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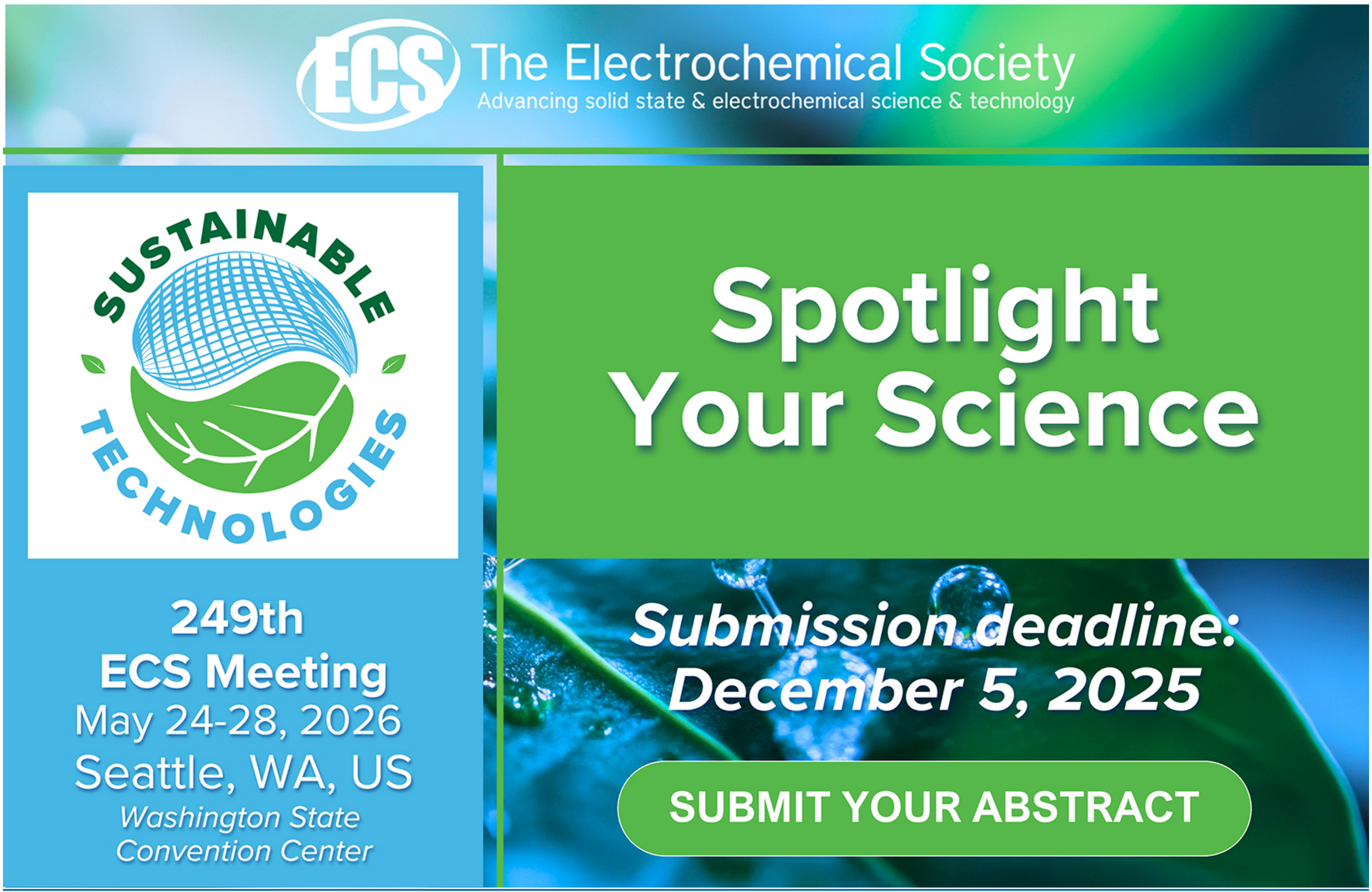

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PAPER

Decoding farmers' choices in a changing climate: an agent-based model to elucidate risk preferences and water resilience

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Abstract

Agricultural systems are increasingly vulnerable to climate change due to rising temperatures, shifts in runoff patterns, and fluctuations in seasonality. Farmers, as primary stakeholders, provide invaluable first-hand insights into the manifestation of water-related extreme events and the effectiveness of different adaptation strategies to enhance climate resilience. This study introduces ABNexus, an agent-based model designed to capture the complexity of farmers' decision-making processes and their interactions with agrohydrological systems under climate change. Using a bottom–up approach that incorporates realistic human behavior, we conducted 460 randomly sampled surveys among farmers across the main irrigation districts of the Lake Como and Adda River basin in northern Italy. The analysis revealed substantial heterogeneity in adaptive capacity and risk preferences, influencing farmers' crop selection and irrigation methods under different climate scenarios. Our simulations show that risk aversion significantly shapes adaptation decisions, with more cautious farmers tending to retain traditional crop-irrigation combinations and showing reluctance toward the adoption of water-efficient practices. These insights support policymakers and irrigation managers in refining local water management and climate adaptation policies, enhancing decision-making robustness, and reducing maladaptation risks for more resilient agricultural systems.

1. Introduction

Agriculture is among the sectors most vulnerable to water-related changes and climate-induced stressors, as shifting weather patterns and extreme events influence water availability and the reliance on its management, also exacerbating water scarcity (Karimi *et al* 2024) and conflicts due to multifunctional water demands (Karesdotter *et al* 2025). Rising temperatures, erratic rainfall patterns, and the increasing frequency of droughts and floods are impacting negatively agricultural practices, amplifying uncertainty for farmers (Brás *et al* 2021, Ricart *et al* 2022). These climatic disruptions amplify pressure on water resources and trigger cascading challenges, including crop failures, reduced yields, altered growing cycles, soil erosion, and increased outbreaks of pest and disease (Karki *et al* 2020, Barik *et al* 2022). The threats to global and regional water and food security are substantial, as climate change modifies hydrological dynamics and limits both crop productivity and land suitability for cultivation (Raj *et al* 2022). At the farm level, climate variability can disrupt both environmental and market conditions, undermining crop yields, reducing farm income, and compromising sustainability (Necula *et al* 2024). In addition, climate change has significantly slowed global agricultural productivity growth, with total factor productivity decreasing by 21% over the past six decades (Ortiz-Bobea *et al* 2021).

Risk perception-individuals' subjective judgment about the likelihood and severity of adverse outcomes in socio-ecological systems (Hasibuan *et al* 2020)—is a key factor for understanding water and climate-related impacts and formulating effective adaptation strategies. It provides a framework for evaluating the probability, uncertainty, and potential consequences of climate risks, as well as the capacity to respond effectively (Han *et al* 2022). Equally important are risk preferences, which reflect individual attitudes toward risk and significantly influence decision-making processes, such as investment and the adoption of new technologies or practices (Garcia *et al* 2024). These preferences are shaped by self-perception, personal experience, and individual assessment of external risks—mostly focused on water-related impacts conditioning the crop-growing environment (Oyinbo *et al* 2019). Understanding risk preferences is essential for comprehending farmers' climate adaptation strategies and for designing effective policies that enhance irrigation resilience. This includes providing risk management support and promoting the diffusion of innovative technologies and practices (Rommel *et al* 2023).

Differences in risk preferences can lead to divergent responses to the same policy or intervention (Nie *et al* 2021, Han *et al* 2022). For example, individuals who have experienced climate-related disasters may become more risk-averse and exhibit reduced trust in government recovery efforts (Iyer *et al* 2020, Zhang *et al* 2023). Conversely, others may adopt risk-taking behaviors, actively pursuing innovative adaptation strategies (Peng *et al* 2021, Wu and Xu 2024). Furthermore, regular exposure to extreme weather events, particularly those causing changes in water resources supply, could lead to risk normalization, where individuals minimize or dismiss potential impacts, particularly if these risks are perceived as distant (Duong *et al* 2019, Cisternas *et al* 2024).

Climate change necessitates a paradigm shift in agricultural practices, requiring farmers to adapt to unprecedented climatic variability. Adaptation is a critical strategy to reduce vulnerability, improve resilience, and mitigate the adverse impacts of extreme weather events on livelihoods (Adeboa and Anang 2024). However, adaptation is highly context-dependent, shaped by uncertainties, constraints, and local conditions, and encompasses a broad spectrum of behaviors, mechanisms, processes, and policies (van Valkengoed and Steg 2019). Adaptation refers to the capacity to respond and adjust to actual or anticipated climate impacts (Rijal *et al* 2022). It can be understood as both a process and an outcome, ranging from short-term coping strategies to long-term system transformations (Chhetri *et al* 2019, Bagambilana and Rugumamu 2023). Farmers are already employing various adaptation strategies to cope with the short-term and long-term effects of climate change, being particularly concerned about water availability and management. These include on-farm and off-farm measures, such as soil conservation techniques, water-saving irrigation techniques, drought-tolerant crop varieties, crop diversification, adjusted planting calendars, fertilizer management, insurance, and access to climate information services (Ricart *et al* 2023). Additionally, knowledge sharing and experiential learning within farmer groups have been instrumental in accelerating the adoption of innovative technologies and practices (Norton and Alwang 2020).

Behavioral factors and opportunity costs play a crucial role in shaping farmers' adaptive capacity, influencing their decision-making within the social and biophysical context (Schaub *et al* 2023). Likewise, climate awareness and perception tend to be conceived as drivers for adaptation choices (Mustafa *et al* 2023). Farmers' perception of climate change is a complex process that involves many psychological factors, such as knowledge, beliefs, attitudes, and concerns about future climate conditions (Belay Bedeke and Tebeje 2023, Rodríguez-Barillas *et al* 2024). Perceptions are further influenced by individual characteristics, past experiences, and socio-cultural contexts (Rabbi *et al* 2021). For instance, farmers who have experienced extreme weather events may be more likely to anticipate future climate risks (de Matos Carlos *et al* 2020), while those who feel well-informed and resourced may be less anxious about climate change impacts (Mitter *et al* 2019). Social networks are integral to shaping farmers' decision-making processes, facilitating knowledge exchange and shared information about most relevant agri-environmental practices or most adequate irrigation methods (Skaalsveen *et al* 2020, Wuepper *et al* 2020). Lastly, social learning, or learning through observation and interaction with peers and neighbors, represents a key mechanism driving the adoption of new practices within farming communities (Šúmane *et al* 2018, Vroege *et al* 2020). This 'spillover' or 'neighborhood effect' allows farmers to learn from the experiences of others and base their decisions on the behavior of their peers (Di Falco *et al* 2020).

Explicit modeling of socio-ecological systems can help to unravel unintended and unexpected feedback loops within human–water systems, such as agricultural water management interventions (Di Baldassarre *et al* 2019). However, traditional approaches often conceptualize human and natural systems as separate entities, with human actions imposed as external factors (Lobanova *et al* 2017, Pacilly *et al* 2019). To address this limitation, behavioral models are essential for exploring how individuals, communities, and institutions respond to system dynamics, including perceived or anticipated climate change risks (Beckage *et al* 2022).

In this context, agent-based models (ABMs) serve as a powerful tool for simulating individual behaviors, interactions, and decision-making processes within complex socio-ecological systems (Alam *et al* 2022, Daly *et al* 2022). By employing a process-based, bottom–up approach, ABMs can explore how farmers' decisions impact system-level outcomes under conditions such as water stress and climate variability (Lin *et al* 2020, Burg *et al* 2021). Through rule-based decision-making and dynamic interactions with their environment, ABMs offer valuable insights into the potential consequences of different policies and management strategies (Choquette-Levy *et al* 2021, Harik *et al* 2023). The strength of this modeling approach lies in its capability to incorporate cognitive, emotional, personal, and social factors that underlie human behavior, which is necessary for capturing the full complexity of farmers' decision-making (Brown *et al* 2017, Dessart *et al* 2019). To better understand and model this complex interplay between human behavior and hydrological systems, various behavioral theories can be applied to describe and explain farmers' perceptions and responses to climate change (Sun *et al* 2016).

ABMs also facilitate the exploration of feedback loops between human decisions and environmental systems, enabling the investigation of emergent spatial and temporal patterns resulting from interactions at lower organizational levels (Bonabeau 2002). One of the core challenges of ABM research lies in accurately representing individual-level dynamics, which are critical for understanding the consequences of decision-making (Emami *et al* 2024). Efforts have focused on delving into farmers' sensitivities (e.g. attitudes, influences) and decision heuristics (e.g. imitation, endorsement, see Huber *et al* (2018)) to move beyond the prevailing assumptions of rational choices and access to perfect information (Apetrei *et al* 2024). This approach acknowledges the complexity of decision-making, where farmers' responses to climate change are not static but evolve in response to broader social and ecological changes (Petersen-Rockney 2022). Understanding the cognitive, socioeconomic, and environmental dimensions of farmer behavior remains a crucial frontier in advancing climate change adaptation. By incorporating these dimensions, ABMs can provide deeper insights into how farmers adapt field-management practices and livelihood strategies under dynamic climatic and systemic pressures.

While ABMs offer a powerful means to simulate individual behaviors and complex interactions within agricultural landscapes, their effective application in real-case studies is often hampered by significant calibration challenges. A major hurdle is the need for extensive and detailed empirical data that accurately captures the heterogeneity of farmers' socio-economic, behavioral, and biophysical characteristics. Such a data-intensive calibration process is not only resource-demanding but also restricts many studies to providing only generalized insights, with limited representation of individual risk preferences and adaptive learning from experience and peer interactions (Müller-Hansen *et al* 2017, Farahbakhsh *et al* 2022).

In contrast, our study addresses this gap by leveraging a comprehensive dataset collected from 460 farmer surveys in northern Italy. This rich dataset enables the calibration of the ABM with fine-grained behavioral data and scenario uncertainties, thereby better capturing the diversity in farmers' decision-making processes. By integrating these detailed empirical insights and building on theoretical frameworks that emphasize the cognitive and social dimensions of human behavior (Manson *et al* 2012), our approach bridges this literature gap between qualitative behavioral theories and quantitative modeling, enhancing our understanding of farmers' adaptive strategies, offering a robust tool for exploring climate resilience in agriculture.

The aims of this paper are threefold: a) to enrich the comprehension of farmers' attitudes regarding climate change awareness, perceived impacts, and adaptive capacity considering heterogeneity and social learning; b) to make a methodological contribution by integrating farmers' heterogeneity and scenario uncertainty in an ABM framework (named ABNexus) under different risk preferences and rationalities; and c) to illustrate how these processes and their interactions might influence farmers' decision outcomes. Our analysis of the relationship between farmers' perspectives and anticipated decisions is guided by the following research questions:

- Do farmers perceive climate change impacts differently, and what adaptation mechanisms are they considering?
- What changes in crop selection and irrigation methods might emerge from farmers' behavior?
- To what extent are farmers' decisions conditioned by heterogeneity, risk preferences, and rationalities?

To address these research questions, we developed the ABNexus framework, an innovative ABM integrated with the preexisting soil–crop–water model IdrAgra. This framework captures the complexity of farmers' decision-making processes by incorporating detailed empirical data collected from 460 surveys conducted among farmers in the Lake Como and Adda River basin regions in northern Italy. Our dataset encompasses a rich array of socio-economic, behavioral, and biophysical information, which is critical for accurately simulating farmers' heterogeneity and risk preferences. The ABNexus model uniquely combines farmers' heterogeneity and risk preferences with different behavioral theories, providing an accurate representation of their responses to climate-induced risks. By simulating interactions between farmers, their agrohydrological environment, and climate change scenarios, our approach aims to offer a comprehensive understanding of emerging adaptation strategies and agricultural outcomes, thereby potentially providing valuable insights for policymakers and irrigation district managers, ultimately enhancing efforts to build climate resilience and promote sustainable water management practices.

2. Case study

The Po Valley in northern Italy is one of Europe's most agriculturally productive regions, playing a pivotal role in national agricultural output. The region accounts for one-third of Italy's total agricultural production, with Lombardy alone contributing over 10% of this value. Lombardy hosts nearly 52 000 farms across less than 1 million hectares, underscoring the region's dense and intensive agricultural activity.

Spanning an area of 46 000 km^2-comprising 71% of Italy's plains-the Po Valley is traversed by the Po River, Italy's largest river at 652 km in length. Farmland occupies 40% of the valley, integrating livestock farming with the cultivation of crops such as maize, rice, wheat, meadows, and soybean. These crops are sustained by an intricate and ancient network of secondary rivers, lakes, regulated reservoirs, and highly developed irrigation infrastructure.

A cornerstone of this system is Lake Como, located in the southern Alpine belt. It is one of Italy's deepest lakes and the third largest by surface area (145 km^2; Yang *et al* (2023)). Lake Como is primarily fed by the Adda and Mera rivers, with a catchment area of 4552 km^2. Its sole emissary, the Adda River, originates from the southeastern branch of the lake, flows through the central sector of the Lombardy region, and ultimately joins the Po River downstream (Zaniolo *et al* 2021). In this study, we focus on the agricultural area south of Lake Como, which relies predominantly on irrigation water from the Adda River, as illustrated in figure 1. This complex hydrological network not only sustains agricultural productivity but also examplifies the intricate interdependence between natural water systems and human-engineered infrastructure in one of Italy's most vital farming regions.

The hydrology of the Adda River sub-basin -like the broader Po Valley-is influenced by the mixed snow-rain dominated regime of the Southern Alps. This regime is characterized by dry periods in winter and summer, with peaks of moisture in late spring and autumn driven by snowmelt and rainfall, respectively (Giuliani *et al* 2020). The foothill zone receives the highest rainfall, ranging from 1500 to 2000 mm annually, whereas water availability in the plains is approximately half this amount (Baronetti *et al* 2022). A portion of the snowmelt runoff is captured upstream by several artificial hydropower reservoirs, collectively providing a cumulative storage capacity of 515 Mm^3. Since 1946, the lake outflow from Lake Como has been regulated by the Consorzio dell'Adda via a dam on the Adda River at Olginate. This regulation aims to ensure a reliable water supply for downstream users, supporting hydropower generation and irrigation over a cultivated area of approximately 1300 km^2 (Bertoli *et al* 2022).

By the end of the century, climate change is expected to significantly exacerbate geo-hydrological instability due to rising temperatures, altered precipitation patterns, and more frequent and prolonged extreme weather events. Projections indicate a substantial decrease in flow rates, with a 40% reduction anticipated by 2080 (Spano *et al* 2020), posing severe challenges to agricultural production (Bozzola *et al* 2018). Similarly, Casale *et al* (2021) predicts a progressive decline in average discharges and an earlier decrease in high spring flows due to disruptions in the snow accumulation and melting processes in Alpine regions. These changes will intensify both the magnitude and seasonality of hydrological shifts, particularly through reinforced low flows during summer (Vezzoli *et al* 2015). The region ranks 22nd on the Global Climate Risk Index, reflecting the degree to which countries are impacted by extreme weather events (Eckstein *et al* 2021). This aligns with reports from the Centre for Research on the Epidemiology of Disasters (2022), which identify the past two decades as an unprecedented period of hydrological (flash floods), climatological (convective storms, droughts), and meteorological (cold and heatwaves) events. The spring-summer 2022 drought was deemed the worst in 70 years, following a dramatic decrease in winter snowfall, a prolonged heatwave, and 120 consecutive days without rainfall. These conditions led to severe soil moisture deficits and advanced typical August weather conditions by six weeks, according to the Po River District Basin Authority (Bonaldo *et al* 2022). This episode underscores the vulnerability of the region to evolving climatic extremes, highlighting the urgent need for adaptive water management strategies.

3. Materials and methods

Our methodological approach integrates both behavioral and physical models to capture the multifaceted dynamics of agricultural systems in the Po Valley. Specifically, this approach combines an ABM designed to simulate the decision-making processes of individual farmers with a crop growth model that provides a detailed simulation of soil–crop–water interactions. It enables us to simulate how farmers adjust crop choices, irrigation methods, and adaptation strategies in response to climate change while dynamically

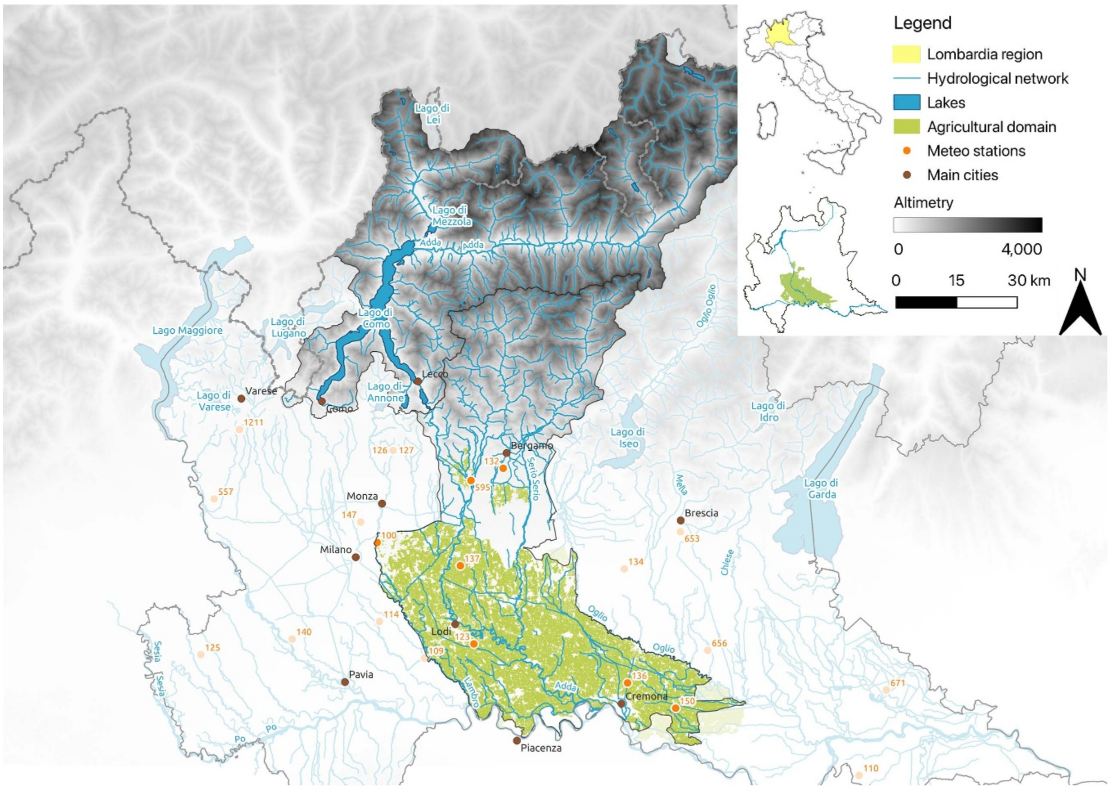

Figure 1. Case study area. Lombardy region hydrographic network is shown, consisting of lakes and rivers originating from the Alps. Lake Como and the Adda River sub-basin are highlighted, with case-study croplands prominently highlighted in green. The upper Adda catchment is also visible, including its alpine sources. Insert boxes in the top-right corner illustrate the location of Lombardy within Italy and the case-study spatial relation to the Po Valley.

interacting with their environment. Drawing on comprehensive empirical data from 460 surveyed farmers, our model accounts for heterogeneous risk preferences, social learning, and other behavioral nuances following a clustering analysis process and the identification of different drivers used to assign differentiated risk profiles. By coupling these models, we not only replicate observed agricultural outcomes under historical climate conditions but also provide a robust tool for analyzing potential future scenarios and policy interventions aimed at enhancing climate resilience and promoting sustainable water management.

3.1. The ABNexus framework

We developed the ABNexus framework to simulate agricultural production decisions at the local scale, capturing the heterogeneous impacts of climate change on farmers' behaviors. The framework, shown in figure 2, integrates an ABM with IdrAgra[4], a distributed-parameter soil–crop–water model (Gandolfi *et al* 2011). The ABM models the decision-making processes of individual farmers, while IdrAgra provides a detailed physical representation of the natural environment. This integration enables a comprehensive analysis of the complex interactions between human decisions and natural systems, across spatial and temporal scales, offering valuable insights into climate adaptation and agricultural resilience.

Rooted in both standard and behavioral economic principles, ABNexus incorporates key individual factors such as risk preferences, social influence, and adaptive behaviors, offering a nuanced reflection of the diverse ways farmers respond to uncertainty. Its flexible design allows for the integration of various behavioral models through inheritance and extension, facilitating the exploration and testing of multiple behavioral theories under consistent scenario conditions. By simulating how farmers respond to climate-induced risks and economic pressures, the ABM offers a comprehensive understanding of decision-making dynamics in localized contexts. Such applications have increasingly demonstrated their potential in agriculture for capturing the interplay of economic, environmental, and behavioral dimensions (e.g. Berger *et al* 2007, Troost and Berger 2015). In particular, they help model decision-making processes under uncertainty, path dependency, and heterogeneity across farm units (An 2012).

[4] IdrAgra resources, including QGIS plugin and source code, available at https://idragra.unimi.it/.

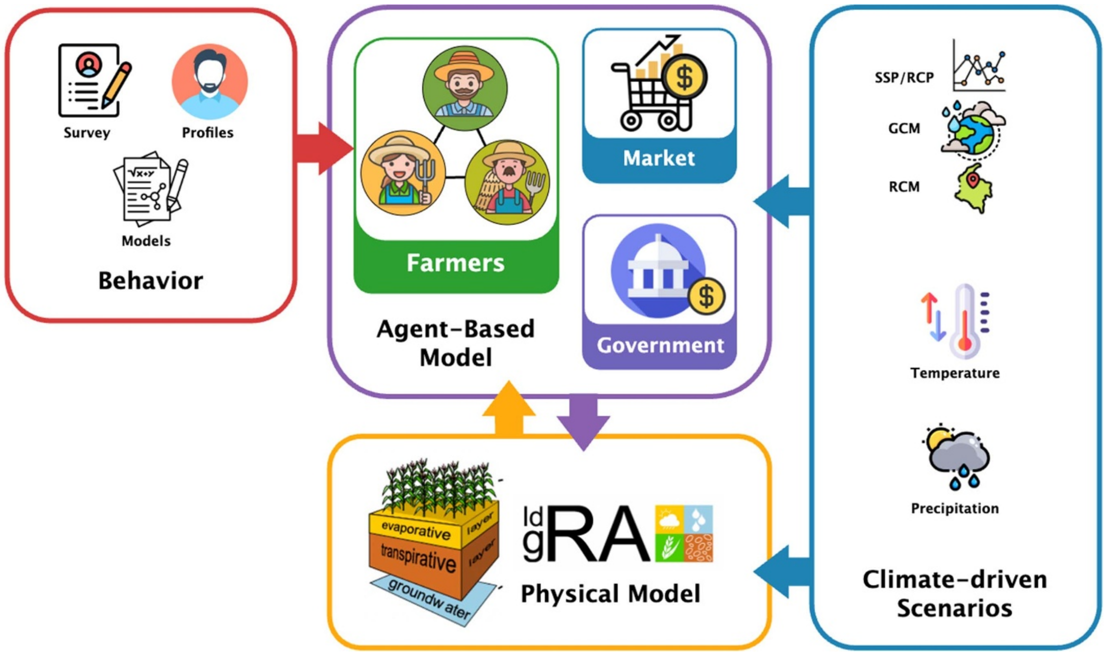

Figure 2. ABNexus framework. The soft-link between the ABM model and the IdrAgra model at its core, with consistent climate scenarios inputs and survey-calibrated behavior.

Developed through extensive consultations with regional experts, the ABNexus framework ensures that the modeled decision processes are grounded in practical knowledge and accurately represent the behaviors and adaptive strategies employed in the area of interest. The integration with the IdrAgra model provides a detailed and accurate representation of the local natural environment, as exemplified in the Adda River case study. This coupling reflects a broader effort in the literature to integrate ABMs with biophysical models, aiming to bridge socio-environmental complexity with dynamic hydrological and agronomic processes (e.g. Ng *et al* 2011). It facilitates a realistic assessment of how farmers' decisions interact with the physical environment, enhancing the accuracy of predictions for key outcomes such as crop yields and water use. Compared to general-purpose models, this integration offers enhanced spatial and environmental granularity, ensuring more locally grounded predictions.

By combining a flexible and adaptive behavioral model with a rigorous physical representation of environmental dynamics, ABNexus serves as a powerful tool for understanding the complex interplay between human and natural systems in agricultural landscapes. Such approaches allow researchers to examine how different adaptation behaviors propagate into system-level outcomes, a practice increasingly adopted in modeling climate adaptation in agriculture (e.g. Filatova *et al* 2013). This understanding can inform and enhance the development of effective policies and strategies to promote sustainable agriculture and mitigate the impacts of climate change.

Framework structure and components

Figure 3 provides an overview of the ABNexus framework, illustrating its main logical components. At its core is the ABM model, which serves as the central coordinator. It synchronizes all components through annual time steps and orchestrates the simulation process to ensure that decision-making and crop-yield simulation phases are executed in the correct sequence, enabling seamless system operation.

The IdrAgra Wrapper, a logical component within the ABM model (as shown in figure 3), abstracts the soft-linked interaction between the ABM and the IdrAgra-model. Specifically it manages critical tasks such as configuring the simulation environment, launching one or multiple IdrAgra executions within isolated environments -sandboxes that prevent input/output conflicts- and retrieving the results. These outputs are then communicated back to the agents, providing them with updated environmental conditions and enabling them to dynamically adjust their decisions in response to changing circumstances.

The spatial dimension of the model is represented by the Domain Grid module, an internal landscape representation composed of thousands of Field-Cell units, each covering 6.25 ha. These cells represent individual parcels of land, enabling high-resolution simulations of agricultural dynamics. Each Farmer is assigned to a subset of these cells corresponding to the size of their actual farm, which reflects differences in farm typology and spatial distribution.

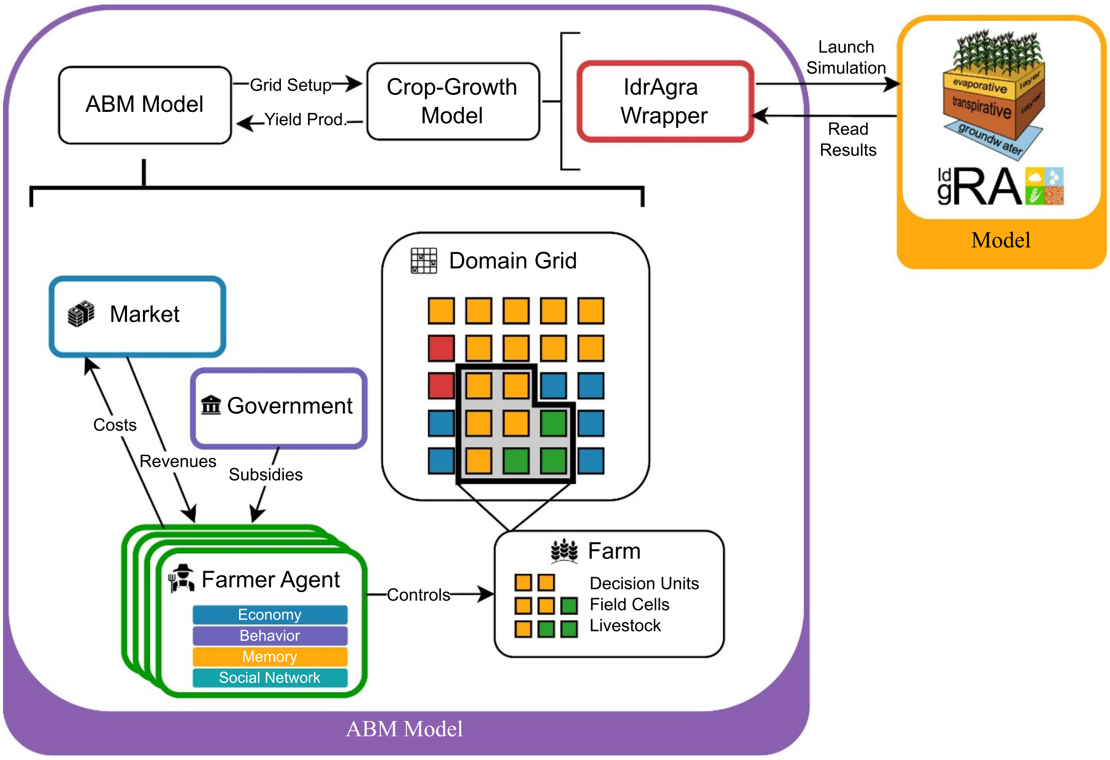

Figure 3. Agent-based model components. Overview of the main logical units and interactions within the ABNexus framework. The purple boundary highlights the scope of the ABM model, which includes internal interfaces for the agent-based model and the Crop-Growth Model (each abstracting the complexity of underlying processes). The IdrAgra Wrapper handles simulation management and establishes the connection between the ABM and the IdrAgra model. Each Farmer Agent manages a Farm composed of Field Cells grouped into Decision Units-homogeneous management areas- and livestock energy requirements. Colored cells illustrate the potential for diverse field configurations, reflecting the multiple Decision Units a single farmer may control.

At the core of the decision-making process is the Farmer Agent, each representing an individual farm within the spatial domain and exercising exclusive decision-making authority over its assigned Field-Cells. Farmers make decisions on these cells regarding crop selection and irrigation methods, which can vary from year to year depending on environmental conditions, economic factors, and adaptive strategies. These agents are highly individualized, initialized with distinct behavioral traits such as varying levels of risk aversion, contributing to decision heterogeneity across the model. Farmer Agents are spatially aware, capable of interacting with neighboring farms, and influenced by internal factors such as fodder demand constraints in livestock-based operations, adding further complexity to their choices. Additionally, they can interact within larger organizational structures such as Irrigation Units sharing experiences on crop and irrigation performances.

Exogenous dynamics, particularly market conditions, also play a significant role in shaping decisions. The Market module simulates fluctuations in crop prices, which directly impact farm profitability and decision-making. The Governor module represents regional or national public administrations, capable of introducing policy-driven incentives such as subsidies for adopting water-efficient technologies. These incentives are intended to encourage decisions aligned with broader sustainability objectives.

To better account for all the decision-making intricacies, Farmer Agents comprise multiple logical components (see supplementary figure 1). The Farm component tracks owned Field-Cells and groups them into independently-manageable decision units to balance complexity and computational efficiency. The Social Network component records interactions with neighboring farmers, accounting for social influence. The Memory component collects performance data, incorporating both farmer's experiences and peer observations. The Behavior component, then, processes and interprets memory data, translating it into yield expectations influenced by the farmer's personal behavioral traits like risk aversion. Lastly, the Economy component monitors finances, including income, expenses, debts, and credits, ensuring key constraints, such as fodder requirements, are met.

These interlinked components create a detailed and dynamic simulation, providing insights into how different farmer behaviors respond to varying environmental, economic, and social conditions under climate uncertainty.

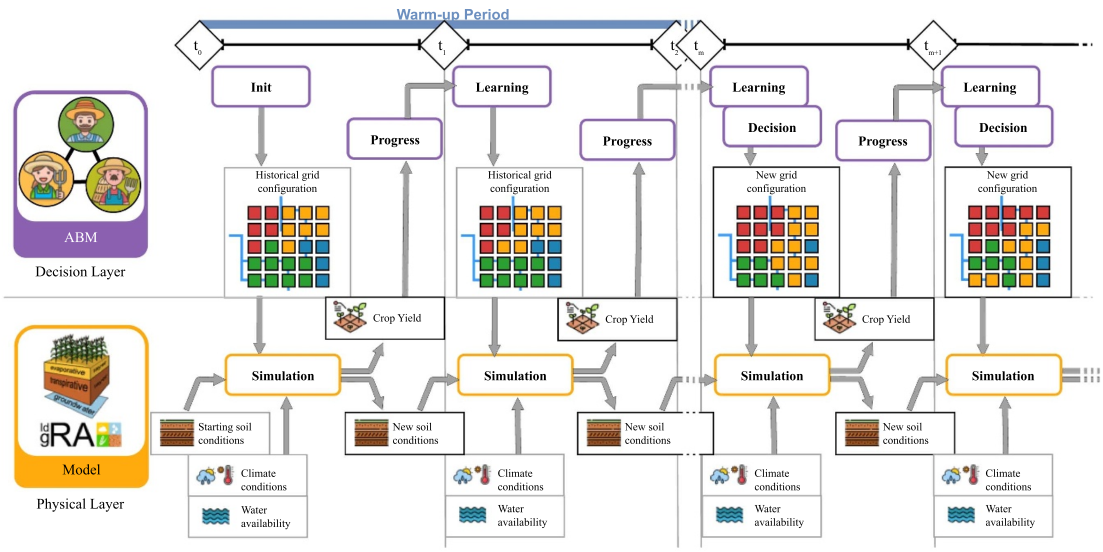

Figure 4. ABM-IdrAgra dynamic integration. Soft-link evolution and synchronization of two main framework components over multiple annual timesteps. Each simulation year is composed of a series of phases. In the *Learning* phase, agents process past experiences and peer outcomes to update expectations and behavioral strategies. *Decision* refers to the selection of crop and irrigation configurations. *Simulation* invokes the IdrAgra model to simulate yields under climate and soil conditions. In the *Progress* phase, the model updates all agents' internal states, advancing to the next timestep. A warm-up period, using historical data, allows agents to build experience before full simulation begins.

Dynamic flow

Agents take a new round of decisions each year. Figure 4 illustrates the co-evolution of the ABM and IdrAgra model over time. At each time step, agents evaluate their past experiences, interact with peers, assess potential decision options, and determine their optimal field cell configurations (crop type and irrigation method) based on their perception of uncertainty. Once the domain configuration is finalized, the IdrAgra model is invoked to simulate and calculate actual yield production under corresponding climate conditions. This sequence is repeated annually. To ensure robust agent initialization, the model includes an 8 year warm-up period (2004–2011), during which agents follow observed historical land-use patterns (i.e. crop and irrigation types) assigned to each Field Cell. Historical climate data (e.g. temperature and precipitation) drives the IdrAgra model in this phase. Although agents do not make independent decisions during the warm-up, they collect experience by observing the simulated outcomes of their allocated historical decisions. This process allows agents to build an experience base and calibrate their behavioral responses before the main simulation begins.

Decision making

Aligned with the bounded rationality assumption, Farmer Agents follow a behavioral strategy aimed at maximizing their expected utility. This decision logic is consistent with the large body of work in behavioral ABM, where actors use heuristics based on past experiences, peer influence, and non-optimizing reasoning (e.g. see Huber *et al* 2018). The decision-making process employs a heuristic-based approach (see supplementary figure 2), in which they evaluate and compare different options, selecting the one with the highest projected utility. Each option represents a unique combination of crop type and irrigation method for each decision unit within the managed Field-Cells.

To project future utility, agents focus on profit and cost factors directly influenced by their decision variables. Costs that remain constant across decision alternatives-such as general labor availability or fixed financial assets-are excluded from this analysis, as they do not affect the relative comparison between options. Utility is calculated over a multi-year horizon (i.e. 10 years by default settings; currently implemented as 8 years due to data availability), providing a long-term perspective on the potential outcomes of each option.

Yield expectations are derived from agents' accumulated experiences, with past data guiding their projections, and can also be shaped by observations of neighboring agents' outcomes, reflecting a form of social learning. Agents carefully assess operating costs and revenues, including seed costs, irrigation energy expenses, fertilizer costs, and income generated from selling yields (excluding fodder) on the market. Agents must also account for livestock requirements. If internal fodder production falls short, agents estimate the cost of purchasing the deficit from the market. Conversely, surplus fodder is sold at market rates, contributing to overall profits.

Investment decisions, such as adopting a new irrigation method, are evaluated by amortizing associated costs evenly over the projection period, ensuring a balanced distribution of financial impacts. Each option's net benefit (or loss) over the full projection horizon is aggregated into an overall utility score. Thereafter, agents assess the costs of deviating from their current practices, considering any available government subsidies for transitioning to more water-efficient systems. They also verify whether pre-existing subsidies, contingent on specific conditions, remain applicable under the new option. Similarly, for crop changes, agents factor in the costs of switching to a different crop type and any subsidies that might support such transitions. The final decision is based on selecting the option with the highest expected utility. This structured process reflects agents' adaptive strategies in navigating the complexities of agricultural decision-making under uncertainty.

Behavioral theories

The explicit testing of alternative behavioral theories has been highlighted as a major contribution of ABMs for social-ecological systems, allowing more realistic and adaptive modeling under climate change (Brown *et al* 2017). The ABNexus model has a flexible and extensible design that exploits inheritance, allowing the modeler to easily define new and different behaviors. For the current paper, and to quantify the added value of proper heterogeneity accounting, we implemented three main behavioral modes.

Under perfect foresight mode (1), agents have advanced knowledge of temperature and precipitation data for the upcoming season before making decisions on farm configuration. With this information, they can select the best response based on actual circumstances, leading to optimal decision-making. This mode assumes that agents can perfectly predict future environmental conditions, enabling them to make highly informed and precise decisions. This serves as a valuable counterfactual reference point, providing a benchmark against which the performance of other decision-making modes can be compared. In rational uniform mode (2), agents do not have knowledge of future conditions but rely on their memory of past choices and performances, as well as observations of their neighbors' decisions. By learning from these experiences, agents evaluate the expected yield for each potential field configuration by averaging observed performances and then selecting the most profitable option. Even though all agents follow the same behavioral rule, differences in their managed field characteristics and accumulated experience lead to heterogeneous decision outcomes. Expected yields for each crop-irrigation configuration are computed as the average of past outcomes observed both in the agent's own Field-Cells and in the Decision Units of spatially adjacent farms. Peer influence is spatially defined through first-order neighborhood relationships-i.e. only those agents whose managed fields directly border the agent's land are considered. These peer observations are integrated into the yield expectation calculation, giving agents access to socially available information beyond their individual experience. This mode reflects a more realistic scenario where agents use historical data and peer influence to guide their decisions but do not account for any heterogeneity. Lastly, in the Rational Differentiated mode (3), agents estimate expected yield based on collected experience and observations as before. However, their decision-making process is influenced by their individual and differentiated risk aversion profiles. This means that even if an option appears profitable based on past data, a risk-averse agent might opt for a less risky alternative to avoid potential losses. This mode captures the heterogeneity and variability in risk tolerance among farmers, which can significantly impact their decision-making strategies.

Risk preferences

Risk propensity is not directly observable and requires elicitation methods to translate survey insights into variables for agent modeling (Nainggolan *et al* 2023). A literature review guided this process, correlating risk preferences with farmers' demographic and socioeconomic characteristics (e.g. age, off-farm income) and adaptation behaviors (e.g. fertilization, insurance, adoption of new technologies, see Hossain *et al* (2022), Pace and Daidone (2024)). This preliminary framing effort aimed at informing our survey questions and the interpretation of the clustering results. We set three distinct levels of risk preference-risk-averse, risk-neutral, and risk-taking-aligning these categories with the farmer clustering results (described in the Results section below). Eventually, differentiated decision rules were integrated into the model using three well-established criteria from decision theory: the Wald criterion, the Hurwicz criterion, and the Maximax criterion. These rules offer alternative behavioral heuristics for decision-making under uncertainty and reflect varying levels of optimism or risk aversion among Farmer Agents. Let $a \in A$ be a decision option (i.e. a unique crop-irrigation configuration for a Decision Unit), and let $\omega \in \Omega$ represent a possible environmental scenario (e.g. a specific climate realization). The utility of option a under scenario ω is denoted by $U(a,\omega)$, where $U: A \times \Omega \to \mathbb{R}$.

Wald's criterion (Wald 1949), also known as the Maximin criterion, is suitable for a pessimistic decision-maker (thus for risk-averse agents), as it selects the option that maximizes returns under the least favorable scenario (Hansen and Sargent 2024):

$$a^* = \arg\max_{a \in A} \left[\min_{\omega \in \Omega} U(a, \omega) \right].$$

The Maximax criterion is instead representative of an individual with a highly optimistic perspective (thus suitable for very risk-prone agents), as it selects the best alternative under the most favorable scenario:

$$a^* = \arg\max_{a \in A} \left[\max_{\omega \in \Omega} U(a, \omega) \right].$$

Hurwicz's criterion (Hurwicz 1951), also known as the optimism–pessimism rule, is an hybrid approach that balances the extremes, weighing the most and least favorable scenarios. The parameter α adjusts the emphasis on optimism versus pessimism, accommodating a spectrum of risk preferences:

$$a^* = \arg\max_{a \in A} \left[\alpha \cdot \max_{\omega \in \Omega} U(a, \omega) + (1 - \alpha) \cdot \min_{\omega \in \Omega} U(a, \omega) \right].$$

These criteria were implemented in the ABM framework to model agents' decision-making processes under varying risk preferences, effectively capturing the behavioral heterogeneity observed in the survey data.

3.2. Data collection

Survey data

To replicate the behavior of farmers, the empirical information was sourced from a detailed online survey conducted between January and April 2022 on the Microsoft Forms platform (figure 5, and see table A.1 in supplementary information). Out of 511 samples gathered, 460 were deemed valid. Utilizing Cochran's formula for finite populations, the calculated representative sample size was 382, which corresponds to a 95% confidence level and a 5% error margin. Conducted in Italian, the survey featured 75 questions split into six blocks and had an average duration of 13 min for completion.

The opening two sections emphasized the characteristics of farmers and their farming practices. By adopting quota sampling strategies used in similar studies (e.g. Yang *et al* 2021, Petrescu-Mag *et al* 2022), these sections covered information on population characteristics and structural aspects such as age, educational background, farm size, primary crops, types of livestock, irrigation surface and methods. Next, four sections explored the dimensions related to behavior. They investigated potential factors influencing awareness of climate change, main perceived impacts, strategies for and barriers to adaptation (e.g. Ceci *et al* 2021, Montcho *et al* 2022). Within the climate awareness section, there were 10 items assessed on a 5-point Likert scale, covering topics such as occurrence, exposure, and responsibility. A following groups of 14 questions gauged their views on how alterations in weather and disturbances affect farming output and livestock (Yes/No/I do not know options). Through a series of 20 binary questions (Yes/No options), the study also examined the methods farmers employ to cope with climate extremes., and in the concluding sections, 9 questions aimed at recognizing the key internal and external obstacles faced when attempting to improve farmers' adaptive capacity. A Cronbach's alpha score of 0.76, derived from standardized items, demonstrates a strong level of reliability (Golden *et al* 2024).

Irrigation district managers data

The questionnaire was trialed and refined with support from the 12 irrigation districts within the regional irrigation districts' union (ANBI Lombardy). This was part of a wider strategy to maximize stakeholders' engagement and enhance knowledge exchange and co-designed outputs. Managers from two irrigation districts conducted a pre-test of the survey to evaluate its suitability and the duration needed for completion. In conjunction with the dissemination of the survey, managers were interviewed to explore their perceptions and responses to water-related management issues and climate risk, both on their own and as a result of their interactions with farmers (André *et al* 2023). A script was crafted to delve into three main topics: 1) main attributes of the irrigation districts and priorities regarding food production and water management, 2) major concerns related to climate change and water supply, and 3) awareness and experiences of extreme weather events, along with evaluation of potential risks, including those transmitted by farmers. Open-ended questions were used during the interviews, encouraging detailed and nuanced responses (Veisi *et al* 2022). Managers were contacted via phone or email, with recruitment facilitated by ANBI Lombardy. Between February and March, managers took part in a one-on-one virtual interview that was held in Italian. The discussions spanned between 50 and 90 min, yielding valuable qualitative insights into the interplay between irrigation districts' role in addressing climate change and farmers' needs to be more resilient when facing current and future water stress scenarios.

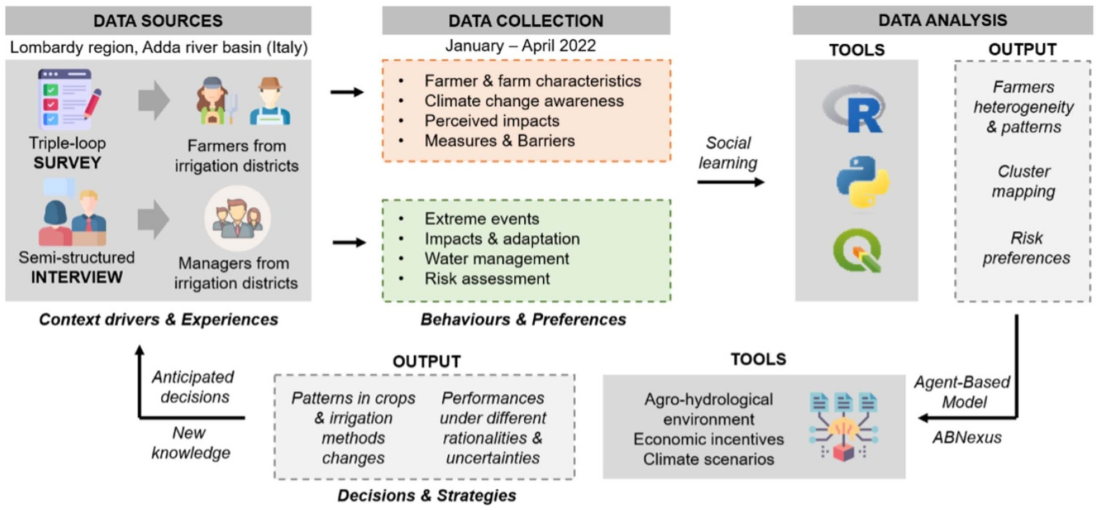

Figure 5. Survey design and analysis workflow. Structured overview of the methodological steps followed for the design, implementation, and processing of the farmer survey. This includes survey formulation, data collection, typology construction, and integration with model initialization procedures.

ABM data

The ABNexus model integrates several datasets to inform climate conditions and economic variables. Crop prices were retrieved from ISMEA's agro-food price database[5] and from the Granaria Milano market reports [6]. Operational costs associated with crop production and irrigation were sourced from RICA (Italian Farm Accountancy Data Network)[7], which offers localized agricultural cost data. Historical climate data (temperature and precipitation) were obtained from ARPA Lombardia's meteorological station network[8], ensuring spatial consistency with the Adda River case study. Geospatial land use were retrieved from ERSAF Lombardia[9] while water infrastructure data series were provided by regional consortia, which manage the irrigation network.

3.3. Data analysis and clustering profiles

The goal of the clustering analysis was to reflect the heterogeneity among farmers by evaluating survey data and exploring the connections between farmer attributes, farm features, climate change awareness, perceived impacts, and the main strategies and barriers in adaptation. In order to delineate farmer profiles, we applied multivariate analysis techniques, specifically hierarchical clustering on principal components (HCPCs) and multiple correspondence analysis performed using R software (v4.2.3) with the FactomineR and Factoextra packages. We found similar agricultural patterns and pointed out the main exploratory variables that impact the decision-making process achieved by farmers. To evaluate the similarities between farmers and identify the set of profile types, a factorial map was constructed (Soltani and Mellah 2023, Ricart *et al* 2024).

We employed the minimum variance clustering approach developed by Ward to group the farmers based on significant correlations in their patterns (Lurka 2021). Given the high dimensionality of the dataset, 10 key dimensions were uncovered through factor analysis as statistically significant, although they only capture 34% of the overall variability in the data. The first two components are mainly associated with the farm's size (#FA1) and the agricultural practices (i.e. irrigated surface #FA8 and irrigation method #FA9). The analysis revealed that the best way to categorize the sample was into four distinct clusters, which were then evaluated using a bivariate analysis with the Cramer's V index. The agents in the model were parameterized reflecting the strength and type of association between the categorical variables that influence behavior (Burg *et al* 2021, Datta and Behera 2022). Within these clusters, three were classified as irrigated farming and subsequently assigned varying levels of risk preference for their integration into the ABM framework. The rainfed cluster was excluded, as it pertains to farms outside the irrigated area modeled.

[5] www.ismeamercati.it/prezzi-agroalimentari/origine/banca-dati.
[6] www.granariamilano.it/listini-granaria/.
[7] https://rica.crea.gov.it/.
[8] www.arpalombardia.it/dati-e-indicatori/.
[9] www.ersaf.lombardia.it/.

4. Results

4.1. Farmers profiles

Cluster 1: Adapting through crop diversification and rotation

This group stands out as the largest cohort, mainly consisting of older farmers, with 50% of its members aged 55 years or older and approximately two thirds of its members having vocational training or a college degree. A significant number have accumulated over 30 years of expertise and predominantly work at the familial level. Agriculture practices are mainly conventional, accounting for 84%, and typically involve medium-to large-scale farms that average 20 ha or more. There is a high demand for irrigation and surface irrigation is the most widely adopted technique, comprising 75% of the methods applied. Most water sources (53%), consist of canals that are fed by diverted rivers, with about one-third of farmers opting for a blend of canals and wells for irrigation. Only 31% of farmers utilize renewable energy sources, with solar energy being the most frequently used. On the other hand, a significant 83% rely on mineral, compound, or organic fertilizers. The leading crops grown are maize (83%), temporary forages (35%), and wheat and spelt (32%), and approximately 50% of farmers also keep animals, mainly cattle (36%).

The majority of farmers have reported warmer weather and heat waves (90%), an increase in the occurrence or intensity of droughts (87%), and more frequent flooding (78%). They have generally employed a mix of strategies to tackle these impacts, primarily concentrating on crop diversification and rotation (65%). Additionally, farmers are aware of various barriers to enhancing climate resilience, including inadequate or poor government support (81%), the high costs associated with investments in their farms (77%), and the overly complex nature of regulations (74%). Notably, this group has the highest rate of unknown responses (14%), which can be attributed to lack of interest, awareness, or knowledge (see supplementary table A.2 for full descriptive statistics).

Cluster 2: Adapting through risk insurance

Half of the farmers in this group are older than 55 years, showcasing a range of educational backgrounds (38% with vocational training and 44% with higher education) and considerable experience in agriculture, as 63% have been farming for over three decades. The female workforce makes up 9%, with the bulk of farms employing a combination of family and non-family workers, which accounts for 63%. Agriculture serves as the primary source of income for three-quarters of farmers, with over half expressing a desire to hand over their farming methods to future generations. Farms tend to be quite large, with 86% of them being over 50 hectares, and they mostly practice conventional agriculture (81%). Surface irrigation serves as the primary water supply for 59% of farms, sourced from canals (44%) or a combination of canals and wells (39%). The use of mineral, compound, or organic fertilizers is still prevalent, comprising 87% of the practices, and nearly half of the farmers are incorporating renewable energy, especially solar energy (36%). Maize is the most widely cultivated crop at 83%, while temporary forages, wheat, and spelt are also important, representing 52% and 29%, respectively. Additionally, nearly 63% of the farms are engaged in livestock farming, particularly concentrating on cattle (46%) and pigs (19%).

Like the previous group, farmers recognize the challenges posed by rising temperatures and heat waves (89%) and the increased frequency or intensity of droughts (88%), and are more aware of new pest infestations (77%). This group adopts a broader spectrum of adaptation measures compared to others, including purchasing insurance for extreme weather events (84%), cutting down fertilizer use (81%), and utilizing weather services (81%). They also identify insufficient government support (82%), complex regulations (80%), and high investment costs (79%) as significant barriers to adaptation. Significantly, they demonstrate the greatest level of assurance (18%) in the ability of innovation and technology to tackle climate-related challenges (see supplementary table A.3 for comprehensive descriptive statistics).

Cluster 3: Adapting through climate services

Farmers are recognized as the youngest and most academically qualified, with 72% under the age of 55 and half having attended college. Nonetheless, they have the least amount of farming experience, with only 18% having over 30 years in the profession. The demographic of the group shows a lower male predominance, with females making up 38% of the members. Farming practices are largely reliant on family labor, accounting for 53% of the work. Small-scale farms are prevalent, with 69% of them being under five hectares in size. A significant portion of these farms either engage in organic or agroecological methods or are transitioning towards them, representing 44%. The favored method of irrigation is drip irrigation, utilized by 72% of the farmers, while wells serve as the primary water source for 44%. The use of fertilizers is infrequent, and nearly half of the farmers (47%) have adopted renewable energy solutions, predominantly solar energy at 34%. Livestock farming is not a major focus, and maize is less significant compared to other groups, with only 22% of production, as the emphasis lies on growing vegetables (38%), vineyards (28%), and wheat and spelt (22%).

This group exhibits higher levels of agreement than the average when it comes to beliefs about climate change awareness: all farmers (100%) fully acknowledge climate change as the most critical issue the world faces, and unlike the previous group, they do not believe that technology alone can solve the problem. Similarly, they can recognize the greatest variety of climate effects, including those noted by other groups, while also introducing new factors such as changes in plant species and biodiversity (88%). They primarily adjust by utilizing weather and climate information services (84% and 69%, respectively). In contrast to other profiles, they view the business-as-usual scenario (81%) and skepticism about climate change (78%) as significant obstacles to addressing climate change (see supplementary table A.4 for comprehensive descriptive statistics).

4.2. Farmers' risk preferences

We identified five variables of the survey that aligned with indicators of risk preferences commonly cited in literature (table 1). After evaluating the correlation between the literature-based assumptions and the responses from the farmers' survey, each cluster was categorized according to the three levels of risk previously defined: risk-averse, risk-neutral, or risk-taker. Specifically, Cluster 1 (farmers adapting through crop diversification and rotation) was classified as having a 'risk averse' attitude, while Cluster 2 (adapting through risk insurance) was considered partially risk-averse or neutral, and Cluster 3 (adapting through climate services) was identified as a risk-taker. Subsequently, we assigned a specific decision-making criterion to each risk attitude. For Cluster 1, the risk-averse cluster, the Maximin criterion was chosen to represent a risk-averse behavior. For Cluster 2, the partially risk-averse or risk-neutral cluster, the optimism–pessimism rule was chosen, with a value of $\alpha = 2/3$ indicating a slight bias towards a pessimistic approach. In contrast, Cluster 3, the risk-taker cluster, was also represented by the optimism–pessimism rule, but with a value of $\alpha = 1/3$ to reflect a preference for risky options. This solution was deemed more realistic than the completely risk-taking approach represented by the Maximax metric.

4.3. Experiment setup

To validate the framework, we simulated the historical period from 2004–2014. The choice of this timeframe was dictated by the full data availability, including meteorological data (temperature, precipitation, wind), water flow in canals, and granular spatial soil use detail. The simulation included an 8 year warm-up period (2004–2011) to allow agents to gather experience from the data, followed by a 2 year decision-making phase (2012–2014). This adjustment from the originally intended 10 years was due to limitations in the availability of historical soil use data. The warm-up years encompassed both 'normal' years and significant drought years (2005, 2006), where March–September cumulative precipitation was significantly below average (see supplementary figure 3). In contrast, the free decision-making years (2013, 2014) had relatively abundant water availability. Due to the lack of georeferenced farm location data on the grid map (not disclosed by regional authorities), Farmer Agents were assigned control over spatial Field-Cells based on the regional statistical distribution of farm sizes (see supplementary figure 4). This allocation involved assigning a set of adjacent Field-Cells to each agent, such that the total area matched a plausible farm size class. Risk aversion levels were then attributed to Farmer Agents according to their farm size category, following the typology derived from survey responses. Historical land use data (crop type and irrigation method) were retained at the cell level and assigned to the corresponding controlling agent, enabling consistency with observed land management patterns during the warm-up phase. The simulation tested three behavioral assumptions-perfect rationality, rational-averaged behavior, and rational risk aversion-against historical soil use patterns. The results demonstrate that the model reproduces key historical patterns at the system level while differentiating outcomes across behavioral assumptions. While no single behavior mode perfectly matches observed trends, the outputs are qualitatively consistent with historical dynamics. This validates the model as a coherent platform for exploring how behavioral diversity shapes agricultural decision-making and lays a solid foundation for integrating further complexity in future work.

4.4. Crops and irrigation methods patterns

Figure 6 illustrates the distribution of crops and irrigation methods for the year 2014, the final year of the free-decision phase. The bar heights represent quantities, while the colors denote different underlying behavioral assumptions. Blue bars indicate actual historical values measured within the domain. The results show that the overall distribution is broadly comparable with historical observations, though there are fluctuations across different behavioral experiments. Grain maize, cultivated for market sale, emerges as the

Table 1. Indicators, proxy variables, and criteria to associate risk preferences with survey data. Note: A label is assigned to each cluster considering proxy variables in the literature. The overall label (used in the ABM implementation) is assigned considering the average value in behavioral patterns of each cluster. Legend: RA (risk averse), RN (risk neutral), RT (risk taker). These categories (RA, RN and RT) are assigned after internal comparison between clusters percentages, being RA for the highest value, RN for the second one, and RT for the lowest one. When values are very similar (e.g. only 1%–2% difference) we opted to assign the same category.

Literature data		Survey data								
Indicator	References	Variable(s)	Avg.	C1	C2	C3	Criterion	C1	C2	C3
Age	Senapati (2020) Wodaju *et al* (2023)	Age (FE1)	53%	50%	51%	28%	The older, the more risk averse	RA	RA	RT
Off-farm income	Ahmad *et al* (2020) Danso-Abbeam *et al* (2021)	Off-farm activity (FE9)	31%	35%	25%	28%	The more off-farm income, the more risk averse	RA	RT	RN
Fertilizer use	Qiao and Huang (2021)	Fertilizer use (FA5)	85%	90%	92%	72%	The more fertilizer use, the more risk averse	RA	RA	RT
	Tevenart and Brunette (2021)	Reduce of fertilizers (AD15)	70%	65%	81%	88%		RA	RN	RT
Insurance	Bao *et al* (2021) Visser *et al* (2020)	Insurance use (AD17)	61%	58%	84%	41%	The more insurance use, the more risk averse	RN	RA	RT
New technologies	Bahrami *et al* (2022) Fevisa *et al* (2023)	Average number of implemented adaptation measures (out of 20)	8	7	9	8	The more implemented measures, the less risk averse	RA	RT	RN
% of RA								100%	50%	0%

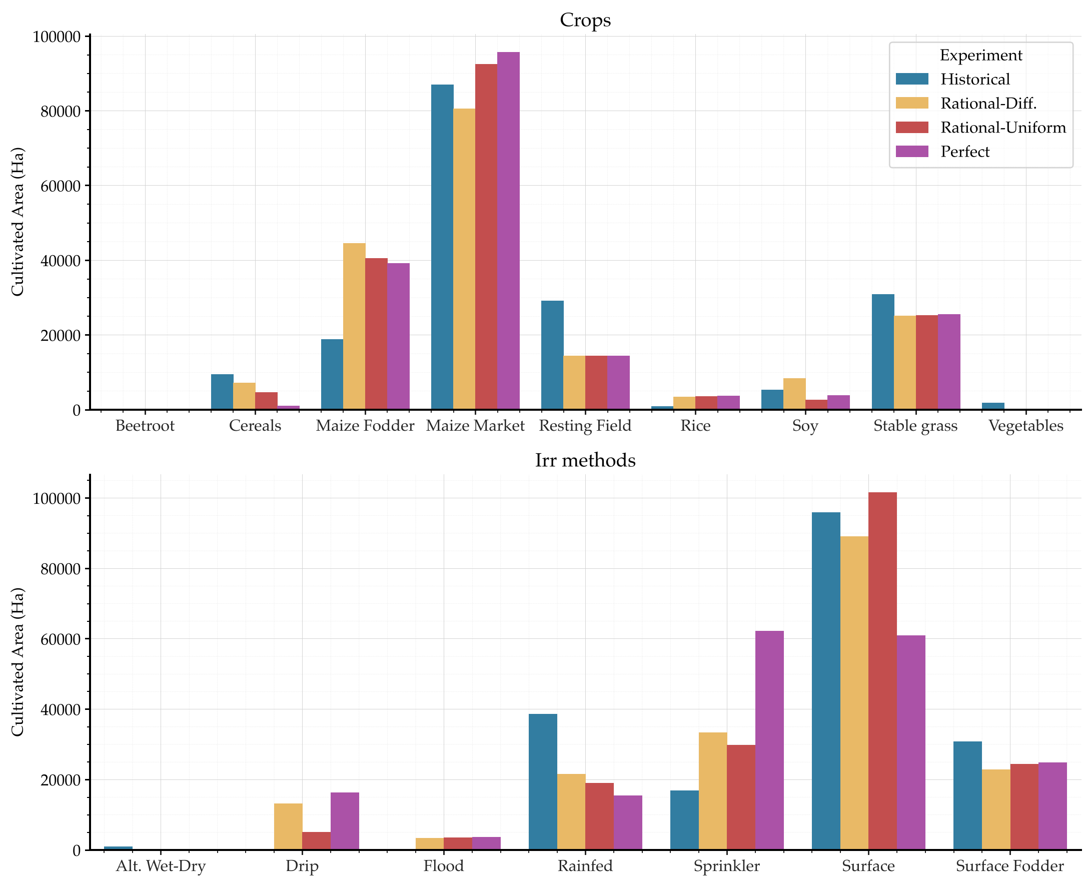

Figure 6. Distribution of crops and irrigation methods in 2014. This barplot shows the distribution of various crops and irrigation methods for the final year of the free-decision phase. Bar heights represent quantities, while colors denote different behavioral assumptions. Blue bars indicate actual historical values.

most attractive choice for income generation. Cereals, rice, and soy play more minor roles in this regard. For fodder production, which is crucial to fulfill internal livestock feed demand, stable grass and maize silage (for animal feed) are both important. Agents seem to exhibit a preference for maize compared to historical records, possibly because it is more efficient due to its higher fodder-energy potential (in terms of Joules per ton). Regarding irrigation methods, agents operating under bounded rationality (Rational Uniform or Rational Differentiated) tend to reproduce real-world patterns more closely, predominantly favoring surface irrigation. In contrast, simulations using the Perfect Foresight mode exhibit a significant transition toward more water-efficient methods, driven by agents' awareness of upcoming climate conditions. This highlights an important model feature: the decision inertia typical of human systems is preserved better under bounded rationality. Outcomes of rational-averaged and rational-differentiated agents show noticeable fluctuations in all choices, showcasing the systemic impact of introducing heterogeneity.

Complementing the previous analysis, figure 7 provides a spatial view of irrigation method adoption across the domain under different behavioral assumptions. (Supplementary figure 5 offers a similar visualization for crop distribution). While surface irrigation, categorized by fodder and non-fodder use, predominates in the Historical and Rational scenarios, the Perfect Knowledge scenario signifies a substantial shift towards sprinkler and drip irrigation. This spatial analysis also reveals noticeable patterns. Rice, cultivated using flooding or alternate wet–dry methods, is concentrated in the western part of the domain. Potential transitions towards sprinkler and drip irrigation methods are concentrated in specific hotspots from the western to the middle area of the domain. This discrepancy underscores how behavioral assumptions influence spatial outcomes and potentially indicates the most favorable areas for transitioning to more water-efficient techniques.

Figure 8 compares choices across the three behavioral experiments, providing a detailed breakdown of the differentiated rationality clusters (C1, C2, and C3). The figure highlights that the combination of grain maize and sprinkler irrigation, the most preferred option for perfect knowledge agents, is not replicated in

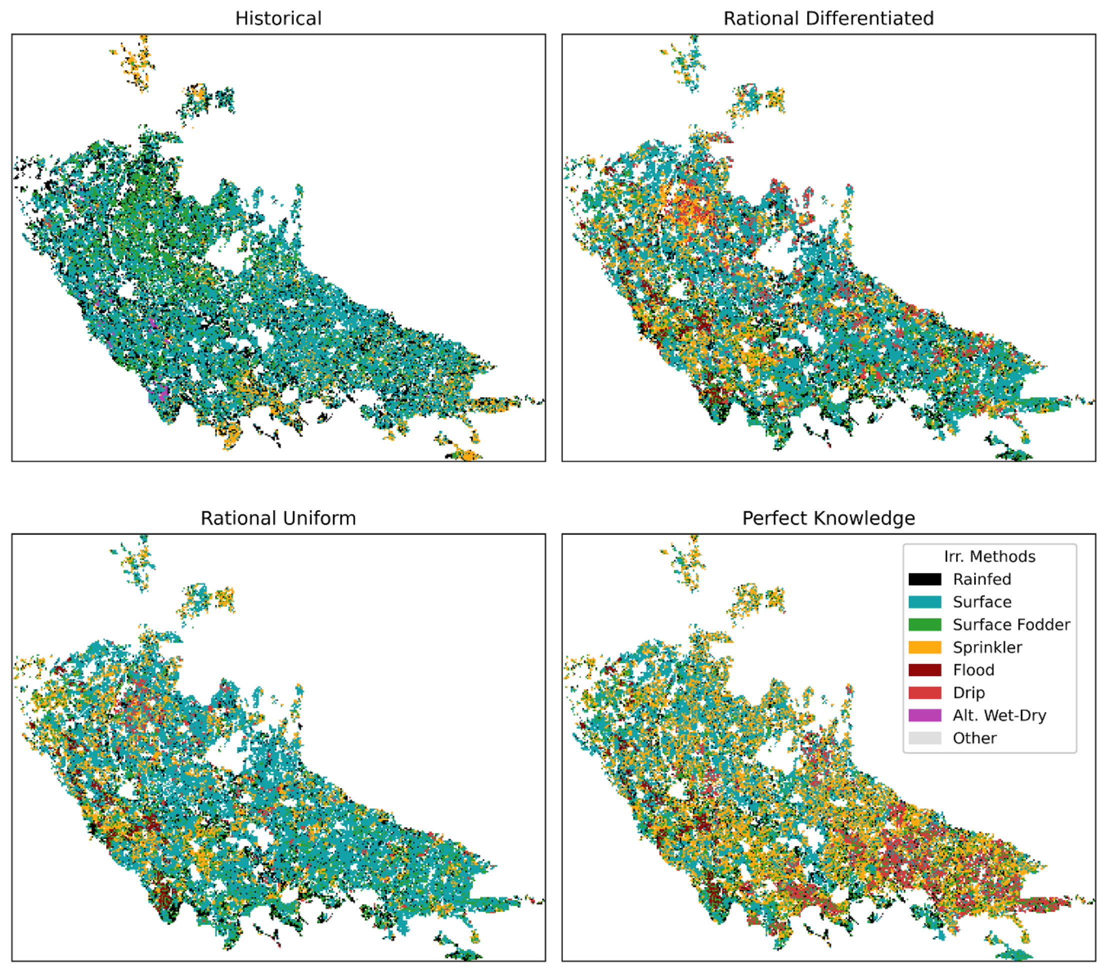

Figure 7. Irrigation method choices in 2014: modeled vs historical spatial distribution. The first quadrant displays the historical irrigation methods for 2014. Subsequent maps show the simulated spatial distribution of irrigation method choices when all agents operate under a single behavioral assumption: Rational Differentiated, Rational Uniform, and Perfect Knowledge. The figure highlights how varying decision-making logic influences aggregate irrigation patterns. Notably, bounded rationality modes more closely reproduce observed trends such as the predominance of surface irrigation, while the Perfect Knowledge mode results in a stronger shift toward efficient methods.

other scenarios. Non-differentiated rational agents show a stronger preference for grain maize combined with surface irrigation, reflecting a more overall conservative approach. For differentiated rational agents, clusters exhibit varied preferences. Cluster C1 demonstrates higher diversification across options, with no single dominant preference. Cluster C2 aligns more closely with the overall distribution observed in the non-differentiated rational experiment, reflecting a balanced choice pattern. Cluster C3 stands out for its vast preference for stable grass paired with surface irrigation, diverging from other clusters.

Water use represents a key indicator of adaptive capacity in agricultural systems. As shown in figure 9, agents operating under perfect foresight adopt significantly more water-efficient irrigation methods, thereby reducing total water withdrawals. Conversely, agents with bounded rationality especially those modeled with differentiated risk profiles-tend to replicate historically prevalent practices such as surface irrigation, resulting in higher but more realistic water use levels. These patterns underscore the profound influence of behavioral assumptions on environmental outcomes and system-wide water demand, reinforcing the need to understand farmers' actual cognitive and social drivers when designing adaptation strategies.

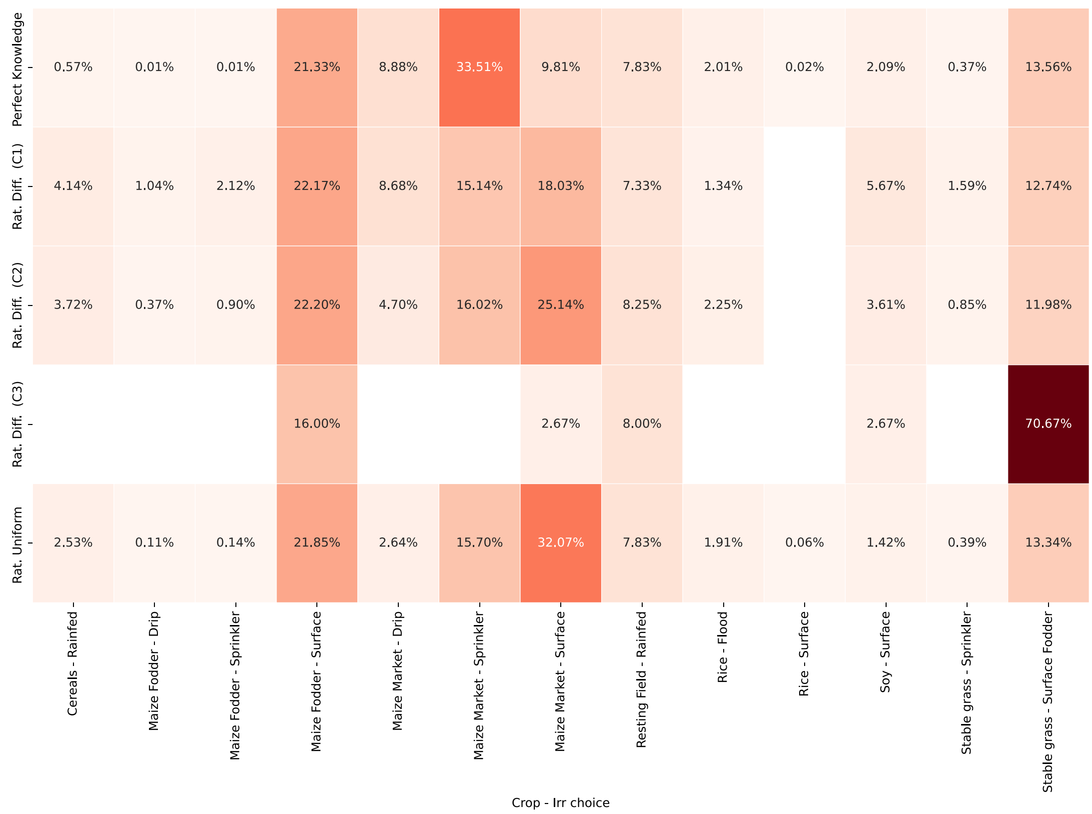

Figure 8. Comparison of behavioral experiments and clusters. This heatmap compares the full-combination of choices across three behavioral experiments, providing a detailed breakdown of the differentiated rationality clusters (C1, C2, and C3).

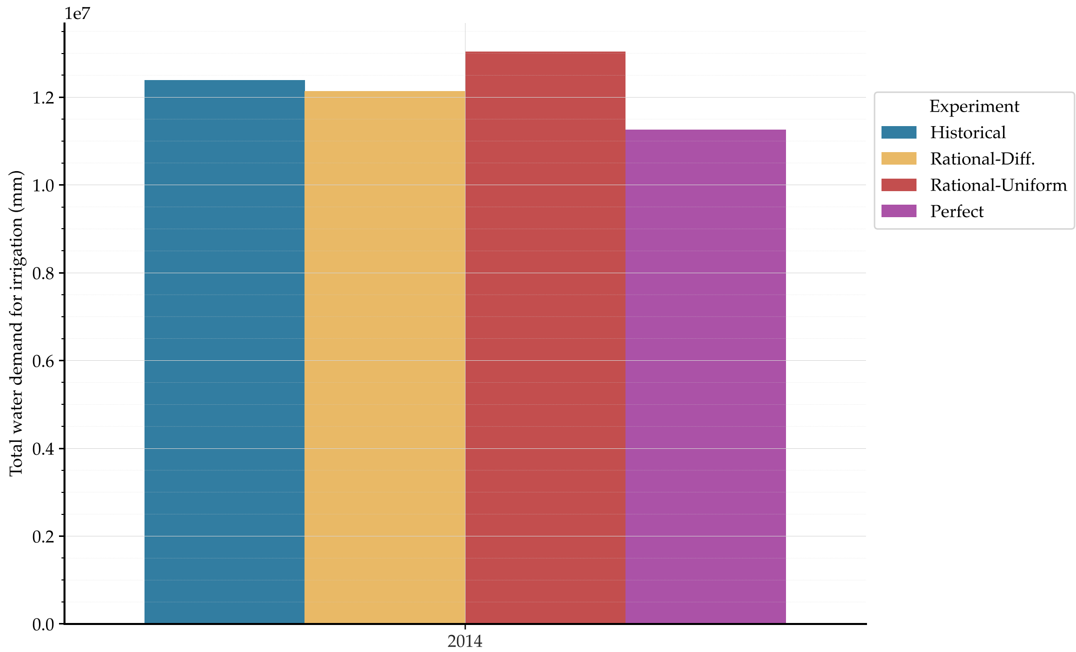

Figure 9. Total water demand for irrigation under different behavioral scenarios. This barplot compares the aggregate water demand across all simulated fields in the final year of the decision-making phase (2014), highlighting how different behavioral assumptions influence total water use. Historical data provide a benchmark, while the scenarios reflect perfect foresight, averaged rationality, and differentiated risk preferences.

5. Discussion and conclusion

Despite the global importance of climate change, understanding its localized impacts and farmers' adaptive capacities, preferences, and resilience mechanisms remains a major challenge (Loucks 2023). Farmers' perceptions and responses to water-related extremes and climate risks, along with the key drivers shaping their priorities, are critical for effective irrigation planning and water resources policymaking aimed at enhancing climate risk management (Naderi *et al* 2024). Anticipating cognitive factors and adaptation intentions offers a foundation for designing interventions that foster capacity and resilience (Mitter *et al* 2024). These efforts are essential for safeguarding water resources, ensuring food security, and implementing targeted climate focused incentives, strategies, or institutional reforms to reduce farmers' exposure and vulnerability (Monteleone *et al* 2023). Adapting to climate change often involves adopting unfamiliar practices, underscoring the importance of knowledge exchange within farmers' networks. These exchanges shape perceptions of the costs, risks, and benefits of adaptation measures (Kreft *et al* 2023). Peer interactions and experiences significantly influence farmers' decisions, introducing heterogeneity that determines a highly nonlinear and complex system. This complicates the identification of farming strategies and their associated crop and irrigation method.

Incorporating diverse behavioral theories into formal models enables sensitivity analyses of human behavior within water resources management contexts. This approach allows for evaluating the implications of mismatched behavioral assumptions when designing policies (Schlüter *et al* 2017). For instance, an incentive policy optimized under the assumption of rational, self-interested decision-makers may yield different outcomes when alternative behavioral theories are considered, such as decision-making driven by social norms or other preferences (Wens *et al* 2020). Such analyses provide critical insights into the robustness of policy options under varying assumptions of human behavior. Knowledge accumulation and exchange with well-informed peers and neighbors can contribute to behavioral change, underscoring the importance of fostering regional and local networks and promoting extension services. Initiatives such as living labs that emphasize social learning can enhance farmers' adaptive capacities while promoting and testing co-designed practices. These approaches also support trust and transparency in policy-making processes (Gardezi *et al* 2024). A persistent challenge in land use and water planning is the inadequate integration of socio-economic and socio-cultural data with biophysical information. This issue is particularly pronounced in agriculture, where farmers' decisions, spanning large tracts of land, directly influence land and water resource use. Despite their significant cumulative effects, farmers' actions are often overlooked in current land-use planning tools. Addressing this gap requires incorporating on-farm decision-making processes into these tools, enabling more informed decision-making at broader scales. Such integration is essential for developing strategies to shape the future of agricultural land sustainably (Shahpari and Eversole 2024).

Addressing the complexity of climate change impacts and the heterogeneity of farmers' decision-making processes requires flexible tools such as ABMs (Noeldeke *et al* 2022). ABMs enable the simulation of individual behaviors and interactions within a system, offering detailed insights into how various factors influence decision-making and capturing farmers' diverse responses to water-related and climate-induced risks and economic pressures. The development and calibration of ABMs require extensive data, particularly behavioral data collected in the field. Integrating observational data enhances the accuracy and realism of these models, while theories and frameworks from the ABM literature provide a scientific foundation for representing human behavior and its drivers.

In this paper, we introduced the ABNexus model, which is designed to simulate key agricultural production and water management decisions at the local scale and capture the heterogeneous effects of climate change on farmers' behavior. The model combines a novel agent-based framework with IdrAgra, a distributed-parameter soil–crop–water model, to provide a detailed representation of the natural environment in the Adda River case study. ABNexus aims to explore how farmers' decisions affect system-level outcomes under varying conditions of water stress and climate variability. Field data collection included comprehensive surveys and clustering techniques to categorize farmers based on their risk preferences. The surveys gathered detailed information on demographics, farming practices, climate change awareness, perceived impacts, and adaptation strategies. Clustering methods identified homogeneous farming patterns and key behavioral drivers, enabling the modeling of risk aversion and the integration of these traits. This combination of spatial biophysical modeling and empirically grounded behavioral logic provides a framework to better represent farmers' adaptive behavior under climate uncertainty and policy stress.

This study used the ABNexus model to simulate agricultural production decisions under historical climate conditions. While ABM outputs are not expected to perfectly match historical records, the capacity to reproduce general trends while also capturing behavioral differentiation represents a strong validation of its internal logic (Bonabeau 2002, Grimm *et al* 2005). Incorporating real-world heterogeneity from survey data allows ABNexus to generate both plausible aggregate outcomes and distinct decision patterns, which are fundamental for robust scenario analysis and policy design. Although all behavioral configurations reproduced broad system trends (e.g. dominant irrigation practices), the differentiated behavioral mode provided a richer representation of internal heterogeneity, revealing distinct cluster-based patterns in irrigation adoption and water use. This suggests that modeling risk profiles explicitly adds explanatory depth to understanding spatial variability in decision-making.

Taken together, these findings highlight the value of this framework in supporting policy-making and planning. In this regard, the study contributes to the literature in three main aspects. First, by integrating a survey-based approach that captures cognitive factors and interactions among agents, the ABNexus can forecast complex risk behaviors and decision patterns related to crops and irrigation methods at the farm scale. By drawing on insights from economics and psychology, the model highlights transformative adaptation strategies. Second, the modeling framework explicitely accounts for the heterogeneity of farmers' risk preferences, enabling targeted actions based on farmers' preferences and opportunity costs. This approach supports the design of tailored interventions for diverse crop requirements and water management practices. Finally, by incorporating empirical survey data on risk preferences, the model enhances the predictive accuracy of farmers' decision-making across different socioeconomic and climate scenarios. This underscores the importance of using observational information to anticipate decisions, thereby advancing the realistic replication of farmers' choices across various socioeconomic and climate scenarios.

This supports the model's value as an exploratory tool for understanding potential adaptation pathways and the design of climate-resilient strategies under heterogeneous behavioral conditions (Bonabeau 2002). Unlike static survey analysis, which captures what farmers say they will do, ABNexus dynamically simulates what they actually do-under stress, over time, and in interaction with others. This enables the quantification of agent responses and system-level consequences under varying climate conditions, behavioral assumptions, and policy interventions. For instance, the model can simulate alternative designs for targeted subsidies (e.g. drip vs sprinkler irrigation), incentives for crop diversification, insurance uptake, or payments differentiated by farm size. This allows for ex-ante policy testing, allowing decision-makers to compare tailored versus uniform approaches in terms of adoption rates, yield outcomes, and vulnerability reduction over time, providing an evidence base to assess whether the additional cost of tailoring is justified. These contributions are especially important in the context of climate change resilience. For example, ABNexus shows that risk-prone agents are more likely to under invest in efficient irrigation systems, while risk-averse ones may resist change even when beneficial. These differences imply different levels of exposure to climatic shocks and different capacities for adjustment. ABNexus can spatially simulate behavioral inertia and vulnerability hotspots, helping to identify priority zones where infrastructure upgrades or support measures may require stronger incentives. This insight goes beyond survey data by providing a spatially heterogeneous and dynamic view of where vulnerabilities are most persistent (e.g. see Troost and Berger 2015, Huber *et al* 2018). By being grounded in real behavioral data, the model supports policy testing that reflects actual farmer constraints and responses (Kremmydas *et al* 2018). It also facilitates the testing of alternative behavioral theories to better match observed decision patterns-especially under stress- and to support the design of targeted drought response plans, such as early advisory messages or conditional support mechanisms tailored to each group's adaptive profile (Jones *et al* 2017). This makes ABNexus a promising tool to explore alternative adaptation pathways and to co-design resilience-enhancing strategies with stakeholders.

Despite the strengths of the ABNexus model, several limitations must be acknowledged. Calibrating ABMs remains challenging, particularly when moving beyond qualitative comparisons. Quantitative validation is often limited by the availability and precision of data, making it difficult to ensure the model's accuracy and reliability (Grimm *et al* 2016). ABMs like this require extensive and detailed data to accurately represent the diverse behaviors and interactions within the system, including socio-economic, behavioral, and biophysical data, which can be difficult and costly to collect (Sun *et al* 2016). Additionally, the model does not account for all external dynamics influencing agricultural systems. For instance, the livestock production chain is not explicitly modeled, potentially affecting the outcomes and limiting interpretability in certain contexts. Ensuring the validity and credibility of ABMs is a complex task, necessitating rigorous validation and testing procedures. However, achieving such validation is often hindered by data limitations and the inherent complexity of agricultural systems. The model's outcomes may also be influenced by unintended biases or incompleteness in survey responses, which can affect its representation of farmers' behaviors and decision-making processes. Addressing these issues requires continuous efforts to improve data collection methodologies, enhance validation techniques, and integrate a broader range of external dynamics.

Future work will focus on refining the ABNexus model to better capture the complexities of agricultural systems and expanding its application across diverse contexts to further validate its effectiveness. The model offers numerous opportunities for scenario exploration, including analyzing extreme events, projecting future climate scenarios, validating behavioral assumptions, examining thresholds, and simulating market shocks. For example, it can simulate the impact of extreme events, such as the severe drought of 2022, on agricultural production and decision-making. It can also project shifts in farming practices and outcomes under future climate scenarios, validate behavioral patterns that best align with historical observations, determine thresholds where the system undergoes abrupt transitions due to extreme events or water stress scenarios, and assess the effects of market shocks on agricultural decisions and outcomes. These applications are highly relevant to improving resilience, as they allow stakeholders to test how different behavioral responses to climate and market shocks affect vulnerability and resource use. By enabling more detailed representations of behavioral diversity, ABNexus can support the co-design of adaptive strategies that reflect real-world complexity, rather than relying on idealized assumptions of rationality.

The methodology presented in this study can be replicated across different contexts, facilitating the adaptation of ABNexus to other regions and water-agricultural systems. This flexibility provides tailored insights for local adaptation strategies. Furthermore, the study underscores the importance of integrating socio-economic and behavioral data with biophysical models to enhance the realism and relevance of simulation outcomes. By incorporating diverse behavioral theories and detailed field data, the ABNexus model serves as a robust tool for exploring complex agricultural systems and informing strategies to address the challenges of climate change.

Data availability statement

The data that support the findings of this study are available upon request from the authors.

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Ethics

The Data Protection Officer (DPO) of the Politecnico di Milano, Italy, through a privacy review panel evaluation, confirmed that the study satisfied the security standards and data protection requisites under GDPR regulations. The survey data used in this research did not collect identifying information of the respondents; they were duly informed of the objective of the research, the type of information collected, and data treatment process in the first page of the online survey. All participants gave written informed consent (first page of the survey) to participate in the research, specifying that collected information and related results will be used for scientific purposes only. Survey data has been collected under the research project 'Modelling individual farmer behaviours in Coupled Human Nature Systems under changing climate and society (MODFABE), granted by the European Commission under the H2020 Marie Sklodowska-Curie Action program, 2018 call for Individual fellowship (ID 832 464), active from September 2020 until August 2022. Second author (S Ricart) was the beneficiary of the fellowship, and last author (A Castelletti) was the coordinator of the project. As part of the initial data requirements by the EC Project Officer, a mandatory ethics self-statement consisting of various deliverables on Ethics issues and a detailed Data Management Plan (DMP) have been reported on February 2021 through the EU Funding and Tenders Portal and the associated SyGMA platform, with the support of the DPO. The Ethics reports together with the DMP have been approved by the EC Project Officer and the Ethics review panel on May 2021, ensuring alignment with the H2020 standards for data privacy, ethics and data protection, the European Code of Conduct for Research Integrity and in accordance with the principles embodied in the Declaration of Helsinki and related local statutory requirements.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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