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Understanding human–water feedbacks of interventions
in agricultural systems with agent based models: a reviewMohammad Faiz Alam^{1,2,*}, Michael McClain^{2,3}, Alok Sikka¹ and Saket Pande²¹ International Water Management Institute, Delhi, India² Delft University of Technology, Delft, The Netherlands³ IHE Delft Institute for Water Education, Delft, The Netherlands

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E-mail: m.alam@cgiar.org**Keywords:** sustainable, equitable, agriculture water management, agent based modeling, sociohydrologySupplementary material for this article is available [online](#)

Abstract

Increased variability of the water cycle manifested by climate change is a growing global threat to agriculture with strong implications for food and livelihood security. Thus, there is an urgent need for adaptation in agriculture. Agricultural water management (AWM) interventions, interventions for managing water supply and demand, are extensively promoted and implemented as adaptation measures in multiple development programs globally. Studies assessing these adaptation measures overwhelmingly focus on positive impacts, however, there is a concern that these studies may be biased towards well-managed and successful projects and often miss out on reporting negative externalities. These externalities result from coevolutionary dynamics of human–water systems as AWM interventions impact hydrological flows and their use and adoption is shaped by the societal response. We review the documented externalities of AWM interventions and present a conceptual framework classifying negative externalities linked to water and human systems into *negative hydrological externalities* and *unexpected societal feedbacks*. We show that these externalities can lead to long term unsustainable and inequitable outcomes. Understanding how the externalities lead to undesirable outcomes demands rigorous modeling of the feedbacks between human and water systems, for which we discuss the key criteria that such models should meet. Based on these criteria, we showcase that differentiated and limited inclusion of key feedbacks in current water modeling approaches (e.g. hydrological models, hydro-economic, and water resource models) is a critical limitation and bottleneck to understanding and predicting negative externalities of AWM interventions. To account for the key feedback, we find agent-based modeling (ABM) as the method that has the potential to meet the key criteria. Yet there are gaps that need to be addressed in the context of ABM as a tool to unravel the negative externalities of AWM interventions. We carry out a systemic review of ABM application to agricultural systems, capturing how it is currently being applied and identifying the knowledge gaps that need to be bridged to unravel the negative externalities of AWM interventions. We find that ABM has been extensively used to model agricultural systems and, in many cases, the resulting externalities with unsustainable and inequitable outcomes. However, gaps remain in terms of limited use of integrated surface–groundwater hydrological models, inadequate representation of farmers' behavior with heavy reliance on rational choice or simple heuristics and ignoring heterogeneity of farmers' characteristics within a population.

1. Introduction: agricultural water management (AWM) interventions for sustainable development

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 (Mendelsohn 2009, GCA and WRI 2019). Already extreme weather events of floods and droughts account for more than 80% of agriculture losses (in crop and livestock production) (FAO 2015) and have reduced global agriculture total factor productivity by 21% since 1961 (Ortiz-Bobea *et al* 2021). Thus, there is an urgent need for adaptation in agriculture without which global agriculture yields could reduce by up to 30% by 2050, impacting 500 million small farms the most (GCA and WRI 2019). With climate change impact on water and the reliance of agriculture on water, adaptation in agriculture is inextricably linked to how water is managed (United Nations 2019).

AWM interventions are extensively promoted and implemented as adaptation measures in multiple development programs (Evans and Giordano 2012, Sharda *et al* 2012, Shah *et al* 2021). AWM interventions can be broadly defined as interventions on land that alter the water balance or partitioning of rainfall into different fluxes such as transpiration, evaporation, and runoff (Calder *et al* 2008, Barron *et al* 2009). They can be broadly categorized under supply (increasing storage through *ex-situ* or *in-situ* storage) and demand-side (e.g. reducing demand via increasing efficiency, cropping system changes) interventions (Barron *et al* 2009, Sikka *et al* 2022).

Widely reported and established benefits of implementing AWM interventions include increased water availability, improved agricultural yields, increased incomes, and increased community awareness about water use (Calder *et al* 2008, Joshi *et al* 2008, Glendenning *et al* 2012, Sikka *et al* 2022). Despite overwhelming documented positive impacts, there is a concern that such studies highlighting the benefits may be biased towards well-managed and successful projects (Kerr 2002) and often miss out on reporting negative externalities (Kerr *et al* 2007, Barron *et al* 2008, 2009, Glendenning *et al* 2012). Externalities are indirect or accidental feedback associated with interventions (Lodha and Gosain 2007) and can be both positive and negative.

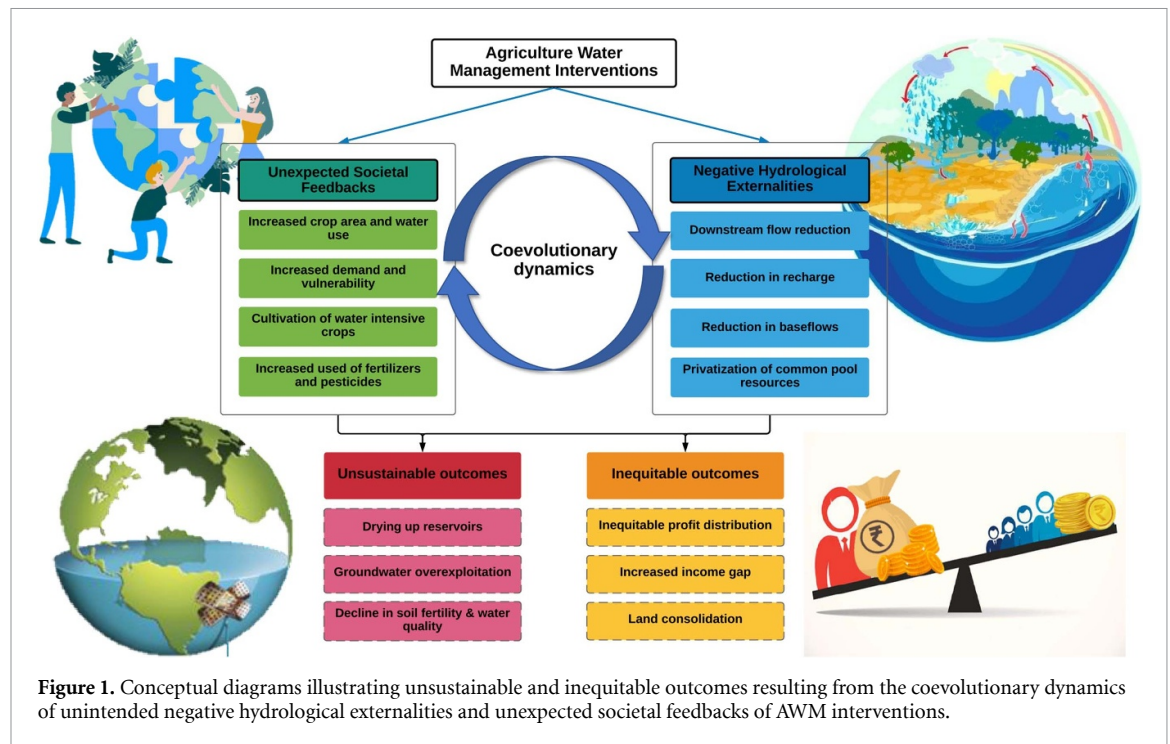
Negative externalities often result from excessive or ill-planned implementation of interventions not accounting for its interactions, often unintended and unexpected, with hydrological and social systems. Examples include reduction in downstream flows resulting from water harvesting in upstream areas (Kumar *et al* 2006, Calder *et al* 2008) or unexpected dynamics such as increased water use in response to

the introduction of water-efficient irrigation practices (Birkenholtz 2017). These externalities often lead to unsustainable (e.g. groundwater depletion, drying of reservoirs) and inequitable outcomes (e.g. uneven distribution of costs and benefits).

Explicit modeling of coupled human–water systems is needed to unravel unintended and unexpected feedbacks of AWM interventions to enhance positive benefits while mitigating the negative externalities of the interventions (Khan *et al* 2017, Pande and Sivapalan 2017, di Baldassarre *et al* 2019). Conventional AWM modeling studies have very limited inclusion of such feedbacks between the human and the water systems. Often the human–water systems are considered independent with human actions explicitly imposed as exogenous scenarios or boundary conditions to its corresponding water system (Lobanova *et al* 2017, Srinivasan *et al* 2017, van Niekerk *et al* 2019). Unexpected and unintended outcomes such as social inequalities and vulnerabilities may emerge as a result of AWM interventions that are designed without due consideration for such feedbacks (Troost and Berger 2015, di Baldassarre *et al* 2019).

Modeling of coupled natural-human systems with bi-directional feedbacks is central to interdisciplinary approaches of coupled human and natural systems (Madani and Shafiee-Jood 2020), socio-ecological systems (Filatova *et al* 2013), and sociohydrology (Sivapalan *et al* 2012, 2015). The latter approach of sociohydrology has an explicit focus on hydrology. Among the two main methods used in sociohydrology, agent-based modeling (ABM) and system dynamics, the use of ABM has been gaining popularity because of its potential to integrate and model natural (hydrological) and human systems while explicitly accounting for the role of individuals, their behaviors, and micro-level constraints (Troost and Berger 2015, di Baldassarre *et al* 2019). These capabilities are critical to understanding the spatiotemporal and often inequitable impacts of negative externalities of AWM interventions on human water systems. In contrast, system dynamics focus on the dynamics and evolution of complex overall lumped systems, making them less suitable to unravel the inequitable impacts within a population resulting from the externalities of AWM interventions (Martin and Schlüter 2015, Yu *et al* 2017, di Baldassarre *et al* 2019).

The focus of this paper is to explore how ABMs can unravel the unsustainable and inequitable outcomes of AWM interventions in human–water systems. First, an overview of negative externalities and unexpected outcomes of AWM interventions that can lead to unsustainable and inequitable impacts is provided. Next, the potential strengths of sociohydrology based ABM approach over AWM modeling studies, in unraveling hydrological negative externalities and societal unexpected feedbacks, are summarized.



Thereafter, a systematic review of ABM applications in agriculture water systems is carried out to provide an overview of the current state of the application, key advances and discuss the remaining shortcomings of ABM with respect to capturing AWM externalities. Finally, the paper concludes with what future research is needed to further strengthen the use of ABM for understanding the human–water feedbacks of interventions in agricultural systems.

2. Externalities and outcomes of AWM interventions: implications for sustainability and equity

Externalities, defined as indirect or accidental feedbacks 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 its hydrological impacts (especially across spatial scales) or social feedbacks. Though the focus of the paper 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* 2022). 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 feedbacks (figure 1). *Negative hydrological externalities* are unintended or unexpected changes in spatial and temporal availability and allocation of water flows (figure 1). They arise from the interaction of AWM interventions with hydrological flows (Kumar *et al* 2006, Calder *et al* 2008, Barron *et al* 2009, van Oel *et al* 2010, Bouma *et al* 2011). For example, reduction in downstream runoff due to water harvesting or storage interventions and reduction in recharge (percolation and return flows) due to efficient irrigation interventions (table 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 i.e. coevolutionary dynamics. This response influenced by socio-economic and cultural contexts, here termed *unexpected* societal feedbacks, is usually non-linear and highly heterogeneous and is typically not expected at the stage of planning (Walker *et al* 2015, Pande and Sivapalan 2017, di Baldassarre *et al* 2019) (figure 1). Examples include increased water use, rather than expected decrease, in response to efficient irrigation interventions and increased demand in response to supply side interventions (table 1).

This coevolutionary dynamics of hydrological externalities and unexpected societal feedbacks in a society, unequally structured with unequal capacity and power can lead to outcomes for social and biophysical systems that are unsustainable and inequitable (figure 1) (Kerr 2007, Calder *et al* 2008,

Table 1. Illustrative examples of negative externalities linked with AWM interventions.

Negative externalities	AWM interventions		
	Water harvesting, storage interventions	Irrigation efficiency interventions	Subsidies (inputs, electricity, water, etc)
Hydrological externalities	Reduction in runoff leading to upstream–downstream impacts (Calder <i>et al</i> 2008, Bouma <i>et al</i> 2011)	Reduction in return flows and percolation leading to reduction in groundwater recharge (Fabbri <i>et al</i> 2016, Perry and Steduto 2017)	Increased evapotranspiration demands from shifting toward more profitable and water-intensive crops (Shiferaw <i>et al</i> 2008, Sarkar 2011)
Societal unexpected feedbacks	Supply-demand cycle where more supply may lead to more demand (di Baldassarre <i>et al</i> 2018, Shah <i>et al</i> 2021)	Increased water use, rather than expected reduction in the absence of any regulation limiting water use or abstraction (Zhang <i>et al</i> 2014, Birkenholtz 2017)	Increased water use; increased use of fertilizers and pesticides (Berka <i>et al</i> 2001, Zhang and Shan 2008)
Unsustainable outcomes	Drying of downstream lakes or reservoirs (e.g. Aral Sea) (Wood and Halsema 2008, Nepal <i>et al</i> 2014, Albert <i>et al</i> 2021); reduction in environmental flows	Groundwater depletion; wetland degradation and lack of environmental flows (Zhang and Shan 2008, Kopittke <i>et al</i> 2019, Albert <i>et al</i> 2021)	Hasten groundwater depletion (e.g. Northwest India) (Shiferaw <i>et al</i> 2008, Mukherji 2020); water quality deterioration of rivers and aquifers (Berka <i>et al</i> 2001, Zhang and Shan 2008)
Inequitable outcomes	Benefits of water harvesting (and recharge) concentrated to nearby farms in low-lying areas (Shah <i>et al</i> 2021) and to influential and richer farmers having the financial capacity to invest in irrigation infrastructure (Calder <i>et al</i> 2008, Bouma <i>et al</i> 2011, Sarkar 2011)	Increased cost of pumping and drilling, well failure, and abandonment of wells disproportionately borne by the resource-poor farmers (Shiferaw <i>et al</i> 2008, Reddy 2012, Narayanamoorthy 2015)	Women farmers with less access to support services fail to make the most of AWM interventions aggravating the existing inequity between male and female farmers (Namara <i>et al</i> 2010); high-value crop cultivators and wealthier farmers benefit the most from investments made in farmer-led irrigation projects (Kafle <i>et al</i> 2020)

Barron *et al* 2009, Bouma *et al* 2011, Pande and Sivapalan 2017). Examples of unsustainable outcomes include 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, benefits of AWM (and their negative impacts) are distributed unequally (Shiferaw *et al* 2008, Linton and Budds 2014, Shah *et al* 2021) 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). 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).

3. Unraveling the negative externalities of AWM interventions: co-evolutionary dynamics

With agriculture water demand accounting for 70% of freshwater withdrawals globally, going 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). It is critical that investments in AWM interventions 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 should be able to capture the coevolutionary dynamics of negative hydrological externalities and unexpected societal feedbacks to avoid inequitable and unsustainable outcomes (figure 1).

Conventional modeling approaches used to study the impacts of AWM interventions (e.g. hydrological models, hydro-economic, and water resource models) have generated 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 (Harou *et al* 2009, Andersson *et al* 2011, Garg *et al* 2012, Hassaballah *et al* 2012, Satoh *et al* 2017, MacEwan *et al* 2017). However, they do not explicitly model the feedbacks between the human and water systems, thus missing out on the coevolutionary dynamics that limit their prediction power over long term (Sivapalan *et al* 2012, Srinivasan *et al* 2017, Pouladi *et al* 2020). In these models, human actions (or societal feedbacks) are mostly prescribed externally (mostly as scenarios) (Satoh *et al* 2017, Srinivasan *et al* 2017, Pouladi *et al* 2020) and human–water systems are treated as independent of each other, ignoring the reality that humans think and act independently with their responses (e.g. irrigation and cropping decisions, land use) influenced by the changes in the environmental and socio-economic conditions (Srinivasan *et al* 2017, van Niekerk *et al* 2019, Pouladi *et al* 2020).

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) (Andersson *et al* 2011, Garg *et al* 2012, Satoh *et al* 2017). Similarly hydro-economic modeling and water resources 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 feedbacks that such interventions have on human decision making, e.g. with regards to the perception of scarcity (Harou *et al* 2009, Hassaballah *et al* 2012, MacEwan *et al* 2017, Srinivasan *et al* 2017).

The interventions could lead to long term unintended consequences exacerbating social inequalities and vulnerabilities without accounting for these human–water feedbacks in its design (Sivapalan *et al* 2012, Pande and Sivapalan 2017, Srinivasan *et al* 2017, di Baldassarre *et al* 2019, Pouladi *et al* 2020).

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 (di Baldassarre *et al* 2015, Pande and Sivapalan 2017). Thus, there is need to expand conventional AWM models to integrate human–water dynamics, especially for longer term planning horizons when human–water feedbacks become increasingly important.

3.1. Sociohydrology: an approach to understanding the coevolutionary dynamics

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, Pande and Sivapalan 2017, Srinivasan *et al* 2017, di Baldassarre *et al* 2019). Sociohydrology models are being increasingly applied to understand and model 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 Wheeler 2014), and the evolution of ancient societies (Pande and Ertsen 2014, Kuil *et al* 2016).

3.1.1. ABM: a promising tool for sociohydrology

The two main methods that have been used to model sociohydrological systems are ABM and system dynamics (Pande and Sivapalan 2017, di Baldassarre *et al* 2019). 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/interactions (Martin and Schlüter 2015, Yu *et al* 2017, di Baldassarre *et al* 2019). 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 is at the core of AWM externalities (figure 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 Ringler 2002, Berger *et al* 2006, Troost and Berger 2015, Khan *et al* 2017).

Table 2. Illustrative examples of the potential capabilities of ABM to expand or complement AWM studies to capture externalities.

AWM interventions	Externalities leading to undesirable or unintended outcomes	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 <i>et al</i> 2020), ABMs potential lies in its capacity to simulate farmers' behaviors and decisions regarding changes in irrigation or cropping patterns. This in return influence the hydrological fluxes such as increased water use in response to increased efficiency measures.
Water harvesting	Increased water supply leading to increased demand (Supply—demand cycle); 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 <i>et al</i> 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 incentives/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 <i>et al</i> 2016), ABMs can potentially simulate 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.

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 (Khan *et al* 2017, di Baldassarre *et al* 2019). 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* 2013). This also makes it a promising tool for sociohydrology to understand and explore the evolution of coupled human–water systems, to unravel and understand AWM externalities and resulting in unsustainable and inequitable outcomes. Thus, ABMs can expand and complement conventional AWM model to integrate human–water feedbacks. Table 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.

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 small-holder farming systems and how this is influenced by farmer 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 (Berger 2001, Schreinemachers *et al* 2007, 2009), modeling the impact of farmers' agricultural decisions on hydrological systems (Becu *et al* 2003, van Oel *et al* 2010) and simulating a range of policy, trade, and market mechanisms (Schlüter and Pahl-Wostl 2007, Farhadi *et al* 2016, Aghaie *et al* 2020a, 2020b).

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 as discussed above (figure 1). 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 AWM–ABM 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).

Table 3. Overview of questions on different components of AWM–ABM models for the review.

Overarching question	Sub-questions	Link to AWM externalities and outcomes (conceptual framework in figure 1)
How does AWM–ABM resolve negative hydrological externalities?	Can hydrological models used in AWM–ABM: (a) Resolve the spatially explicit impact of AWM on water flows? (b) Model surface–groundwater (SW–GW) 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 feedbacks (e.g. increases in crop area and water use)
How does AWM–ABM 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)

4. Review of ABMs application to agricultural water systems (AWM–ABM)

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 2001, Troost and Berger 2015, Dziubanski *et al* 2020). Methods employed for modeling these biophysical, economic, and social processes differ substantially (Le Page *et al* 2013, Kremmydas *et al* 2018) and have a direct bearing on the ABMs ability to resolve negative hydrological externalities and unexpected societal feedback of AWM interventions (figure 1). For example, whether AWM–ABMs can model spatially explicit hydrological impacts depends on the hydrological models employed and the simulations of realistic societal feedbacks depends on behavioral theories used.

Since ABMs differ substantially in terms of methods employed, our review focuses on assessing AWM–ABM methods for their capability to unravel negative hydrological externalities, assess inequitable impacts and capture societal unexpected feedbacks (figure 1). We broadly focus on three overarching questions (derived from figure 1): (a) How does the AWM–ABM resolve negative hydrological externalities?; (b) How are farmers' responses, behavior and interactions simulated?; and (c) How does the AWM–ABM resolve inequitable impacts by accounting for the heterogeneity of society? These were broken down into sub-questions (table 3) 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.

4.1. 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 AWM–ABM 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 AWM 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.

5. Review results

5.1. 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 AWM–ABMs 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 (SW–GW) systems, the hydrological models should at least be: (a) semi-distributed to account for the spatial heterogeneity of water quantity and quality processes and (b) include groundwater–surface water interactions (Glendening *et al* 2012, Khan *et al* 2017). The following section explores the extent to which these criteria are met.

5.1.1. Hydrological models in AWM–ABMs

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 AWM–ABM studies. AWM–ABMs where spatial scale is either individual farm or administrative region (figure 2(a), 27%), is not conducive for modeling hydrological flows and interactions. In these AWM–ABMs, water flows are largely modeled at individual plot/farm levels either using one-dimensional soil water balance (Tamburino *et al* 2020, Wens *et al* 2020) or empirical models (van Duinen *et al* 2016, Zagaria *et al* 2021). AWM–ABMs 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 The Food and Agriculture Organization of the United Nations (FAO) crop model AquacropOS.

AWM–ABMs 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, Barnaud *et al* 2008, Troost and Berger 2015, Hampf *et al* 2018). However, hydrology, if modeled, is still mostly modeled at individual farm scales (Schreinemachers *et al* 2007, Troost and Berger 2015). With hydrological impact not the focus in many AWM–ABMs at an administrative scale, more than 50% of such studies do not employ any hydrological model (figure 2(a)). For example, Troost and Berger (2015) modeled regional land user and crop production dynamics resulting from individual farmer 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 income, crop changes, and agriculture supply.

Hydrological flows and interactions, via surface and groundwater, can be explicitly modeled in AWM–ABMs where the spatial scale is either watershed/basin (Berger 2001, Becu *et al* 2003, Schreinemachers *et al* 2009, van Oel *et al* 2010, 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 AWM–ABMs have the watershed and irrigation systems as their spatial scale, respectively (figure 2(a)). In these AWM–ABMs negative hydrological externalities can be captured as agents' actions impact other agents' water flows and availability, simulated as the change in surface water flows (Becu *et al* 2003, van Oel *et al* 2010, Pouladi *et al* 2020), groundwater depth (Noël and Cai 2017, Hu and Beattie 2019, Du *et al* 2020) and water quality (Pouladi *et al* 2019). In AWM–ABM modeling irrigation systems, water flows and availability are determined by canal flows, rather than watershed hydrology (Barreateau and Bousquet 2000, Barreateau *et al* 2004). This is done largely using empirical models (figure 2(a)).

In AWM–ABMs at the watershed scale, both semi-distributed and distributed hydrological models have been used (figure 2(a)). In semi-distributed hydrological models, aggregated hydrological response (e.g. runoff, recharge, drainage) of sub-units (sub-watershed, hydrologic response unit (HRUs)) is modeled at the overall basin/watershed outlet (Becu

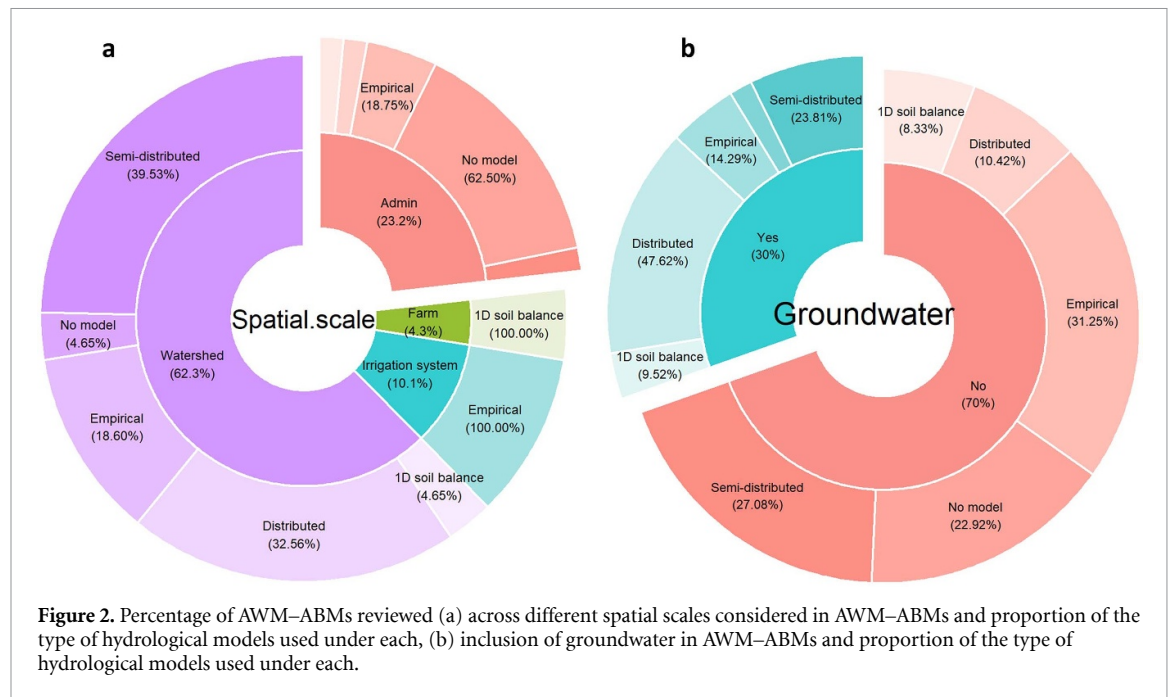


Figure 2. Percentage of AWM-ABMs reviewed (a) across different spatial scales considered in AWM-ABMs and proportion of the type of hydrological models used under each, (b) inclusion of groundwater in AWM-ABMs and proportion of the type of hydrological models used under each.

et al 2012, Dziubanski *et al* 2020). Examples of semi-distributed models include using soil conservation service (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 soil & water assessment tool (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 distributed models as part of AWM-ABM and linked each point/grid in space with underlying agents. This allows for modeling two-way feedbacks between individual actions/decisions and hydrology. The most often used distributed models in AWM-ABM come from studies assessing groundwater management and sustainability (~47%, figure 2(b)). In these studies, the use of the distributed modular groundwater flow model (MODFLOW) have been frequent (Farhadi *et al* 2016, Noel and Cai 2017, Nouri *et al* 2019). 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(b)) 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).

5.1.2. Groundwater-surface water interactions in AWM-ABMs

The examples of negative hydrological externalities discussed earlier show that they often result from interactions of 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 SW-GW interactions. However, our review shows that there are large gaps in this part. First, only ~30% of reviewed papers had considered groundwater (figure 2(b)). 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, Tambourino *et al* 2020, Wens *et al* 2020).

Second, very limited studies use integrated models with SW-GW interactions in place (~14% of studies) (van Oel *et al* 2010, Du *et al* 2020, Mirzaei and Zibaie 2021). Most studies model surface water (Nikolic *et al* 2013, Dziubanski *et al* 2020) or groundwater (Farhadi *et al* 2016, Noël and Cai 2017,

Nouri *et al* 2019, Aghaei *et al* 2020a, 2020b) in isolation. One explicit case of distributed integrated SW–GW model use in AWM–ABMs 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 SW–GW process means that many of the AWM externalities cannot be captured or predicted.

5.2. Modeling society unexpected feedbacks in AWM–ABMs

Incorporating agent responses and feedbacks to the environment to capture unexpected society feedbacks is central and critical in AWM–ABMs models. 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 AWM–ABMs into two types: AWM–ABMs where agent behavior is modeled in isolation without accounting for social interactions, and AWM–ABMs 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.

5.2.1. Simulating individual farmers' responses and behavior in AWM–ABMs

Individual decision-making and behavior in AWM–ABMs 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 AWM–ABMs (figure 3(a)).

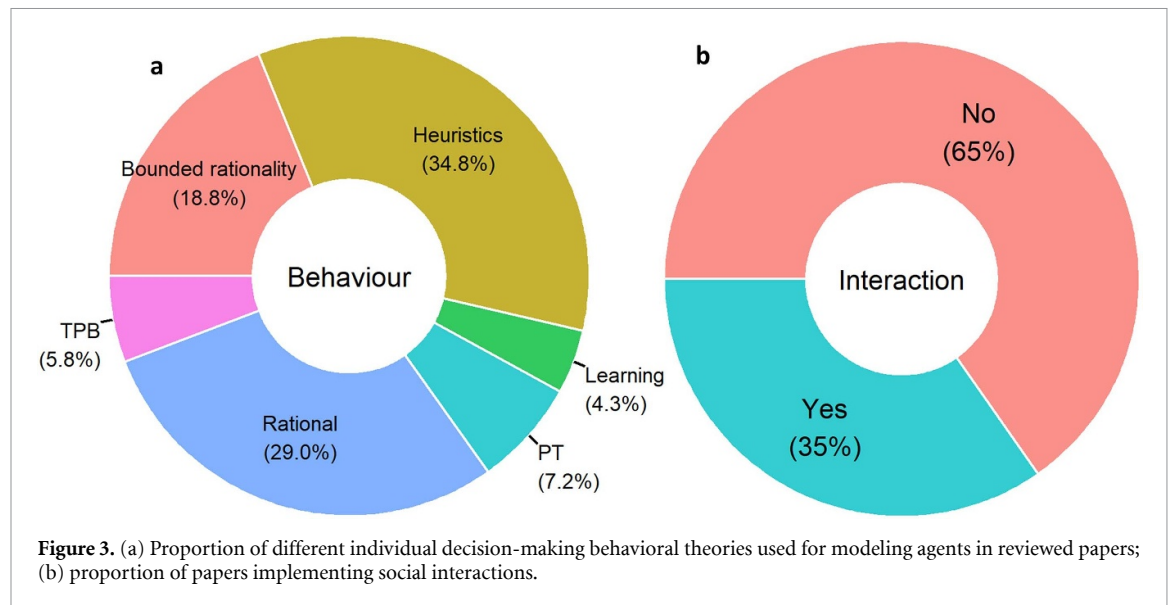
Our review shows that the most used theories in AWM–ABMs are rational choice and bounded rationality (including heuristics) (figure 3(a)). *Rational and bounded rationality* are both based on expected utility maximization where an agent's decision-making is goal oriented. Agents choose a strategy, under given constraints, with the best-expected outcome or utility (An 2012, Schlüter *et al* 2017). 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 AWM–ABMs is the application of the mathematical programming-based multi agent systems (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 (Bluening *et al* 2010, Howley *et al* 2015, Dessart *et al* 2019). Examples include farmers' unwillingness to convert 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 (Bluening *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 (van Duinen *et al* 2016, Dessart *et al* 2019, Du *et al* 2020).

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 (An 2012, Schlüter *et al* 2017). There are many different approaches to formalize bounded rationality with respect to limited information, quality of information, and cognitive capacities of decision-makers (van Duinen *et al* 2016, Schlüter *et al* 2017). The most often used approach is heuristics, where agents are assigned rules, derived from empirical data or observations, that drive their decision-making (Schlüter and Pahl-Wostl 2007, van Oel *et al* 2010, An 2012). In heuristics, decisions emanate from farmers' experience, accumulated knowledge, and *p* (Schlüter and 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 (PMT), theory of planned behavior (TPB), learning) rather than rational or simple heuristics (Schlüter *et al* 2017, Taberna *et al* 2020, Wens *et al* 2020). PMT, a version of bounded rationality, offers an example (Dziubanski *et al* 2020, Wens



et al 2020, Zagaria *et al* 2021). In PMT, farmer adaptation is simulated as the integration of farmers' perceived risk and appraisal of their capacity to adapt (Wens *et al* 2020, Zagaria *et al* 2021). 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 AWM-ABMs, namely the habitual or reinforcement learning theory, TPB, and prospect theory (PT) (figure 3(a)). In Habitual or Reinforcement learning, positive and negative experiences (history) are stored in the state (knowledge) and reflected in the habit formation of agents (Nikolic *et al* 2013, Schlüter *et al* 2017, 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. TPB focuses on farmer intention, shaped by agent attitudes, subjective norms, and perceived control, as the main determinants of implementing a certain behavior (Kaufmann *et al* 2009, Pouladi *et al* 2019, Yang *et al* 2020). Pouladi *et al* (2019) used TPB to assess farmer decisions on the conservation of water resources in the Zarrineh River Basin, Iran. 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 (Ng *et al* 2011, Balbi *et al* 2013, Ding *et al* 2015, Gonzalez-Ramirez *et al* 2018). 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.

5.2.2. Simulating social interactions in AWM-ABMs

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 sideways 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* 2020a). Of the reviewed papers, only one-third incorporate agent social interactions or sideways looking theories (figure 3(b)).

These AWM-ABMs have used social interactions to model diffusion and adoption of adaptation practices (Berger 2001, Schreinemachers *et al* 2007, 2009, Ng *et al* 2011, Schreinemachers and Berger 2011), mimicking of behaviors (such as cooperative or non-cooperative behavior) and decisions regarding cropping practices (Barreuteau *et al* 2004, Nikolic *et al* 2013, Castilla-Rho *et al* 2015, Farhadi *et al* 2016, Cai and Xiong 2017, Ghazali *et al* 2018, Bazzana *et al* 2020).

The model of diffusion is based on a principle that agents mimic and learn from other farmers' decisions. Most AWM-ABMs 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* (2013) 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 AWM-ABMs 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 (Monu 1995, AgriFutures 2016). 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 (Kaufmann *et al* 2009, Daniel *et al* 2019). 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 AWM-ABMs (Kaufmann *et al* 2009).

5.3. Modeling inequitable outcomes of AWM interventions in AWM-ABMs

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 AWM-ABMs 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: (a) each farmer located within the study domain should be represented to simulate their impact on hydrology and vice versa and (b) farmers' characterization in the model should capture their relevant socio-economic characteristics and associated biophysical endowments.

5.3.1. Representation of farmers in AWM-ABMs

Our reviews show there are two broader methods of representing spatially distributed farmers: modeling individual farmers (Berger 2001, Schreinemachers *et al* 2007, 2009, Arnold *et al* 2015) and modeling aggregate farmers (Hu *et al* 2015, Farhadi *et al* 2016, Hu and Beattie 2019). 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 AWM-ABMs 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 (Berger 2001, Schreinemachers *et al* 2007, 2009, van Oel *et al* 2010, Arnold *et al* 2015, Noël and Cai 2017). These AWM-ABMs 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 farmers' 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 2015). 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 AWM–ABMs 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 (Nikolic *et al* 2013, Xiao *et al* 2018, Hu and Beattie 2019, Nouri *et al* 2019). It is the aggregated responses and feedbacks of agents that are simulated and integrated with biophysical systems (Nikolic *et al* 2013, Hu *et al* 2017, Hu and Beattie 2019). For example, Hu and Beattie (2019) modeled 46 counties with each county aggregated as one farmer, Farhadi *et al* (2016), and Nikolic *et al* (2013) 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.

5.3.2. Representing farmer's heterogeneity in AWM–ABMs

Agent characterization in AWM–ABMs 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 S1). This determines the availability of labor, consumption, and expenses of agents. Other often used socio-economic characteristics, based on the objective of AWM–ABMs, 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 AWM–ABM studies. The data for these socio-economic characteristics are either collected from existing microeconomic datasets (obtained from sample surveys, censuses, and administrative systems) (Noël and Cai 2017) or

through primary surveys (such as household surveys and focus group discussions) (van Oel *et al* 2010, Pouladi *et al* 2019, Wens *et al* 2019).

Biophysical endowments of agents are mostly derived from underlying maps of biophysical datasets (e.g. soil, elevation, rain). Biophysical endowments characteristics considered (table S1) 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, van Oel *et al* 2010, Arnold *et al* 2015, Noël and Cai 2017). For example, Noël 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.

6. Synthesis

The review confirms the ability of AWM–ABMs to expand the capabilities of conventional AWM studies, as stated in table 2, by incorporating human–water feedbacks (a key limitation of conventional AWM studies and models) and capturing the negative externalities possibly generated by AWM interventions and unraveling the unintended consequences including unsustainable and inequitable outcomes.

The review shows that methods employed by AWM–ABMs can successfully integrate a range of farmer behavior including the adoption of AWM interventions (Ng *et al* 2011, Schreinemachers and Berger 2011, Wens *et al* 2020), investing in farming inputs, choice of crops (Becu *et al* 2003, Schreinemachers *et al* 2009, Schreinemachers and Berger 2011, Arnold *et al* 2015) and land use (Troost and Berger 2015) and irrigation (Van Oel *et al* 2010, Nikolic *et al* 2013, 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 (Berger 2001, Schreinemachers *et al* 2007, 2009, Dziubanski *et al* 2020, Wens *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). AWM-ABMs do this by linking farmers and societal modules (human systems) with coupled spatially distributed surface (Becu *et al* 2003, Du *et al* 2020) and groundwater hydrological models (Noël 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 farmer's decisions on spatial and temporal distribution of surface water resources in a river basin in Brazil.

Further, the modeling of human–water feedbacks in AWM-ABMs 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, AWM-ABMs have modeled inequitable adoption of AWM interventions based on land size and financial resources (Holtz and Pahl-Wostl 2012, Wens *et al* 2020); (in) equity in water allocation (Mirzaei and Zibaie 2021), and inequitable water distribution and interaction between upstream and downstream farmers (Becu *et al* 2003, Barreteau *et al* 2004, van Oel *et al* 2010). Yet the review also brings to fore the remaining methodological gaps of AWM-ABMs in resolving AWM externalities and the resulting unsustainable and inequitable outcomes.

6.1. Gaps and future research need in AWM-ABMs 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 3) in AWM-ABMs that limit their capacity to unravel one or more of the externalities. In the section below, we identify these gaps under each component of AWM-ABMs and the research needed to bridge these gaps (table 4).

6.1.1. Modeling negative hydrological externalities

Despite AWM interventions being intricately linked with hydrology (section 2), our review shows that a quarter of AWM-ABMs simulate dynamics at indi-

vidual farms or administrative regions (figure 2(a)) 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 AWM-ABMs 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 SW–GW models (figures 2(a) and (b)). 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 AWM-ABMs to resolve inequitable impacts. Additionally, the non-inclusion of the groundwater system and lack of integrated SW–GW limits AWM-ABM 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 AWM-ABMs 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, spatial processes in hydrology (SPHY)). An example of the latter is by Du *et al* (2020) where GSFLOW, an integrated SW–GW model, was tightly coupled with ABM at the source code level.

6.1.2. Modeling society feedbacks

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 AWM-ABMs. The empirical field research has shown that human behavior is shaped by a range of factors such as socio-economic, cultural norms, risk

Table 4. Identified remaining research gaps and future AWM–ABMs research needs to bridge these to fully unravel the negative externalities of AWM interventions.

Unpacking externalities and unexpected outcomes of AWM interventions (see the conceptual framework in figure 1)	Gaps	Future research
Negative hydrological externalities	(a) No consideration of hydrological impacts in ~25% of studies, thus ignoring any negative hydrological externalities of AWMs.	(a) 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 or changing cropping patterns) on water use. (b) 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 SW–GW stocks.
	(b) Lack of inclusion of spatially distributed hydrological models, limiting ABMs capacity to model spatially distributed and inequitable impacts of AWM interventions	
	(c) Lack of representation of integrated SW–GW systems in ABMs	
Society feedbacks	(a) Over-reliance on rational behavior and simple heuristics to model individual behavior and decisions.	(a) Move away from rational and simple heuristics to behavioral theories grounded in social science (e.g. TPB, bounded rationality, PT) 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-behavioral (e.g. farmers' perception of risk, confidences in one's ability) characteristics on farmers' decisions. (b) 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.
	(b) Lack of very simplistic representation of social interaction based on simple diffusion and contagion models	
Inequitable impacts	(a) Limited ability to account for inequitable impacts of AWM interventions among farmers in ABMs where aggregated farmers (e.g. watershed, city, basin) are simulated.	(a) Supplement or complement ABMs where aggregated agents are modelled with studies that model individual agents, thus accounting for the heterogeneity of farmers 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). (b) 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).
	(b) 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.	

attitudes, perceptions, and other psychological characteristics (Kaufmann *et al* 2009, Daniel *et al* 2019, Pouladi *et al* 2019). However, there is a large gap in incorporating the same in AWM–ABMs. Our review shows that the use of rational choice theory and simple heuristics is still dominant (figure 3(a)). 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, farmers' 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. PMT, PT, and TPB). There is a greater need to formalize these theories in AWM–ABMs. 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 water, sanitation and hygiene (WASH) sector (Mosler 2012). RANAS combines multiple important behavioral theories (including the TPB) 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 AWM–ABM studies is the lack of incorporation of social interactions among agents (figure 3(b)). 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 (Kaufmann *et al* 2009, Daniel *et al* 2019). Thus, like individual theories, there is a need to expand the AWM–ABMs social interactions theories in use, employing more holistic adoption and diffusion models.

6.2. Modeling inequitable outcomes

There remain gaps in fully exploiting the ABM capabilities to resolve spatially explicit and inequitable

externalities of AWM interventions. Multiple AWM–ABMs 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 AWM–ABMs 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 Noël 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 AWM–ABMs to model human–water feedbacks, 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 feedbacks are still poorly understood, especially over longer time periods (di Baldassarre *et al* 2016, Srinivasan *et al* 2017). The calibration and validation of AWM–ABMs is more complex in comparison to that of the conventional AWM models (Sivapalan and Blöschl 2015, Troy *et al* 2015, Pande and Sivapalan 2017). 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 AWM–ABMs is required. For long term strategic investment decisions, AWM–ABMs 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, Pande and Sivapalan 2017, Srinivasan *et al* 2017).

7. 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 feedbacks. 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 feedbacks 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 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 3). The main gaps include: (a) lack of spatially distributed and integrated hydrological models, which limits the capacity of AWM–ABMs to resolve hydrological negative externalities; (b) over-reliance on rational and simple heuristics for modeling individual behavior and (c) lack of inclusion of social interactions. Our review highlights the need for further research and development of AWM–ABMs 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 feedbacks resulting in long-term unsustainable and inequitable outcomes.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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