2015) is highest among large farmers (approximately 50%), followed by medium-sized farms (approximately 9%), while adoption is negligible (less than 1%) for small and marginal farmers. Similarly, the adoption of borewells (Figure 7.3c) is low overall but follows a similar trend: the highest adoption is among large farms (4.2%), followed by medium (4.0%), small (3.4%), and marginal farmers (2.2%). However, there are less clear differences for borewell adoption with uncertainty bounds overlapping across the farmer types.

The impact of increased cotton area due to CDs, which leads to higher income given cotton's higher returns, on difference in adoption rates (between farmers in grids with CD and without CD) is shown in Figures 7.3b and 7.3d. These figures compare farmers living in grid cells with CDs, with those living in grids cells without CDs (WoCD). Only the former benefit from CDs. The results show that adoption rates are higher for both drip irrigation and borewells among all types of farmers in grid cells with CDs compared to those in grid cells without CDs. For drip irrigation, the difference is highest among large farmers (approximately 16%), followed by medium, small, and marginal farmers. Similarly, for borewells the differences are small but still largest for large farmers (approximately 0.96%), followed by medium, small, and marginal farmers. The largest difference between large farmers with and without CDs aligns with the largest increase in area (Figure 7.2), which leads to the highest increase in income.

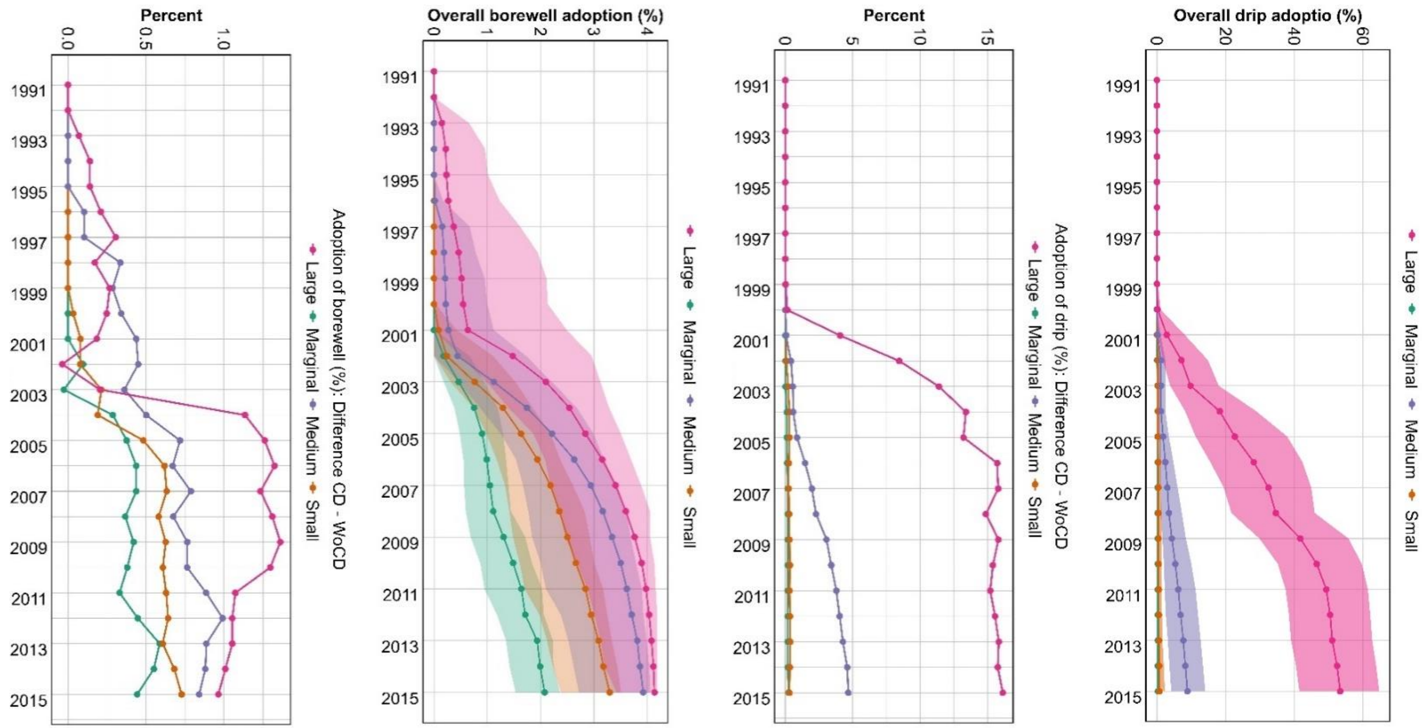


Figure 7.3: For marginal, small, medium and large farmers a) Overall adoption (% of area) of drip in the catchment; b) Difference in adoption (% of area) of drip for farmers with CD and without a CD (WoCD); c) overall Adoption (% of farmers) of borewell in the catchment; d) Difference in adoption (% of farmers) of borewell for farmers with CD and without a CD (WoCD)

The adoption of drip irrigation and borewells further increases farmers' income, with adopters experiencing higher and more stable yields. Figure 7.4 shows the impact of adoption on cotton yields by comparing the yields of non-adopters to i) adopters for both drip irrigation and borewells, ii) only borewells, and iii) only drip irrigation respectively. Yields for adopters are higher, particularly in dry years (year 1999-2002, 2012) when efficient water use, and greater water access are more valuable. The yield differences are most significant for cotton, which is fully irrigated and where drip irrigation is commonly used. For borewells, since the water yields are limited, cotton is prioritized, which might explain why wheat yields do not improve as significantly (Figure E.2). With farmers adjusting wheat area based on groundwater levels, impact of dry years is reflected in wheat areas cultivated by the farmers rather than the yields.

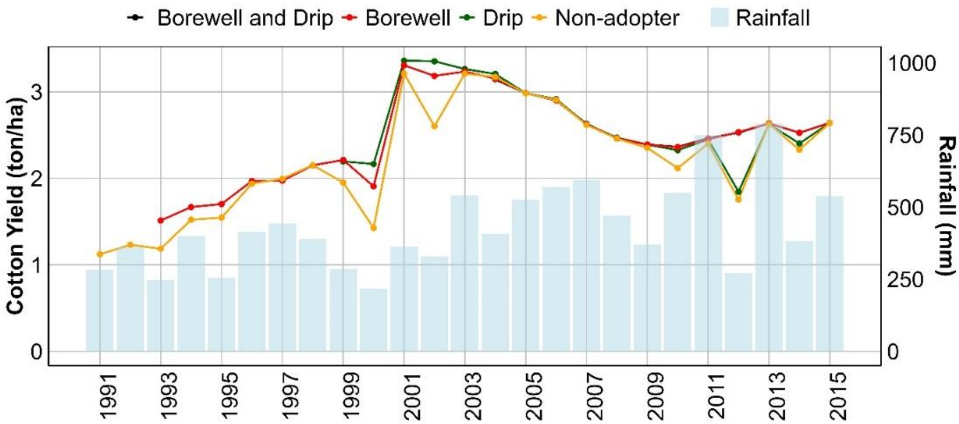


Figure 7.4: Comparing Cotton yield of adopters i) Both Borewell and Drip; only borewell and only drip with non-adopters

7.3.3 Impact on Income

The increase in cotton cultivation area due to change in farmers behaviour in response to increase (perceived) supply of water (represented by HBon – HBoff) (section 2.2), which offers higher returns compared to groundnut, has led to higher incomes for all farmers in grid cells with check dams (Figure 7.5a, Table 7.2). This increase is modest (0.6–1.6%) and is particularly affected by low or negative growth during drought years. This contrasts the continuous positive growth in cotton area (Figure 7.2) and highlights the impact of drought on income (section 3.1, Figure 7.1c). For instance, the maximum increase in income is significant (5 – 6.1%) but only occurs in years with favourable rainfall, when both the amount and distribution of rainfall are sufficient to recharge groundwater and check dams.

However, the *average* increase in income is highest among large farmers (1.6% compared to 0.6% for marginal farmers). This disparity reflects the effect of larger landholdings and leads to inherent differences in capital and income. Large farmers also have greater access to water due to higher ownership of wells, a larger relative increase in cotton area, higher adoption of drip irrigation and borewells, and higher yields associated with these interventions.

The decrease in income during low rainfall years indicates that cotton-intensive cropping is less resilient to drought, as cotton requires more irrigation (ET_{demand} ~500 mm/year, average irrigation water requirement ~ 300 mm/year) compared to groundnut (ET_{demand} ~300 mm/year, average irrigation water requirement ~ 50 mm/year). The increased irrigation demand for cotton cannot be met during drought years, resulting in low yields (Figure E.3a). This higher irrigation requirement also negatively impacts groundnut yields, as groundwater availability reduces due to increased irrigation need of cotton, in grid cells with higher cotton area (Figure E.3b). Consequently, there is an overall reduction in income from both cotton and groundnut, demonstrating the increased vulnerability of a water-intensive cropping system in drought years.

This vulnerability is higher for marginal farmers, as shown by the variation in income and the associated risks (Table 7.2). Marginal farmers face the highest downside risk, measuring downside standard deviation from the acceptable change (Hanemann et al., 2016) taken as 0 %, of 2.3 % reflecting losses during drought years, compared to large farmers who have the lowest downside risk at 1.8%. Conversely, large farmers experience the highest upside benefits, measuring upside deviation from the acceptable change taken as 0 %, with gains of 2.7% compared to 2.1% for marginal farmers. This indicates that large farmers generally gain the most during good rainfall years and lose the least during low rainfall years and vice versa for marginal farmers. This results from higher access to water for larger farmers due to a higher number of wells and a higher adoption of drip irrigation, which means they can use water more efficiently that is critical for higher yields in dry years (Figure 7.5b).

Table 7.2: Income difference (HBon – Hboff) and associated statistics.

Type of farmer	**% increase**	**Maximum**	**Min**	**Downward risk[a]**	**Upside risk/benefit[a]**
Marginal	0.6	5.0	-8.4	2.3	2.1
Small	0.9	5.3	-7.6	2.1	2.2
Medium	1.2	5.7	-7.0	1.9	2.4
Large	1.6	6.1	-6.5	1.8	2.7

[a] Same as standard deviation with difference is that mean is replaced by minimum acceptable risk which in this case is taken as 0 %. Risk = $\sqrt{\frac{\sum(x(i)-r)^2}{N}}$ where x(i) is the change in year I, r is the minimum acceptable change (taken as 0 %). Downside risk considers only those changes (x) that are below r and upside risk considers the opposite.

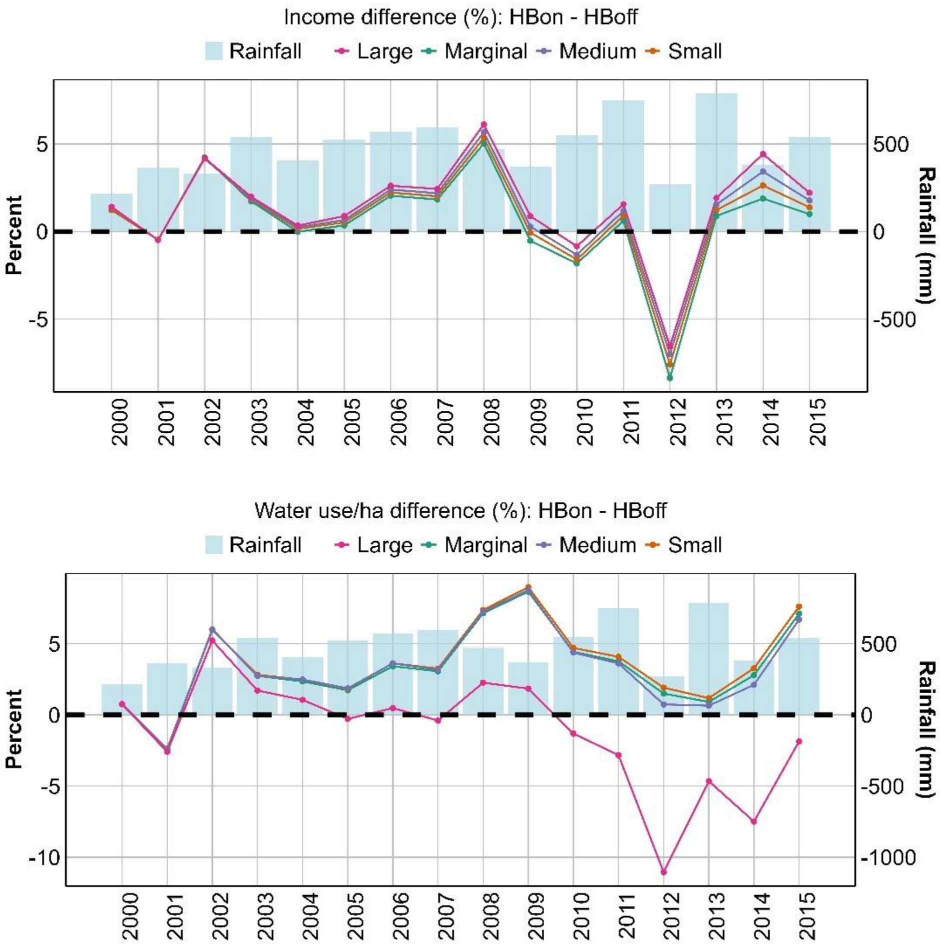


Figure 7.5: For marginal, small, medium and large farmers a) Change in income (%) and b) Change in water use (mm/ha) after introduction of behavior ($HB_{on} - Hb_{off}$)

7.3.4 Unexpected externality: Increase in water use per hectare

Figure 7.5b shows the resulting unexpected externalities arising from the introduction of CDs, leading to an increase in income and subsequent adoption of drip irrigation. Figure 7.5b shows the change in water use (mm) per hectare among different farmer types. It indicates that, despite the highest percentage increase in areas cultivated by large farmers (Figure 7.2), their water use increase (mm/ha) sees the smallest increment. This paradox can be attributed to the adoption of drip irrigation, which enhances irrigation efficiency, resulting in overall water savings for large-scale farmers. These savings get partially spent on increasing post-monsoon cultivated areas which relies on groundwater storage at the end of monsoon season (chapter 6). However, groundwater, being a common pool resource with the same aquifer accessed by multiple users (Gardner et al., 1990; Asprilla-Echeverria, 2021), means that the benefits of water savings, which remain in the aquifer, may not be limited to individual farmers who adopts drip but extend to all farmers within a grid cell tapping the aquifer. This aspect may negatively influence farmers adoption of drip irrigation if other farmers continue to use groundwater without drip irrigation.

7.4 Discussion

The results show that large farmers, often richer and socially dominant, gain the most from the additional groundwater supply given that they have the largest number of wells that enables them to use higher share of groundwater (Table 7.2). At the same time, higher adoption of drip and borewell by them also makes them least vulnerable to drought years. This demonstrates the success to the successful dynamics where large farmers, due to their more favourable initial conditions, also gain the most. These results align with earlier results that have shown that intensive water harvesting, recharge, and soil moisture agriculture water interventions that shift common pool water resources to individual farms (and groundwater) benefit relatively influential and richer farmers. This is because they have the financial capacity to invest in irrigation infrastructure and other agronomy investments to reap private benefits of improved conditions of common pool resources (Bouma et al., 2011; Calder et al., 2008; Sarkar, 2011; Shah et al., 2021).

This is in addition to the geographical inequities involved with drainage-related works (i.e. weirs, dams, stream deepening), concentrating the distribution of benefits to nearby farms in low-lying areas (Shah et al., 2021; Alam et al., 2022c; chapter 6). Although not directly assessed in this context, access to lands near irrigation water infrastructures is often associated with wealthier and more influential farmers. Over time, due to land consolidation, poorer households lose their rights to productive land with reliable water availability, exacerbating absolute poverty (Namara et al., 2010; Sharma et al., 2008; Shah et al., 2021). This may further accentuate the inequitable distribution of benefits. For example, Sharma et al. (2008) in a case study of an irrigation project in the state of Andhra Pradesh, India, showed that the tail region of a command area, with less water, was dominated by lower castes with less social power. The better-off farmers and certain communities benefitted disproportionally more from the irrigation project.

Additionally, results show that negative impacts are felt more by the poor with marginal farmers being most vulnerable to drought years. This is also in line with earlier results (Kerr, 2002; Batchelor et al., 2003; Reddy, 2012). For example, impacts of groundwater exploitation leading to increased cost of pumping and drilling, well failure, and abandonment of wells (Shiferaw et al. 2008; Reddy, 2012; Narayanamoorthy, 2015) are disproportionately borne by the resource-poor farmers as they are unable to invest capital to change technology or deepen the wells (Sarkar, 2011) and often become hostage to indebtedness and poverty (Batchelor et al., 2003). This could over time also lead to increased difference in income/capital and further differences in adoption of interventions, making smaller and marginal farmers more prone to climate change impacts.

The above results call for a more targeted approach and a holistic set of investments to ensure that small and marginal farmers, who are the most vulnerable, receive equal or greater benefits. While access to groundwater cannot be controlled due to existing rights, it is essential to explore ways to support these farmers. For example, since adoption of drip irrigation is lower among small and marginal farmers, providing more financial incentives could help them maximize its benefits (Sidenburg et al., 2012). Similarly, implementing area-based approaches for soil moisture management, improved seeds, and strategic location of water structures could further support these farmers.

The findings also underscore the capacity of developed ABM-AWM to reveal unforeseen externalities. They demonstrate that increased income incentivizes larger farmers to adopt agricultural water interventions (e.g., drip irrigation) more readily, leading to decreased water usage. The saved water remains in the aquifers and may benefit the broader community (e.g., increasing post monsoon cultivation area) though disproportionately. For example, larger farmers with more wells and higher capacity pumps may end up accessing more of the saved water to expand cultivated area further. However, adoption of drip may be hindered due to the common-pool resource (CPR) nature of groundwater as individual adoptee farmers may not solely reap the benefits of saved water. This shows that collective benefits in CPR resources emerge when all stakeholders collectively participate (Herzog and Ingold, 2019).

7.5 Conclusion

Agricultural water interventions are increasingly promoted for climate change adaptation. However, unplanned implementation can lead to negative consequences, including inequitable distribution of benefits and impacts. This chapter uses an agent-based model to demonstrate how unequal resource distribution among farmers, based on land size, can result in "success to the successful" dynamics, where larger (wealthier) farmers benefit the most from AWM interventions (such as CDs). The results show that large farmers gain the most and face the least vulnerability compared to small and marginal farmers following the introduction of CDs. The chapter highlights the need for a more targeted approach and a comprehensive set of investments to ensure that small and marginal farmers, who are the most vulnerable, receive equal or greater benefits.

8. Conclusion

The thesis objective and research questions are reflected upon in this chapter. The thesis had the overall objective "*To improve understanding and consideration of potential hydrological externalities and unexpected societal feedback resulting from the implementation of Agricultural Water Management (AWM) interventions to avoid or mitigate unsustainable and inequitable outcomes using modeling approaches incorporating dynamic and coupled human-water systems interaction*". This was addressed by pursuing four main research questions. The findings for the individual research questions posed are summarized first.

8.1 Research questions

8.1.1 Research question 1

The first research question was: *'How have agent-based sociohydrology approaches been used to uncover the negative hydrological externalities and societal feedback associated with AWM interventions?'*

This question was addressed through a systematic review of published literature (Chapter 2). By systematically reviewing the application of Agent-Based Models (ABMs) in agricultural systems, thesis analyzed how ABMs have been utilized to reveal the negative hydrological externalities and societal feedback linked with AWM interventions, while also identifying existing knowledge gaps.

The findings indicate that ABMs have been extensively employed to simulate agricultural systems and AWM interventions (e.g., drip irrigation, dams) along with their resulting externalities. This includes modeling negative hydrological externalities such as groundwater overexploitation, water quality degradation, and alterations in downstream flows, as well as societal feedback such as inequitable adoption of AWM interventions, inequity in water allocation, and inequitable water distribution, along with interactions between upstream and downstream farmers. ABMs have achieved this by effectively integrating hydrological models with a range of farmers' behaviors (e.g., adoption of interventions, irrigation practices, crop choices, investment decisions), enabling the modeling of human-water feedback loops and their resultant impacts on both natural and human systems.

However, the review reveals that despite the extensive development of ABMs, gaps and opportunities for improvement exist in fully unraveling AWM externalities and their resulting unsustainable and inequitable outcomes. Firstly, there is a need to enhance the integration of spatially distributed and integrated (surface-groundwater) hydrological models, with most ABMs using lumped or individual surface or groundwater models. These are essential for capturing the spatially explicit impacts of AWM interventions. Secondly, there is a need to incorporate socially grounded behavioral theories, replacing the current overreliance on rational decision-making and simple heuristics, in order to explicitly account for the social, economic, and cultural experiences of farmers in their decision-making processes. Lastly, there is a need to better represent individual farmers, rather than aggregating them as a single unit, to account for the heterogeneity among them. This recognizes that farmers have unequal access to resources and power dynamics that results in the inequitable distribution of benefits and losses.

This review and the identified gaps serve as the foundation for the development of the ABM presented in Chapter 6. It uses a spatially distributed model that integrates groundwater dynamics with farmers' behavior, incorporating both the RANAS behavioural theory and data-driven rules to model individual farmers.

8.1.2 Research question 2

The second research question was "*How sustainable and equitable are the impacts of AWM interventions implemented to enhance water supply for agriculture?*". For this research question and the remainder of the thesis, the case of Kamadhiya catchment in the western state of Gujarat in India, where intensive construction of check dams (CDs) have taken place was studied. The sustainability and equitability of impacts resulting from the introduction of CDs was assessed by using a mixed method approach combining catchment water balance (Chapter 3) and farmers surveys (Chapter 4). The catchment water balance shows that after the introduction of the CDs (> year 2002), the irrigation water needs almost doubled, primarily due to an increase in the areas of more water intensive crops such as cotton, indicative of supply-demand feedback. This increase in demand has outpaced the increase in groundwater recharge from the CDs. As a result, there is no discernible positive impact on groundwater storage, given additional recharge from CDs is comparatively less (only ~11 % of increased demand in dry years, 35 % in normal and 60% in wet years). Also, the increase in irrigation demands has made the area, underlain by a hard rock aquifer with no inter-annual carry over storage, more vulnerable to drought, given limited rainfall recharge and negligible additional recharge from CDs.

The farmers surveys (Chapter 4) complemented and corroborated the catchment water balance results showing that the main perceived benefit of CDs by farmers was an increase in water supply and reliability that helps them expand crop and irrigation intensity. As were the findings of the catchment water balance (Chapter 3), surveys also show that CD benefits were mostly in good rainfall years with farmers reporting limited benefits of CDs in dry years when average water in CDs lasts only 3 months as compared to 5 and 9 months in normal and wet rainfall years, respectively. Additionally, farmer surveys show that benefits of CDs are not distributed equally among farmers. Despite high desnity of CDs, ~ 40%–50% of the sampled farmers reported no benefits from CDs and the benefits decreased with distance from CDs. This reflects a spatially inequitable distribution of benefits skewed towards the farmers nearest to the CDs. Given the skewed distribution of AWM towards supply interventions on drainage lines in development projects, this warrants consideration. Further, surveys show that the structural sustainability of CDs is also a challenge with already ~40% of CDs reportedly not working and 72.8% of farmers reportedly doing no maintenance activity. Dysfunctional CDs threaten the long-term benefits that could be/have been accrued.

Combined, Chapters 3 and 4 demonstrated that the supply-demand feedback exacerbates the challenge of groundwater sustainability and equitability of benefits remains a concern. The findings emphasize that without concurrent emphasis on broader groundwater resource management and demand reduction strategies, singular focus on increasing supply through interventions such as building storages, CDs and Managed Aquifer Recharge (MAR) will remain inadequate for both sustainable development of groundwater storage and irrigation expansion.

8.1.3 Research question 3

The third research question was *"How to assess and represent human behavior associated with the implementation and uptake of AWM interventions needed to simulate their externalities and impacts?".* This is addressed by conducting a descriptive analysis and applying RANAS behavioural theory that also inspired the farmer surveys (Chapter 4 and 5). The RANAS 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). Using the

RANAS model, thesis assessed farmers behaviour towards maintenance of check dams, adoption of drip irrigation and drilling of borewells.

For CDs, the analysis of the survey data shows that both contextual (such as participation during construction, distance from CDs, land size) and sociopsychological (such as attention to CD condition, perceived maintenance effort) factors significantly affect the maintenance behaviour. The participation of farmers during CD construction comes out as the key determinant (positive) of farmers' behavior towards maintenance along with distance from the CDs (reflecting farmers benefits from the CDs) and how much attention they pay to CD conditions regularly. Also, significance of socio-economic factors including wealth (land area, house type) indicate that CD maintenance is effortful and an expensive task that may be difficult for individual farmers to carry out. Based on the results, multiple activities were recommended including formation of community/farmer groups (which can also reduce the financial burden on individual farmers), adhering to a truly participatory program (e.g., enforcing provision for token contribution from the beneficiaries which is supposed to be used later for minor upkeep and maintenance) and placing stronger emphasis on project exit protocols for maintaining sustainability of CDs. This should be combined with behavioural change techniques, such as communication and visualization of CD state of repair and a more systematic recording of the maintenance behaviour. This can lead to more farmers contributing to its maintenance.

For the drip adoption, the results show that despite subsidies being available for drip irrigation systems, the adoption rate remains low (~16%). The results show that farmers' sociopsychological factors play a critical role in explaining farmers' adoption decisions, for both drip and borewell. It increased the employed regression model's power to explain observed adoption behaviour by three times as compared to a model that only considered socio-economic and biophysical factors. Key sociopsychological factors include farmer's perceived ability (financial and technical knowledge), perceived risk and beliefs about the agriculture water interventions. For example, higher availability of water and higher drought risk, counterintuitively, negatively impact drip adoption, whereas high perception of one's ability to practice (operate, maintain, and financially afford), positive belief about the reliability and benefits of the technology and positive societal norms increase drip adoption. Based on this, thesis recommend broader strategies, such as increasing financial support (e.g., interest-free loans), strengthening the subsidy delivery program, capacity building efforts, increased extension support visits. Along with it we also recommend post-adoption support for increasing ability, awareness and exposure to build positive attitudes and building trust in social, formal, or informal networks.

The understanding of sociopsychological factors that contributes to farmers' adoption behaviour opens the way to plan behavioural change interventions and also assist in interpreting farmers' adoption patterns for inclusion in diffusion/adoption models.

8.1.4 Research question 4

The fourth research question was *"How to apply an agent-based sociohydrology approach to model human-water feedback from AWM interventions for planning long-term sustainable and equitable outcomes?".* The thesis applied the learnings from RQ1, RQ2, and RQ3 to develop an agent-based model for agricultural water management (ABM-AWM) interventions integrating a spatially explicit hydrological model (including a module on CD recharge) with an agent decision-making module in Chapter 6. The decision-making module incorporates the developed understanding on farmers' behavior

(Chapter 4 and 5) and data driven rules based on observed catchment scale data (Chapter 3). The decisions of 38,447 individual farmers (the number determined based on population census data) were simulated.

In Chapter 6, the model simulations show the unfolding of the phenomenon of supply-demand feedback in the catchment, aligning with the observations in the area (Chapter 3 and 4). The results reveal that the perceived increase in water supply from CDs has led nearby farmers to increase their cotton and wheat cultivation areas. This resulted in increased water demand, which reduces expected benefits of increased groundwater storage from CD recharge. Also, increase in recharge and associated increase in water availability is limited to farmers nearby CDs (model grids with CD), reflecting the inequitable geographical distribution of benefits (Chapter 4). While farmers near CDs experience an increase in water availability leading to increased production, the results show this may not be sustainable given high inter-annual variation in rainfall compounded by the fact the area is underlain by low storage hard rock aquifers and CD recharge is negligible in dry years, echoing findings from Chapter 3. The chapter shows that there should be equal focus on demand side management to avoid such a self-reinforcing supply-demand cycle and sustain supply side measures. Additionally, simulations reveal unintended consequences on farmers' investments. The introduction of CDs resulted in higher income for farmers living nearby, which led to increased adoption of drip irrigation systems and borewells among them.

In Chapter 7, the ABM-AWM model is used to explore how externalities and resulting impacts from the introduction of CDs vary based on farmers' land size. Land size often serves as an indicator of wealth and social power in the region. The results show the evolution of the *success for successful* archetype, where most benefits are accrued to already successful large farmers who have more access to groundwater given larger area and wells to start with. The relative increase in income along with relative decrease in vulnerability are highest for large farmers. This adds another level of inequity in terms of socio-economic in addition to the geographic one (Chapter 6).

Overall, Chapters 6 and 7 show how the application of the ABMs within the context of agricultural water management can be valuable for informing future investments. They further demonstrate its capability to integrate hydrological and social sciences for unravelling unexpected feedback, which are valuable for informing future investments in agricultural water interventions, not only in the Kamadhiya catchment but also in other similar study areas.

8.2 Insights for Agricultural Water Management

Overall, the findings of thesis provide some critical insights for AWM.

8.2.1 Mitigating externalities of AWM

The thesis commenced with the proposition that the ill unplanned implementation of AWM interventions can lead to unintended negative externalities, with implications for long term sustainability and equity of outcomes for farmers. Subsequent chapters illustrated this through the case study of a catchment where intensive implementation of check dams (CDs) has taken place. The thesis integrated water balance assessments (Chapter 3), farmers' surveys (Chapters 4 and 5), and agent-based modeling (Chapters 6 and 7) to unravel the evolution of supply-demand feedback in the study area resulting from the implementation of CDs. The thesis further explored its implications for groundwater sustainability and equity of benefits and unintended consequence of AWM adoption.

These findings highlight the necessity of considering AWM externalities during implementation, as they can significantly impact the long-term equity and sustainability of outcomes, potentially surpassing or negating beneficial effects. For supply side AWM interventions, which constitute a major portion of AWM interventions and are capital intensive, avoiding externalities such as supply-demand feedback is crucial to prevent unsustainable and inequitable outcomes. To address supply-demand feedback, the thesis emphasizes the importance of incorporating demand side management, regulations and quotas to prevent self-reinforcing supply-demand cycles. Additionally, there is the need to clearly identify end goals—such as enhancing groundwater storage, expanding irrigation, or reallocating water for other uses—to facilitate clearer and more objective assessments. While the thesis focuses primarily on supply-demand feedback, it also acknowledges that other interventions may lead to different dynamics, underscoring the need to consider human-water feedback in planning and investment.

8.2.2 Increasing adoption of AWM interventions

Governments and non-governmental organizations have invested and continue to invest significant resources in researching and implementing various AWM adaptation interventions. Over the past decades, the effectiveness and benefits of many of these AWM interventions have been widely reported and established. However, despite the clear efficacy and advantages of these interventions, their adoption by farmers has remained slow and limited. Previous research has examined the impact of various socio-economic factors on adoption. This thesis expanded these studies by emphasizing the importance of considering farmers' sociopsychological factors, which have often been overlooked, in addition to socio-economic factors, when assessing barriers to adoption.

This thesis, through the application of the RANAS behavioral theory, demonstrates how including sociopsychological factors can provide deeper insights into farmers' adoption behavior. Beyond socio-economic factors such as land size and available subsidies, farmers' attitudes toward interventions, prevailing social norms, their self-perceived ability, and their perception of risk, all significantly influence their adoption behaviors. Recognizing and identifying these sociopsychological factors can enhance the integration of interventions and outreach activities aimed at influencing farmers' behaviors. This approach includes behavioral change interventions through training, information dissemination, awareness campaigns, and capacity-building initiatives. These campaigns can target various aspects of farmers' decision-making processes, such as presenting facts and scenarios to address farmers' risk perception, using communication strategies, exposure visits, and model farms to positively influence their attitudes, demonstrating the ease of use of interventions and facilitating the subsidy application process to improve their perceived ability, and creating rewards, building role models, and fostering a positive public narrative to shape social norms. Incorporating these strategies can pave the way for increased adoption of AWM interventions and contribute to building a knowledge base for integrating human behaviour into Agent-Based Models (ABMs).

8.2.3 Role of ABMs for planning AWM

The thesis shows that AWM interventions and human/farmer actions are closely linked and actions in one influence the other, which could lead to unintended and negative externalities. To capture this dynamic relationship and resulting feedback, approaches used in sociohydrology that explicitly account for human-water feedback are essential. The thesis highlights the practicality of utilizing Agent-Based Models (ABMs) to implement sociohydrology for AWM interventions. It illustrates how ABMs can effectively integrate and simulate both natural and human systems, while specifically accounting the roles of individuals. This aspect is crucial for assessing the spatiotemporal and inequitable effects of AWM interventions.

While conventional hydrological modelling, empirical studies and surveys provide valuable insights on the impacts and benefits of AWM interventions on hydrology/water, social and economic systems, ABMs offer the tool to integrate this knowledge to bring out interconnectedness and co-evolution of these systems and enable the simulation of future coupled trajectories.

The thesis, through development of ABM-AWM, underscores the utility of ABMs in agriculture to facilitate planning and the mitigation of externalities. The ABMs can serve as both a planning and educational tool to bring out the interdependence of human-water systems and their potential external ramifications. They can play a pivotal role in bridging the gap between social and hydrological sciences. This is essential, particularly in light of future investments in irrigation expansion and other AWM interventions needed to address climate change risks and increasing inter-sectoral competition for limited natural resources.

8.3 Potential applications of developed model and future research

The developed ABM-AWM is characterized by its scalability, editability and utilization of open-source code. This presents a future opportunity to extend its use beyond its current application, providing a platform for evaluating agricultural water management strategies not only in the study area context but also in diverse geographical, environmental and policy settings.

Looking forward, one of the key research priorities for agriculture is to adapt to climate change. The developed ABM-AWM can be used for understanding the human-water feedback that is and will result from implications of climate change on water cycle and agricultural systems and subsequently on farmers behaviour. By simulating different climate scenarios, the model can be used to assess the effectiveness of adaptation measures such as changes in irrigation practices or crop selection, while also highlighting the risk of maladaptation resulting from unsustainable and inequitable outcomes over the long term.

Furthermore, the model can also be used for the assessment of different policy interventions aimed at addressing water-related challenges. For instance, change in financial policies, such as subsidies or changes in crop prices, or awareness and capacity building programs can be simulated to gauge their effectiveness in incentivizing change in farmer behaviour towards improved practices such as water-efficient irrigation and resulting impact on water systems.

However, for further model applications for diverse interventions and scenarios, it will be important to further develop the understanding of farmers' behaviour through surveys and theoretical frameworks (such as RANAS behavioural theory) to improve the model's predictive capabilities. The model offers opportunities for cross-comparison across different basins and regions. By synthesizing data from various geographic areas, researchers can identify common trends, best practices, and potential pitfalls in agricultural water management strategies, fostering knowledge exchange and collaboration on a global scale.

In summary, the developed ABM-AWM represents a valuable tool for policymakers, researchers, and stakeholders alike, providing a dynamic framework for understanding and addressing the complexities of agricultural water management in a rapidly changing world.

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Acknowledgement

As I write this, I can't help but reflect on the privileges I've had in life which has enabled me to reach here. The privilege of attending school, economic security to pursue further studies, and growing up and living in a place with stability and no war. These are the things we take granted for, but hundreds of millions do not have. I wish all could have it and hope I can contribute to that.

A significant part of these privileges can be attributed to my parents. Without their belief, effort, and dedication, I wouldn't be here. My father, dreamt of making us brothers engineers, providing us with all the knowledge and resources he could. A big part of my scientific mindset definitely comes from him. My mother, who though didn't complete her studies, stood strong throughout the years, making our education and success her own mission. An elder brother who is there when you need and someone you can look up to. The protection, comfort, and motivation they provided gave me the freedom to dream and pursue it. And in the end, both of us brothers did become engineers.

I was content with my master's and would never have pursued a doctorate if it weren't for my wife, Tabassum, who encouraged and coaxed me out of my comfort zone. If a thesis could sum up everything it takes to complete one, it would be ten times bulkier, and much of the credit goes to her. During the course of writing this thesis, our beautiful daughter, Raabiya, was born. She unknowingly played a significant role by bringing joy and a new purpose to my life. She, in a way, made sure I stuck to deadlines! While I enjoyed the lighter moments, Tabassum bore the greater burden, allowing me to focus on my work. I'm also grateful to her family, now mine too, for always being there providing a sense of security that made this journey much easier.

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Faiz Alam

June 2024

Chapter 3 Annexure

A.1: Derived irrigated yield and rainfed yield

Overall yield, average of rainfed and irrigated yield, for cotton was available for the whole time (1983-2015) whereas segregated rainfed and irrigated yield was only available starting 1995. Thus, for the time period of 1983-1994, rainfed and irrigated cotton yield was derived based on developed relationship between ration of overall yield to irrigated yield and irrigated area to the overall area (Eqn. A1).

$$\frac{Yield_{irr}}{Yield_{overall}} = \alpha \times \frac{Area_{Irr}}{Area_{oveall}}\, Irrigated(\%) + \beta \quad \text{---------------- Eqn. A1}$$

Figure A1 shows the developed relationship. Overall R^2 is good (0.79) with $\alpha = -0.986$ and $\beta = 1.955$.

This relationship was applied to time period 1983-1994 with overall yield, irrigated and overall area known for the period. With irrigated and overall yield known, rainfed yield was derived using Eqn. A2 where overall yield is the weighted average of rainfed and irrigated area.

$$Yield_{overall} = \frac{Yield_{irr} * Area_{irr} + Yield_{rainfed} * Area_{rainfed}}{Area_{overall}} \quad \text{---------------- Eqn. A2}$$

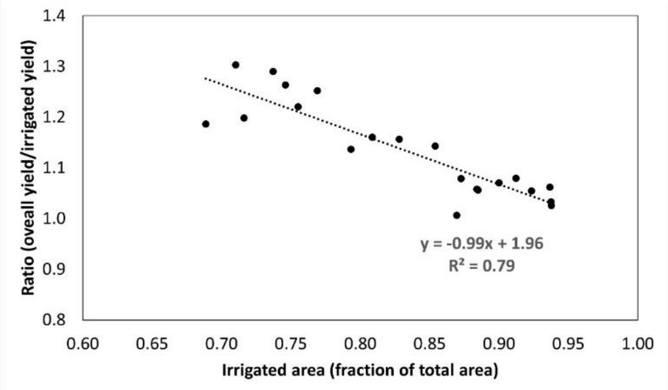

Figure A.1: Relationship between ration of irrigated yield to overall yield and ratio of irrigated area to overall area

Table A.2: Parameters used for check dam simulation

Parameter	Value	Source	Comment
Width[a]	15 m	Mozzi et al., (2021), field visits	width of 15 m and height of 1.5 m giving average check dam storage of 21,486 m^3 which is similar to average check dam storage in Kamadhiya catchment (12.7 MCM / 576 structures = 22,049 m^3)
Height[a]	1.5 m		
Catchment area	2 km^2	-	the average check dam catchment area is set as 2 km^2 (i.e. 1150/576)
Thickness of the weathered upper zone	30 m	*MoWR, RD & GR (2017b)*; *Mohapatra, B. (2013)*	Basaltic aquifers with upper weather zone.
Hydraulic conductivity of the upper aquifer	0.1 m day^{-1}		
Transmissivity of aquifer	100 m^2 day^{-1}		
Inflow	(m^3/day)	State (SWDC) gauge station at Kamadhiya	To get the daily volumetric inflow to CDs, catchment daily outflow at catchment outlet is converted to water height by normalizing according to the total catchment area and multiplying with CD catchment area.
Evaporation	daily mean, minimum and maximum	Hargreaves and Samani, 1985	To simulate losses from water spread is check dam, is calculated using the Hargreaves equation (Hargreaves and Samani, 1985) with daily mean, minimum and

	temperature as inputs	maximum temperature as inputs taken from the IMD (Pai et al., 2014).

Table A.3: Average annual and monthly check dam recharge (GW_{CD}), filling ratio and flow captured (%) for overall, pre and post development period in different SPI classified years.

Parameter	**Rainfall Classification**	**Annual**	**June**	**July**	**Aug**	**Sep**	**Oct**
GW_{CD} (MCM)	Overall	24.2	1.9	6.7	6.3	4.1	3.1
	Dry	13.3	2.2	5.3	3.2	1.7	0.8
	Normal	26.4	1.5	5.5	7.2	5.5	4.6
	Wet	46.5	2.4	14.2	11.7	6.5	4.8
Flow(%)$_{capture}$	Overall	83.9	83.5	78.2	92.1	79.5	89.2
	Dry	93.7	82.6*	100.0	100.	100.0	100.0
	Normal	84.7	87.3	83.4	91.6	77.4	99.7
	Wet	55.0	73.1	18.8	77.7	51.5	61.

*In 2002, being a dry year, runoff was very high 161.9 MCM due to very wet June month. Most of it overflowed with results showing 8% is captured whereas in all other years 100% is captured. However, recharge is not high i.e. 14.8 MCM vs 11.8 MCM in other years. This shows that high intensity rainfall producing runoff is not able to be captured, with much of the runoff exiting the catchment as outflow.

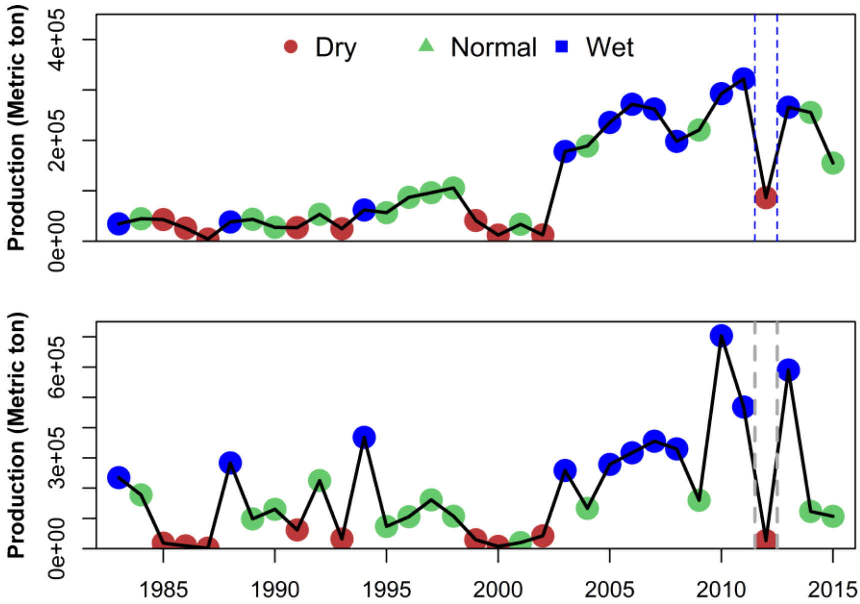

Figure A.2: Annual production (Metric ton) of Cotton (top) and wheat (bottom). Note: Years are indicated according to rainfall class (dry, normal and wet). Blue vertical line shows drop in production in the year 2012.

Chapter 4 Annexure

Table B.1. Villages selected for survey through regularly distributed sampling in state of Gujarat with their census code

DISTRICT	VILLAGE NAME	DISTRICT	type
Gondal	Bandhiya	Rajkot	D/s
Jasdan	Barvala	Rajkot	U/S
Gondal	Dadva	Rajkot	M/s
Gondal	Dadva	Rajkot	M/s
Jasdan	Dodiyala	Rajkot	D/s
Jasdan	Gadhadiya (Jas)	Rajkot	U/S
Jasdan	Jangvad	Rajkot	M/s
Jasdan	Jasdan	Rajkot	M/s
Jasdan	Jivapar	Rajkot	D/s
Kotda Sangani	Juna Rajpipla	Rajkot	M/s
Babra	Kalorana	Amreli	U/S
Jasdan	Kanesara	Rajkot	U/S
Gondal	Karmal Kotda	Rajkot	D/s
Babra	Karnuki	Amreli	M/s
Jasdan	Lalavadar	Rajkot	U/S
Jasdan	Lilapur	Rajkot	U/S
Jasdan	Panchavada	Rajkot	D/s
Kotda Sangani	Pipaliya Karmal	Rajkot	D/s
Jasdan	Pratappur	Rajkot	D/s
Jasdan	Ramaliya	Rajkot	U/S
Rajkot	Sardhar	Rajkot	U/S
Gondal	Shrinathgadh	Rajkot	D/s
Chotila	Vadali	Surendra-nagar	U/S
Jasdan	Virnagar	Rajkot	M/s

* We replace Jasdan town with Vavda village. 24 villages selected [dadva hamirpara being large occurs twice so may be two hamlets can be selected from this]

Table B.2. Overall proportion marginal, small, semi-miedum and large farmers in the region

	Proportion (%)				Numbers			
	Marginal	Small	Semi medium	large	Marginal	Small	Semi medium	large
Gondal	22.8	44.3	25.3	7.5	5	9	5	2
Jasdan	25.5	37.8	27.3	9.3	5	8	5	2
Kotda Sangani	21.5	46.0	24.6	7.9	4	9	5	2
Rajkot	27.0	42.0	24.0	7.0	5	8	5	1
Babra	22.0	34.8	31.6	11.5	4	7	6	2
Chotila	21.6	35.7	29.2	13.5	4	7	6	3

* Marginal < 1 ha; Small 1-2 ha; Semi medium 2-4 ha and Large >4 ha

Table B.3. Descriptive statistics of the number of farmers surveyed for each village with reported median, min and max of total and working CDs in the village with number of farmers (and of village population) benefitting from CDs.

		Total CDs		**Working CDS**		**Farmers benefitting**	
	Total farme	**Media n**	**Min-Max**	**Media n**	**Min-Max**	**Numb er**	**%**
Bandhiya	21	5	2-12	2	1-10	5	23.8
Barvala	20	10	7-15	4	2-14	14	70.0
Dadva Hamirpara	40	12	3-70	6	2-25	31	77.5
Dodiyala	20	9	5-15	7	0-15	12	60.0
Gadhadiya (Jas)	20	8	5-25	4	0-10	9	45.0
Jangvad	20	7	2-40	5	0-40	9	45.0
Jivapar	21	40	5-50	20	1-50	11	52.4
Juna Rajpipla	20	14	8-30	10	3-20	19	95.0
Kalorana	22	6	1-25	4	0-20	7	31.8
Kanesara	20	10	1-30	5	1-30	11	55.0
Karmal Kotda	25	4	1-7	3	0-4	9	36.0
Karnuki	21	10	2-30	3	2-30	18	85.7
Lalavadar	20	10	7-20	7	3-15	20	100.0
Lilapur	20	15	2-21	5	0-15	11	55.0
Panchavada	20	10	1-25	10	1-25	8	40.0
Pipaliya Karmal	20	8	6-20	4	3-18	16	80.0
Pratappur	20	34	15-36	29	12-36	17	85.0
Ramaliya	20	10	7-15	5	2-12	17	85.0
Sardhar	20	10	7-15	8	2-12	18	90.0
Shrinathgadh	22	10	5-28	3	0-10	12	54.5
Vadali	20	3	3-4	2	1-3	18	90.0
Vavda	21	3	1-3	0	0-0	0	0.0
Virnagar	19	20	5-70	12	0-70	7	36.8

Table B.4. Frequency of check dams constructed during different years

Time period	Freq	% of total
1955-1990	93	18.9
1990-1995	32	6.5
1995-2000	78	15.9
2000-2005	123	25.0
2005-2010	94	19.1
2010-2015	55	11.2
2015-2020	17	3.5

Chapter 5 Annexure

Table C.1: RANAS questions for Drip and Borewell.

Category		Drip Irrigation	Borewell
		Questions	
Risk	R1	How many drought/dry years have been there in last 10 years?	
	R2	How high is the risk of groundwater wells going dry in next 5 years?	
	R3	How high is the risk of drought in coming 5 years?	
	R4	How severe will be the impact of drought on your crop production?	
	R5	How much GW decline will impact your crop production?	
Attitude	AT1	How beneficial drip irrigation is for crop production?	How beneficial borewell is for crop production?
	AT2	How time consuming is to get a drip irrigation set up?	How time consuming is to install a borewell?
	AT3	How reliable is applying irrigation with drip irrigation?	How reliable is irrigation water supply from borewell?
Ability	AB1	How confident are you in your financial capability to afford the drip irrigation system? [w/o subsidy]	How confident are/were you in your financial capability to afford the drilling of a BW?
	AB2	How confident are you in your capacity/knowledge to install the drip irrigation system?]	How confident are/were you in your capacity/knowledge to install a BW?
	AB2	How confident you are in your capability to operate and maintain the drip irrigation system?	
Norm	N1	What proportion of people in your village have a drip irrigation system?	What proportion of people in your village have a borewell?

	N2	Most people whose opinion I value think having drip irrigation is good?	Most people whose opinion I value think having borewell is good?
	N3	How important are NGOs/government official opinions to you?	How important are NGOs/government official opinions to you?
Self-regulation	SR1	How much do you pay attention to how much water you use for irrigation?	Do you have a plan to acquire the required personnel and material it takes to drill a BW?
	SR2	-	Do you have a plan if your BW doesn't yield water or stop giving water?

Table C.2: PCA results for Drip and borewell

Category	Question (Table C.1)	PC1 loading	PC2 loading	Renaming
Drip				
Risk	R1	0.785		Load on first two factors: 70 % data explained. Impact load highly on 2nd facto and risk/past on factor 1. They were renamed "risk" and "impact".
	R2	0.791		
	R3	0.847		
	R4		0.846	
	R5		0.827	
Ability	AB1	0.769		70 % data is explained by first factor with all questions loading highly on this. Thus ability question renamed to "Ability".
	AB2	0.879		
	AB2	0.849		

Norm	N1	0.830		Load on two factors explaining 85 % of the data. Proportion of people and their opinion on First and NGO norm on second. Renamed as “Society norm” and
	N2	0.739		
	N3		0.976	
Attitude	AT1	0.880		Load on two factors explaining 85 % of the data. Benefit and reliability on First and time on second. Renamed as “rel_ben” and “time”
	AT2	0.882		
	AT3		0.995	
Borewell				
Risk	R1	0.785		Load on first two factors: 70 % data explained. Impact load highly on 2nd facto and risk/past on factor 1. They were renamed “risk” and “impact”.
	R2	0.791		
	R3	0.847		
	R4		0.846	
	R5		0.827	
Norm	N1	0.858		Load on two factors explaining 85 % of the data. Proportion of people and their opinion on First and NGO norm on second. Renamed as “Society norm” and
	N2	0.808		
	N3		0.976	
Attitude	AT1	0.880		Load on tow factor explaining 85 % of the data. Benefit and reliability on First and time on second. Renamed as “rel_nen” and “time”
	AT2	0.882		
	AT3		0.995	

Chapter 6 Annexure

D.1 Hydrological module

The spatially distributed hydrological module operates at 1 km^2 resolution with 1319 such grid grids within the study area. In the model, runoff is generated through saturation excess overland flow (Hewlettian runoff)[1] from the first soil layer, which also contributes to lateral flow estimated based on slope, soil field and saturation capacities, and soil hydraulic conductivities. Water percolates, based on soil field capacity and saturation capacity, from the top rootzone layer to the bottom subzone soil layer, and from the subzone to the groundwater layer, the latter considered as recharge. Soil moisture is depleted from topsoil (root zone) via root soil moisture uptake by the crops. Groundwater storage is characterized by the depth of the aquifer and specific yield. Groundwater storage above a storage threshold (BF_{thresh}) is added to the baseflow[2]. The total runoff for each grid cell is the sum of saturation excess flow, lateral flow, and baseflow which is routed using a flow direction network. Refer to SPHY model[2] for more information on the hydrological model and equations.

The catchment is delineated using the Shuttle Radar Topography Mission (SRTM) digital elevation model data[3], which is also used for generating slope and flow direction maps. The model integrates gridded daily rainfall derived from rainfall gauge stations in the watershed[4] and gridded temperature (mean, minimum, and maximum)[5]. Runoff routing employs a recession coefficient (Kx) as a calibration parameter, with values ranging between 0 and 1 where values approaching 1 correspond to a slow responding catchment[2]. Soil data, including texture and organic content, were taken from global soil data, Soil Grids, provided by the International Soil Reference and Information Centre[6]. Based on the soil properties, soil water characteristics such as field capacity (FC), saturation capacity (SAT), wilting point (WP), and saturated hydraulic conductivity (k_{sat}) were estimated using the pedo-transfer function[7]. Soil water characteristics were adjusted during calibration by multiplying them with a scaling parameter ranging between 0.7 to 1.3.

The area's aquifers, mainly comprising Deccan Trap basalt, have low porosity and hydraulic conductivity[8], and are confined to water-bearing zones in the upper 15-30 m of weathered and fractured rock[9,10]. The water availability in deeper aquifers is limited and relies on natural joints and fractures. Aquifer characteristics such as depth (D_{gw}), specific yield (S_Y), and hydraulic conductivity (K_{gw}) were calibrated with initial values sourced from the national hydrogeological dataset[11].

Recharge and runoff capture from check dams were simulated using the recharge empirical equations[12], refined for the region[13]. This approach presumes an underlying impermeable layer (bedrock in the area) beneath the aquifers. CD data, including number and storage per village, were derived from secondary data and social surveys[8,14,15]. 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. Each check dam was modeled with a 15 m width[8], and the riverbed's slope, determined from SRTM DEM data, informed the water height and spread area calculations[13]. Refer to check storge model[13] for more information on the check dam model and equations.

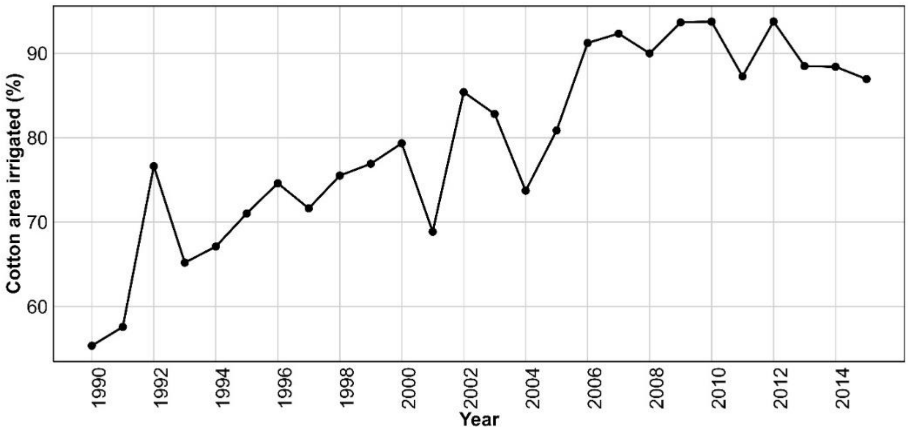

Figure D.1: Time series of cotton irrigated area (%)

Table D.1: Maximum groundwater abstraction rates

Data	Unit	Value	Source
Maximum dugwell groundwater abstraction (GWD(max))	m3 day-1	525	For a 25 m well (depth) and 4 m wide well, storage is around 350 m3. Maximum abstraction is taken as 1.5 times the storage giving 525 m3 day-1
Maximum borewell groundwater abstraction (GWB(max))	m3 day-1	80	Based on deep tubewell abstraction rate of 10m3/hr and average power supply of 8 hr/day, maximum abstraction is set to 8 hour 80 m3.

Table D.2: Crop coefficients and duration of crops

Crop stage	K_c[a,b]			Duration (days) [a,b]			Ky		
	Cotton	Groundnut	Wheat	Cotton	Groundnut	Wheat	Cotton	Groundnut	Wheat
Initial	0.4	0.5	0.4	30	25	20	1.2	1.2	1.1
Development	0.7	0.8	0.8	50	35	25	1.2	1.2	1.1
Mid-season	1.05	1.1	1.2	60	35	45	1.2	1.2	1.1
Late season	0.65	0.55	0.75	55	25	30	1.2	1.2	1.1

[a] Allen et al., (1998).

[b] Kar et al., (2014).

Table D.3: Crop cultivation cost, price and sowing dates

	Crop cultivation cost (per ton)[28]	Price (per ton)[27]	Sowing date
Cotton	23160	41000	15th June
Groundnut	20390	40300	15th June
Wheat	7440	15250	15th November

[#] For the season 2015

Table D.4: Results of binary logistic regression of farmer's decision to adopt drip irrigation

Regression coefficient	Estimate	Significance [a]	Min	Max
(Intercept)	-3.046	***	-3.149	-2.943
Farming experience	0.034	*	0.032	0.036
Higher education	-1.235		-1.370	-1.100
Primary Education	0.486		0.415	0.556
Secondary Education	0.066		-0.014	0.145
Proximity to water	-0.285		-0.333	-0.237
Ability	0.865	***	0.838	0.893
Risk (perceived)	-0.621	***	-0.644	-0.598
Risk (severity)	-0.420	*	-0.446	-0.394
Attitude	0.562	*	0.528	0.596
Norm	0.462	**	0.443	0.481

[a] *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$

Threshold: 0.35: Accuracy: 85.9; Sensitivity: 58.9 and Specificity: 91.4

Threshold: 0.40: Accuracy: 85.9; Sensitivity: 52.0 and Specificity: 93.4

Table D.5: Results of binary logistic regression of farmer's decision to adopt borewells.

Regression coefficient	Estimate	Significance [a]	Min	Max
(Intercept)	-2.30	***	-2.34	-2.261
Self_regulation	0.386	***	0.372	0.401
Attitude	0.455	**	0.435	0.476
Norm	0.449	**	0.431	0.469
Farmer area	0.011	.	0.01	0.013
Livestock ownership	0.076	*	0.072	0.081
Proximity to water	0.748	*	0.711	0.785

[a] *p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001

Threshold: 0.25: Accuracy: 65.9; Sensitivity: 72.9 and Specifity: 57.6

Threshold: 0.21: Accuracy: 65.9; Sensitivity: 80.3 and Specifity: 50

Table D.6: Estimation of residual drought memory for the period stating 2011 based decay rate of 20 % per year

Year	Drought	Drought value	Risk memory[a]
2011	No	0	0
2012	Yes	1	1
2013	No	0	0.8
2014	Yes	1	1.6
2015	No	0	1.4
2016	No	0	1.2
2017	No	0	1
2018	D	1	1.8
2019	No	0	1.6
2020	No	0	1.4
2021			**1.2**

[a] $risk(p)_{f,t} = drought_{f,t} + risk(p)_{f,t-1} - d * risk(p)_{f,t-1}$

##assuming decay rate of 20 % per year

Table D.7: Parameter set for latin hypercube sampling

Parameter	Mean	Min	Max
Capillary rise (Cap) [mm day^{-1}]	0.10	0	0.31
Top soil: Field capacity [m^3 m^{-3}][a]	0.79	0.49	0.90
Top soil: Saturation capacity [m^3 m^{-3}][a]	0.88	0.70	0.91
Bottom soil: Field capacity [m^3 m^{-3}][a]	0.87	0.76	0.99
Bottom soil: Saturation capacity [m^3 m^{-3}][a]	0.70	0.57	0.82
(Intercept)$_{drip}$	-3.046	-3.149	-2.943
Risk (perceived)$_{drip}$	-0.621	-0.644	-0.598
Risk (severity) $_{drip}$	-0.42	-0.446	-0.394
Ability $_{drip}$	0.865	0.838	0.893
Attitude $_{drip}$	0.562	0.528	0.596
Norm $_{drip}$	0.462	0.443	0.481
Adoption_prob_threshold$_{drip}$	0.375	0.35	0.4
(Intercept)$_{BW}$	-2.30	-2.34	-2.261
Self_regulation$_{bw}$	0.386	0.372	0.401
Attitude $_{BW}$	0.455	0.435	0.476
Norm $_{BW}$	0.449	0.431	0.469
Proximity to water$_{BW}$	0.748	0.711	0.785
Farmer area$_{BW}$	0.011	0.01	0.013
Livestock ownership$_{BW}$	0.077	0.072	0.081
Adoption_prob_threshold^{BW}	0.32	0.3	0.35
Cotton slope	0.017	0.016	0.018

[a] Soil water characteristics were adjusted during calibration by multiplying them with a scaling parameter

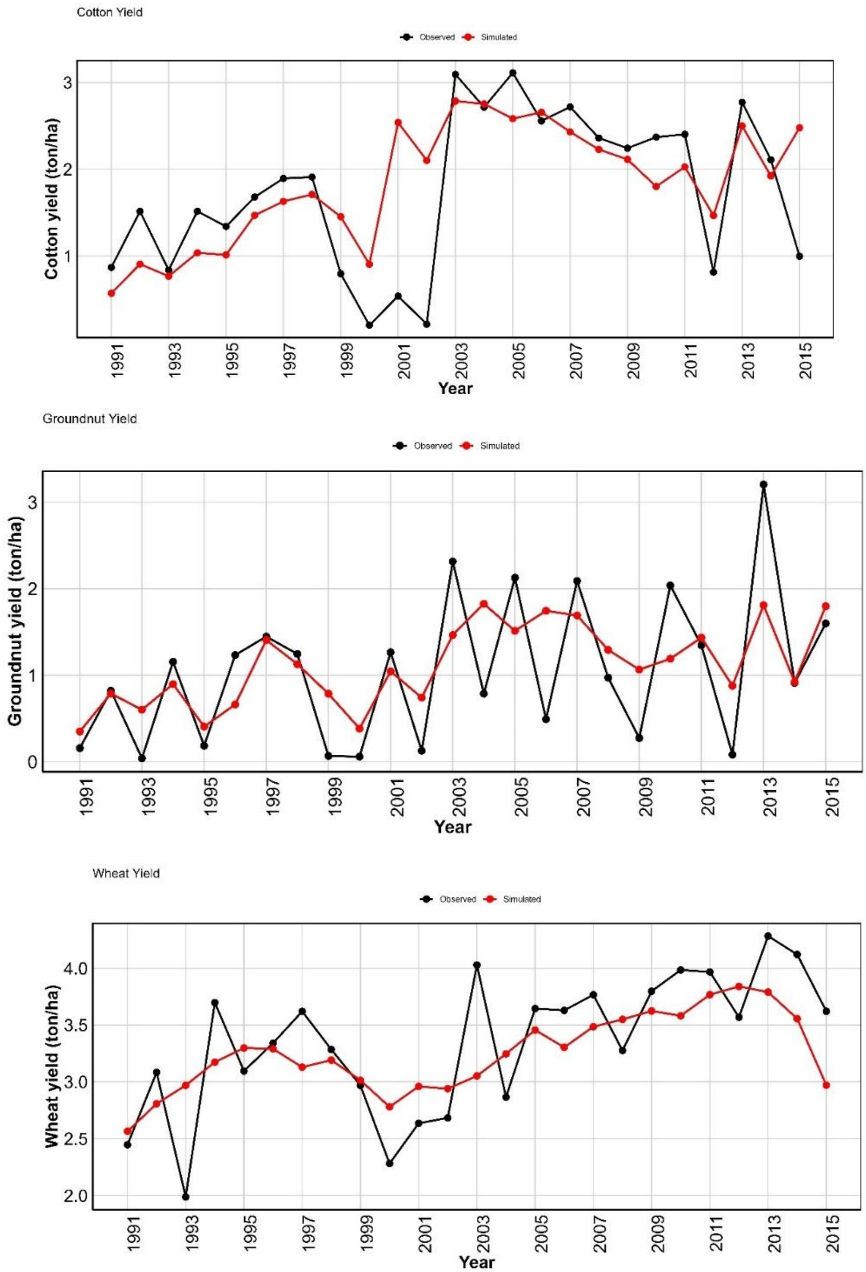

Figure D.2: Cotton, groundnut and wheat observed and calibrated yields

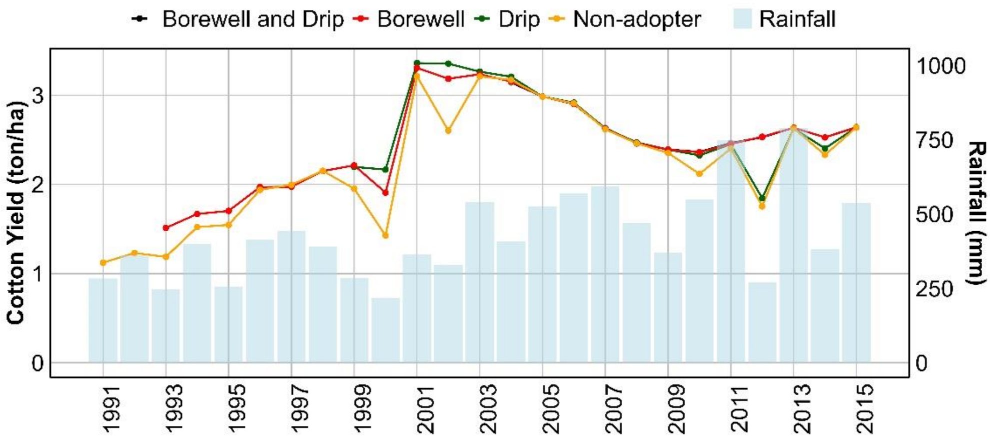

Figure D.3: Comparison of cotton yield of farmers with and without drip

Chapter 7 Annexure

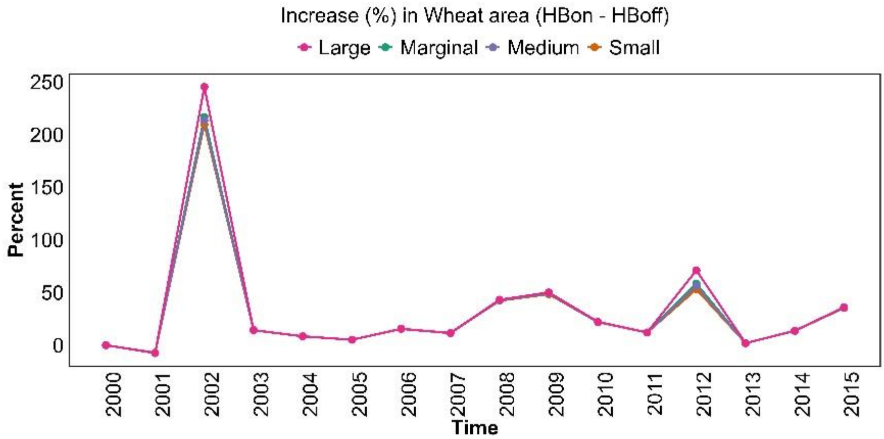

Figure E.1: Increase in wheat area in HB_{on} model compared to HB_{off} model

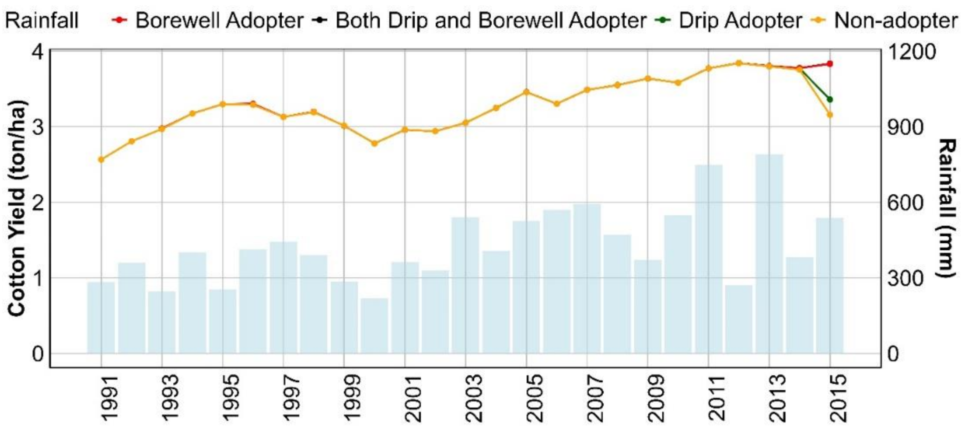

Figure E.2: Wheat yield of adopters and non-adopters

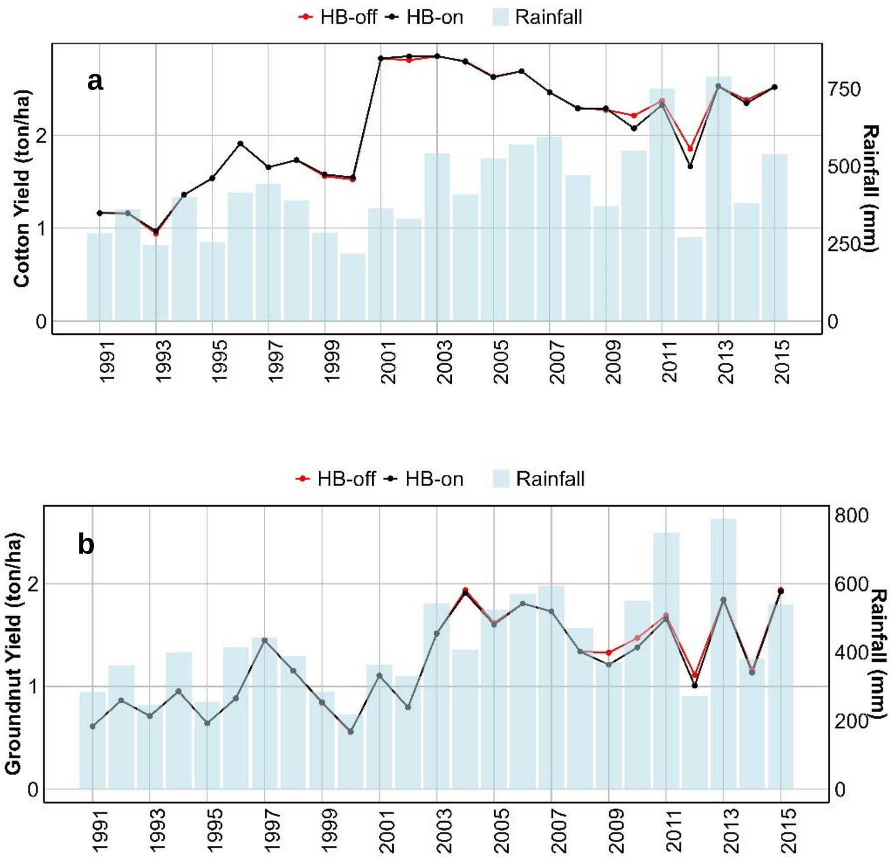

Figure E.3: a) Cotton and b) groundnut yield of in grids with CD in the model HBon and HBoff

Curriculum vitae

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EDUCATION

PhD in Sociohydrology and agricultural water management The Netherlands

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KTH Royal Institute of Technology, Stockholm Aug 2014 – Jul 2016

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Indian Institute of Technology, Delhi Jun 2009 – Jul 2013

EXPERIENCE

Researcher: Water Resources Management Delhi, India

International Water Management Institute (IWMI) Aug 2016 – Present

Co-founder Delhi/Hague

Save IT! Jun 2016 – Jun 2018

Consultant Mumbai, India

PricewaterhouseCoopers July 2013 – Jun 2014

SPONSORSHIPS & AWARDS

Sivapalan Young scientist award (2023) to attend IAHS assembly in Berlin, Germany

Young Leader Delegate for the 2019 Yushan Forum in Taipei, Taiwan

UNESCO Scholarship (2019) to attend ISMAR10 in Madrid, Spain 2019

Understanding Risk Forum (2018) travel scholarship Mexico City, Mexico

Future Earth travel grants (2017) to attend IWA conference in Cape Town, SA

KTH-India Scholarship (2014-2016) for master studies at KTH Stockholm, Sweden

List of Publications

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First Author

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4. Pande, S., Haeffner, M., Blöschl, G., **Alam, M.F.**, Castro, C., Di Baldassarre, G., Frick-Trzebitzky, F., Hogeboom, R., Kreibich, H., Mukherjee, J., Mukherji, A., Nardi, F., Nüsser, M., Tian, F., van Oel, P., Sivapalan, M., 2022. Never Ask for a Lighter Rain but a Stronger Umbrella. Frontiers in Water 3, 204. https://doi.org/10.3389/frwa.2021.822334
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