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Research papers

Investigating uncertainties in human adaptation and their impacts on water scarcity in the Colorado river Basin, United States

Fengwei Hung [a], Kyongho Son [b], Y. C. Ethan Yang [a,*]

[a] Department of Civil and Environmental Engineering, Lehigh University, Bethlehem, PA, USA
[b] Pacific Northwest National Laboratory, Washington, USA

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ABSTRACT

The Colorado River Basin (CRB) supports the water supply for seven states and forty million people in the Western United States (US) and has been suffering an extensive drought for more than two decades. As climate change continues to reshape water resources distribution in the CRB, its impact can differ in intensity and location, resulting in variations in human adaptation behaviors. The feedback from human systems in response to the environmental changes and the associated uncertainty is critical to water resources management, especially for water-stressed basins. This paper investigates how human adaptation affects water scarcity uncertainty in the CRB and highlights the uncertainties in human behavior modeling. Our focus is on agricultural water consumption, as approximately 80% of the water consumption in the CRB is used in agriculture. We adopted a coupled agent-based and water resources modeling approach for exploring human-water system dynamics, in which an agent is a human behavior model that simulates a farmer's water consumption decisions. We examined uncertainties at the system, agent, and parameter levels through uncertainty, clustering, and sensitivity analyses. The uncertainty analysis results suggest that the CRB water system may experience 13 to 30 years of water shortage during the 2019–2060 simulation period, depending on the paths of farmers' adaptation. The clustering analysis identified three decision-making classes: bold, prudent, and forward-looking, and quantified the probabilities of an agent belonging to each class. The sensitivity analysis results indicated agents whose decision-making models require further investigation and the parameters with the higher uncertainty reduction potentials. By conducting numerical experiments with the coupled model, this paper presents quantitative and qualitative information about farmers' adaptation, water scarcity uncertainties, and future research directions for improving human behavior modeling.

1. Introduction

The Colorado River Basin (CRB) provides freshwater for 40 million people and 5.5 million acres of farmland in seven states of the Western United States (US). However, the extensive drought since 2000 and growing water demand have resulted in increasing water scarcity in the basin. In August 2021, the federal government declared the first-tier water shortage for the first time in history due to the extremely low water levels in Lake Mead and Lake Powell. Consequently, water supply to Arizona and Nevada will be curtailed by 18% and 7% of their total water allocations, respectively (USBR, 2021a).

As climate change continues to affect water resource distribution in the basin, human water demands (as well as the ways water is used) also shift in response to the changes (Frederick and Major, 1997; Kallis, 2010). The human-water system co-evolution can be affected by policies and infrastructure that influence people's perceptions of the system. For example, dams and reservoirs are designed to provide a stable water supply during droughts. However, the water infrastructure also provides a false sense of water security that encourages water consumption instead of conservation (Di Baldassarre et al., 2018). This phenomenon, similar to the levee effects for flooding (Di Baldassarre et al., 2017), can contribute to severer water shortage during droughts and consequently causes significant economic losses. Previous studies have highlighted the importance of the co-evolution of human-water systems and urged more research to improve our understanding (e.g., Sivapalan et al., 2012; Vogel et al., 2015; Wagener et al., 2010).

Studies of the CRB have attempted to quantify water scarcity uncertainty and explore human-water system dynamics despite the

* Corresponding author.
E-mail address: yey217@lehigh.edu (Y.C.E. Yang).

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hydrological and institutional complexity of the water system. Several studies examined the hydrological responses in the CRB to various future climate change scenarios (Christensen et al., 2004; Vano et al., 2014; Vano and Lettenmaier, 2014; Yang et al., 2020), explored scenario design for climate adaptation decision-making (Gerlak et al., 2021; Quinn et al., 2020; Smith et al., 2022), developed modeling tools for understanding the human and water system interactions (Hadjimichael et al., 2020a; Hung and Yang, 2021), and investigated institutional and societal influence to the CRB water resources distribution (e.g., Savelli et al., 2022; Taylor et al., 2019; Womble and Hanemann, 2020). Nevertheless, quantification of the human adaptation uncertainty in the CRB and how such uncertainty affects the co-evolution of human-natural interactions remains unexplored. Quantifying and understanding the uncertainty resulting from the co-evaluation is a critical step toward managing the uncertainty, which is the goal of this paper.

Literature has indicated farmers' behavioral change due to climate and environmental changes. For example, both Ding et al. (2009) and Zilberman et al. (2011) concluded that historical droughts had caused farmers' behavioral changes toward water conservation. To investigate human adaptation and behavioral changes, many researchers adopted the agent-based modeling (ABM) technique for its ability to simulate diverse human behaviors in a distributed system (Berglund, 2015; Giuliani and Castelletti, 2013; Yang et al., 2009). ABM is a computation method for simulating actions and interactions of autonomous agents to improve understanding of emerging system behaviors and investigate perturbation impacts, either climatic or human-induced, on water systems across multiple temporal and spatial scales (Berglund, 2015). Traditional ABM studies use deterministic decision rules to describe observed human behaviors in response to environmental signals and algorithms to simulate rational agents who pursue strategies that optimize their objectives (e.g., Ligmann-Zielinska et al., 2014; Noël & Cai, 2017; Yang et al., 2009). Recently, the focus has shifted to simulating human adaptive behaviors due to the increasing concern of water scarcity under future climate change (e.g., Al-Amin et al., 2018; Hyun et al., 2019; and Rieker and Labadie, 2012). However, ABMs, as models for human behaviors, are prone to uncertainty, reflecting our insufficient knowledge of human decision-making processes (Ligmann-Zielinska et al., 2014). Also, the co-evolution of the coupled human-natural systems can amplify the uncertainty due to climate and environmental changes (Solomatine and Shrestha, 2009; Tyre and Michaels, 2011; Vogel et al., 2015). Therefore, it is critical to quantify and manage the model output uncertainty to properly interpret modeling results.

Quantifying and managing the uncertainty of water scarcity has been a topic of interest within the scientific community since the 1990s (Rajaram et al., 2015). Uncertainty studies primarily focused on parametric uncertainty of hydrologic models and its effects on the model prediction uncertainty (e.g., Jung et al., 2011; Samuel et al., 2012; Solomatine & Shrestha, 2009) and future water resources uncertainty caused by climate change (e.g., Knighton et al., 2017; Yang et al., 2020). Recently, the uncertain societal and institutional influence on available water resources also became a concern, and the need to properly handle these human system uncertainties has been recognized in the scientific community (Buchmann et al., 2016; Ligmann-Zielinska et al., 2014; Schindler, 2013). However, ABM studies that explicitly quantify uncertainty are rare, partly for lacking evaluation methods that fit the varieties of ABMs and coupled models (Ligmann-Zielinska et al., 2020) and partly for the deep uncertainty involved in coupled human-natural systems (Moallemi et al., 2020b).

Understanding the uncertainty of human impacts on water systems can facilitate the development of a robust climate adaptation policy to tackle stringent water scarcity issues in major river basins such as CRB. The advancing computer technology enables uncertainty quantification. Recent papers in the water resources and sustainability fields have advocated for using models to explore different scenarios to enhance the robustness of model inference and uncover the possibility of many future pathways for problems under deep uncertainty (de Haan et al., 2016; Moallemi et al., 2020a; Quinn et al., 2017). These studies acknowledge uncertainties in assumptions, data, and model structure and view modeling experiments and results as educated guesses of future realizations. This idea is crucial for modeling human behaviors and coupled human-natural systems due to the intrinsic uncertainty and our insufficient knowledge about the control mechanisms of the system behaviors.

We join forces with the researchers on uncertainty investigation to deconstruct the intricacies in the CRB's water resources management. Focusing on human adaptation (water demand changes), we examine uncertainties at system, agent, and parameter levels through three numerical experiments. The first experiment is the uncertainty analysis, which quantifies the water scarcity uncertainty at multiple spatial scales due to stochasticity in the human system and uncertainty of human behaviors under various human adaptation assumptions. The second experiment, the clustering analysis, classifies agents by their characteristics and quantifies the probability of agents being assigned to the behavioral classes. Finally, the third experiment investigates ABM structure and parameter uncertainties through two sensitivity analyses. The results can be applied to diagnose agents that may be under- or over-parametrized and identify opportunities to reduce the uncertainties.

The remainder of this paper is organized as follows. Section 2 explains the study area, the coupled ABM-water resources management model and methodology. Section 3 shows the results of numerical experiments, and Section 4 discusses the lessons learned from the analyses and limitations. Finally, the conclusions are presented in Section 5.

2. Methodology and study area

2.1. The Colorado river basin (CRB)

The Colorado River is a major water source for the southwestern US and Mexico. The map of the basin is shown in Fig. 1 (left). From the 1906–2018 flow record, an average of 18 billion m^3 (14.8 million acre-feet, MAF) of freshwater is generated annually in the CRB (Salehabadi et al., 2020). The water allocation and dam operations are based on compacts, federal laws, court decisions and decrees, contracts, and regulatory guidelines, collectively known as the "Law of the River" (Stern & Sheikh, 2019). However, the future of the CRB water resources is looming due to the extended drought since 2000 and the increasing human demands. The mean flow in the current drought period is about 15 billion m^3 (12.4 MAF, average from 2000 to 2018) which is 3.5 billion m^3 below the consumptive allocation of 18.5 billion m^3, including 1.9 billion m^3 of Mexico uses (Salehabadi et al., 2020). The increasing water scarcity in the CRB has been a pressing issue for scientific and policy discussions (Castle et al., 2014; Christensen et al., 2004; Garrick et al., 2008; McCabe & Wolock, 2007).

The US Bureau of Reclamation (USBR) regulates water distribution in the CRB through operations of major reservoirs, among which Lake Powell (Glen Canyon Dam) and Lake Mead (Hoover Dam) are served as the indicators of water availability for the Upper and Lower Basins (abbreviated UB and LB hereafter; the left figure in Fig. 1), respectively. The 1922 Compact states that the UB States (comprising Colorado, New Mexico, Utah, Wyoming, and the upper part of Arizona) will not cause the flow to be depleted below an aggregate of 9.2 billion m^3 (7.5 MAF) in any period of 10 consecutive years for the consumptive uses of the LB States (Arizona, California, and Nevada). In Year 2021, water levels in both Lake Powell and Lake Mead have dropped to historic lows (USBR, 2021b;c), which suggests an urgent need for changing current practices to maintain a sustainable water supply.

2.2. Model description

In a river basin, climate change can affect the quantity, timing, and distribution of precipitation and temperature, of which the effects are variable, uncertain, and heterogeneous. Consequently, water users may

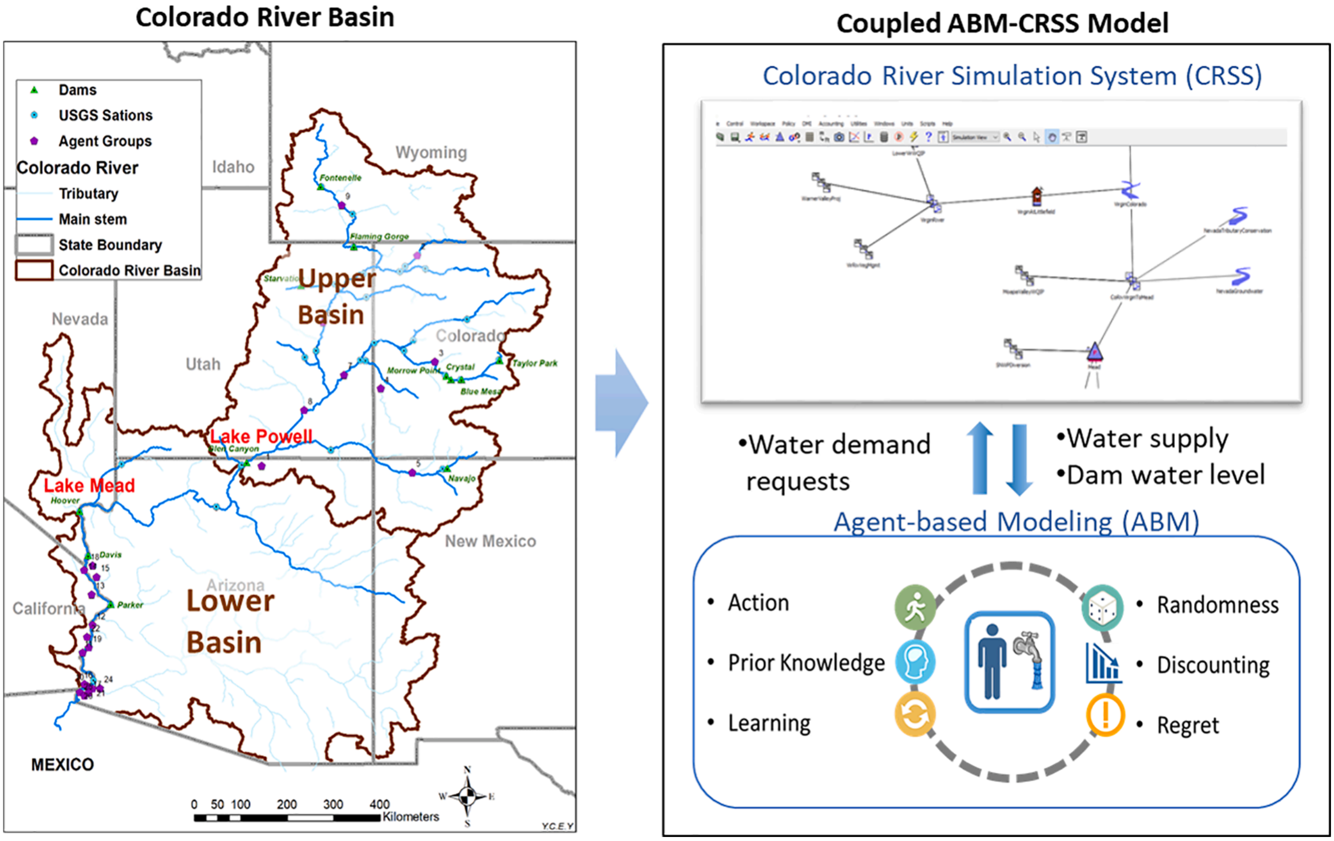


Fig. 1. The CRB map and the schematic of the coupled ABM-CRSS model. The ABM simulates the annual diversion requests of the farmers (i.e., agents) and submits them to the CRSS. Upon receiving the requests, the CRSS will allocate water to farmers following a set of rules and send the allocation information and dams' water level to ABM. The ABM will also receive winter precipitation forecast information in the next year from the input database.

view climate change risks differently. Their perceptions and decision-making (at local scale) can alter water resource distribution in the river basin (at local, sub-basin, and basin scales), affecting future system responses they or others observed and experienced. The dynamic system also involves delayed response and complex interactions among the water users and the water system.

Following the conceptualization of a river basin, we adopt an ABM approach for the CRB from a previous study (Hung and Yang, 2021) in which human water users (agents) are capable of learning to improve their decision-making (i.e., adaptation). The ABM (i.e., the human system) is coupled with a water resources management model, the Colorado River Simulation System (CRSS), as the virtual environment for agents to interact with. For illustration, the right figure in Fig. 1 presents the schematic of the coupled ABM model, where agents' adaptation is modeled by a reinforcement learning algorithm which we will explain shortly in Section 2.2.2. The CRSS, a long-term planning model for CRB water resources administration, provides distributed hydrological information regarding the projected future state of the river basin and rulesets for dam operations and water allocation (USBR, 2007). The rulesets for water allocation were developed based on the current water right system and are assumed unchanged in the future simulation. Below we describe the coupled ABM-CRSS model (Hung and Yang, 2021) and the three approaches for assessing water scarcity uncertainty in the CRB, investigating alternative assumptions and key uncertainties in the ABM.

2.2.1. The coupled ABM-CRSS model

The majority (about 80%) of the water in the CRB is consumed by agriculture irrigation. For simplicity, only agriculture water users and their irrigation decisions are simulated as agents in the ABM. Other water demands, such as industrial and municipal demands, are fixed inputs using the default values in the CRSS. Decisions, such as crop selections, fertilization, and irrigation practices, are not explicitly included in current models. Moreover, the agriculture agents are aggregations of individual farmers, irrigation districts, tribal water users, or a mix of farming entities within a geographical region. Since the agent design is for capturing the emergent phenomena in the water system, an agent only represents the collective behavior of farmers at that location but not individual farmers' decision-making.

Agents' decisions are assumed pertaining to their prior knowledge about the river basin, the new information learned (i.e., hydrological response), and their perception of the future climate change. An agent's decision-making is modeled as a partially observable Markov Decision Process (Monahan, 1982). That is, agents take actions based on their beliefs about the system state (i.e., overall water availability, which is not known to agents) and the observation available to them (i.e., climate forecasts and dam water levels) at the time and location of the decisions.

Following the CRSS model design, the ABM simulates 31 (22 in the LB and 9 in the UB) agents' water demands (i.e., the agriculture water users in CRSS aggregated by locations and indicated by the purple dots in Fig. 1) and sends the water requests to the CRSS. The agent group IDs are enlarged in Fig. S1, and the corresponding agent names can be found in Tables S2 and S3, Supplementary Information. The CRSS then determines the actual water quantities delivered to the agents according to a predefined rule set that mimics the legal institutions and real-world water allocation practices in the basin and provides water quantity and dam water level information to the ABM. Upon receiving the feedback from the CRSS, agents will update their prior knowledge of water availability and optimal strategies for water uses. The updating of agents' prior knowledge and strategies follows a reinforcement learning (RL) algorithm developed by Hung and Yang (2021), of which the key components are presented in the following subsection, and the mathematical equations are presented in Text S1, Supplementary Information.

With new strategies and knowledge of water availability, agents will determine their water requests for the following year.

2.2.2. The reinforcement learning (RL) algorithm

The RL algorithm simulates an agent's decision-making process, including choosing an action (a water request) and updating the optimal water use strategy. Agents are assumed to utilize environmental information to facilitate their decision-making. We assume that the LB agents consider the reservoir's water level information in their decision-making while the UB agents' actions take into account the local precipitation.

The algorithm utilizes a function (Max Q, where Q represents the expected utility) to maximize an agent's utility by increasing or decreasing its diversion and a stochastic process to determine the quantity of change. The stochastic process is assumed to follow a half-normal distribution with mean μ and standard deviation σ (i.e., $|\text{Normal}(\mu,\sigma)|$). After receiving the water allocation from the CRSS, the utility function (Q) is updated by increasing or decreasing the expected value of the action taken. Moreover, this algorithm adopts a penalty mechanism to punish actions that result in water deficits. A multiplier, *regret*, is used to represent an agent's risk attitude toward water deficit, and the penalty is equal to the deficit multiplied by the *regret*. This design forms a reinforcement loop that encourages actions with high expected utilities and discourages the others.

Another feature of the RL algorithm is the inclusion of the exploitation-exploration tradeoff. An agent may take exploration actions to search for better strategies. This feature is critical since a water system can evolve, and agents need to re-assess strategies to learn whether the system has changed and the original strategy remains optimal. The algorithm adopts an ϵ-greedy design that an agent will take an exploration action with a probability ϵ. There are two other parameters that control how an agent learns, the learning rate (α) and discount rate (γ). The learning rate α represents how much an agent believes in the new information relative to its prior knowledge, and the discount rate γ means an agent's view of future utility at the present time. Both α and γ are in the range of (0, 1). $\alpha = 1$ means agents only believe the new information learned, whereas $\alpha = 0$ means agents do not learn. $\gamma = 1$ means the future water is equally valuable as the present water, and $\gamma = 0$ represents an agent who does not consider future water (no value).

In summary, an agent (i.e., a virtual farmer) has six parameters controlling its adaptation actions (i.e., diversion request): two related to water use adjustment (μ and σ) and four for learning (α, γ, ϵ, and *regret*). Interested readers can refer to our previous paper for more details on the reinforcement learning algorithm (Hung and Yang, 2021).

2.3. Methods for water scarcity uncertainty quantification, agent characterization, and human behavior modeling diagnosis

The coupled ABM-CRSS model is a sandbox to test various human adaptation assumptions with different numerical experiments. To improve our understanding of the human-water system dynamics, human behavioral uncertainty, and its impacts on water scarcity, we conducted three analyses: (1) uncertainty quantification, (2) agent classification, and (3) sensitivity analysis. The uncertainty analysis aims to quantify the water scarcity uncertainty due to the uncertainty in farmers' irrigation behavior at basin and sub-basin levels. The results can be viewed as a reference of the water scarcity uncertainty contributed by the human system in the CRB, and subsequently, the following two analyses aim to inform future research directions for reducing the uncertainty. The clustering analysis characterizes agents' decision-making into three classes and quantifies the probabilities of each agent being assigned to each class. The results can inform future policy design to steer irrigation behavior changes. For the sensitivity analysis, the goal is to improve our understanding of the uncertainty in individual agents' modeling and consequently reduce water scarcity uncertainty in the CRB at various spatial scales. Below are detailed descriptions of the methods.

2.3.1. Uncertainty analysis

Uncertainty can be classified as either aleatory – the inherent variation in a quantity that can be characterized by a probability distribution, or epistemic – uncertainty from analysts' lack of knowledge (Roy and Oberkampf, 2011). Both uncertainties can be characterized as probability distributions based on observations. However, the distinction of the uncertainty categories is not clear-cut since we often learn what we thought aleatory is actually epistemic. For example, the aleatory uncertainty in decision-making can be the result of a farmer's prediction errors, and the epistemic uncertainty is related to our insufficient understanding of the farmer's decision-making process.

In the ABM, an agent's action involves two decisions: the direction and quantity of the change in water diversion. Moreover, an agent is assumed to take the optimal action with probability $1-\epsilon$ and the exploration actions (selecting a sub-optimal solution) with probability ϵ. The exploration rate ϵ represents the epistemic uncertainty in the decision since we do not know the exact reasons for that action. The quantity of change is assumed following a half-normal distribution for simulating the aleatory uncertainty in farmers' decision-making. To gain insights into agents' response to the non-stationary climate and the subsequent impacts on water scarcity, we focus on ABM parameter uncertainty and its effects on key system outputs at sub-basin and basin levels.

Table 1 explains the uncertainty analysis workflow, which includes: (a) Identify parameter ranges, (b) Generate parameter sets, (c) Evaluate the parameter set performance, (d) Identify behavioral sets, and I Assess model output uncertainty.

2.3.2. Clustering analysis

The behavioral sets in the uncertainty analysis (Section 2.3.1) are the candidate representation of an agent's cognitive decision-making process and essentially assumptions about the agent's behaviors. Since a parameter set describes an agent's decision-making and learning behavior, we will expect similarity in the behavioral sets, especially when the observed data show a clear pattern. To explore the similarity and dissimilarity among agents' behavioral sets, we applied the K-means clustering for agent classification and investigated the characteristics of the agent classes. K-means clustering is a classification algorithm that partitions data into k clusters (agent classes) and recursively assigns data to the cluster whose centroid is closest to the data point until the assignment is stabilized (MacQueen, 1967). By analyzing the characteristics of the agent classes, we can develop agent-behavior typology and refine the assumptions about agents' behaviors to a few common types.

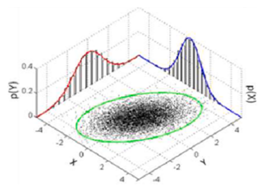
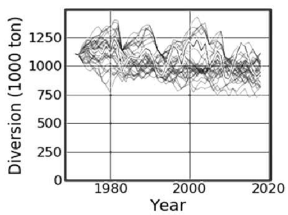
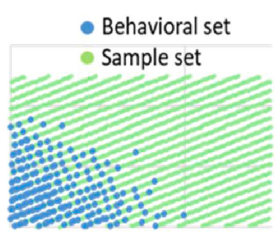
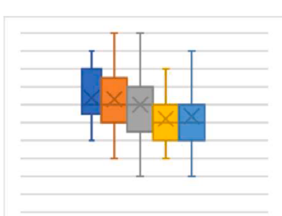
To help visualization and interpretation, we applied the principal component analysis to project data from a high-dimensional parameter space into a lower-dimensional subspace. This is a common practice for clustering analysis to reduce dimensionality and extract information from high-dimensional data sets (Aubert et al., 2013; Hannah et al., 2000).

2.3.3. Sensitivity analysis

The Sensitivity analysis (SA) methods applied in this paper are global sensitivity analysis methods, which investigate the relationships between the parameters (including equation coefficients, thresholds, and input forcing) and outputs of a simulation model (Norton, 2015). In our ABM model, an agent's parameters are related to its cognitive decision-making process (i.e., learning rate α, discount rate γ, exploration rate ϵ, and *regret*) and stochastic actions of water use adjustment (i.e., mean μ and standard deviation σ). The model output of interest is the ABM's performance in simulating the observed water consumption measured by KGE.

There are a variety of SA methods, which can be categorized into five broad groups based on the underlying mathematical concepts: perturbation and derivatives, elementary effect (EE), correlation and regression analysis methods, and variance-based methods (Pianosi et al.,

Table 1
The uncertainty analysis workflow to quantify the effect of ABM parameter uncertainty on model outputs.

Icon	Uncertainty analysis workflow
	a. **Identify parameter ranges**: Parameter ranges are chosen based on the theoretical and suggested values in the literature (Table S1, Supplementary Information).
	b. **Generate parameter sets**: Parameter sets are sampled using Quasi-Monte Carlo methods (Bratley et al., 1992; Saltelli et al., 2010) from the ranges identified in step a. We generated 2,000 parameter sets for each agent.
	c. **Evaluate the parameter set performance**: Due to the stochasticity of the ABM, each parameter set is simulated 30 times to calculate its mean performance for the period in which observation data is available (i.e., 1980–2018). Kling-Gupta efficiency (KGE), a synthesized index consisting of the correlation, variability bias, and mean bias between simulated and observed data (Knoben et al., 2019), is applied as the performance metric. Consequently, the 2,000 parameter sets generate 2,000 mean KGE values (denoted $\overline{KGE}$).
	d. **Identify behavioral sets**: We applied a threshold criterion of the $\overline{KGE}$ to identify "behavioral parameter" sets – parameter sets that reproduce plausible system behaviors (Beven and Binley, 2014; Schaefli et al., 2011; Willems, 1991). We used the ranked performance value to set the threshold, instead of a fixed value, for agents' $\overline{KGE}$ values can vary in a wide range. Specifically, an agent's threshold value is set to the 90%-percentile $\overline{KGE}$ of the parameter sets.
	e. **Assess model output uncertainty**: We define the combination of all agents' behavioral sets as one scenario (one set per agent; a total of 31 parameter sets for a scenario). The coupled ABM-CRSS model is simulated multiple times ($n = 100$ for our analysis) for a single scenario to estimate the output uncertainties of interest. Since it is not realistic to simulate all possible scenarios due to computational limitations, we select scenarios based on the $\overline{KGE}$ rankings of the behavioral sets to elucidate the overall uncertainty of the model outputs. The scenario generation process based on KGE rankings enables the exploration of diverse agent behaviors while maintaining heterogeneity among agents.

2016). Since the SAs methods have different mathematical properties and purposes, applying multiple SA methods is recommended (Ligmann-Zielinska et al., 2020; Wagener and Pianosi, 2019). Therefore, we implemented two widely-applied SA methods: the Morris SA (Morris, 1991) and the Sobol SA (Sobol, 2001) in this study as diagnostic tools to improve our understanding of the ABM and guide future ABM research.

The Morris SA is an EE method that calculates the changes in model outputs for a unit change in a parameter (i.e., the EE). In contrast, the Sobol SA, a variance-based method, uses two variance ratios for the importance of parameters (Saltelli et al., 2010). The first Sobol ratio, called the first-order index, measures the direct contribution to the output variance from individual parameters or, equivalently, the expected variance reduction if a parameter's value could be fixed. The second ratio, called the total-order index, measures the overall contribution from a parameter, including the direct effects and interactions with other parameters (Pianosi et al., 2016).

We applied the Morris SA for model structure diagnosis based on the rationale that the parameters of a proper model should have moderate EE values. A parameter with a low EE value means that the model may be over-parameterized and can be simplified by removing the parameter (as a screening method). In contrast, a parameter with a high EE value may signify a poor representation of the observed behaviors and a need to review the model structure. Meanwhile, the two Sobol indices are calculated for ranking the potentials for uncertainty reduction in the agents' behavior modeling. Therefore, the Sobol indices can inform future research directions on the mechanisms associated with a sensitive parameter or the estimation of that parameter value.

Additionally, the two SAs also have different experiment designs. The Morris method requires generating traces of samples (a trace consists of $n + 1$ samples; n is the number of parameters) in the parameter space and calculates the mean absolute elementary effects. The Sobol method adopts Monte Carlo sampling methods to generate parameter sets and compute two sensitivity indices. The parameter sets for the two SAs are generated independently following the methods' experiment designs. The mathematical definitions of the SAs' sensitivity indices are presented in Text S2, Supplementary Information.

3. Results

3.1. Monte Carlo simulation for water scarcity uncertainty assessment

Following the procedure described in Table 1, we assessed the $\overline{KGE}$ values of the 2,000 parameter sets for each agent (the results are presented in Figs. S2 and S3, Supplementary Information). An agent's parameter sets with $\overline{KGE}$ values higher than a threshold value are selected as the behavioral sets (top 10% ranked parameter sets; 200 sets per agent). Although the same 2000 parameter sets are evaluated for each agent, the resulting KGE value for each set varies from agent to agent due to agents' diverse historical behaviors. Consequently, each agent has its own behavior parameter sets.

Due to the heavy computation burden for simulating the coupled model, we composed only five scenarios for this analysis. A scenario consists of 31 agents, i.e., 31 parameter sets. The agents' parameter sets are selected from their own behavioral sets based on the $\overline{KGE}$ rankings. In doing so, we can maintain heterogeneity in agents' decision-making and fair representations of their observed behaviors. The $\overline{KGE}$ rankings for the five scenarios are 1%, 25%, 50%, 75%, and 99%, rankings of the behavior sets, respectively, and for clarity, the scenarios are named after the percentile values (i.e., Q1%, Q25%, Q50%, Q75%, and Q99%).

Since $\overline{KGE}$ measures how close the simulated results are to the observed data, the scenarios represent hypotheses of how agents' future behavior would deviate from their historical patterns. That is, the Q99% scenario assumes that the agent's future behavior will be similar to the past, while the Q75%, Q50%, and Q25% scenarios represent futures where agents can behave somehow differently from the past.

The five scenarios are simulated from 2019 to 2060 under the same future flow condition (sum of all inflows in the basin, the solid line in Fig. 2a) - a recovering trend from a drought condition to a normal condition (the dashed line in Fig. 2a). The future flow series is generated from historical observation resampling and has two significant drought years in 2033 and 2047. To assess water scarcity uncertainty, we chose the basin storage (monthly average storage of all dams in the CRB) and Mexico delivery shortage year counts as system-level performance metrics. A shortage year is a year with the annual flow to Mexico less than 1.9 billion m^3 stated in the 1944 Mexico Treaty.

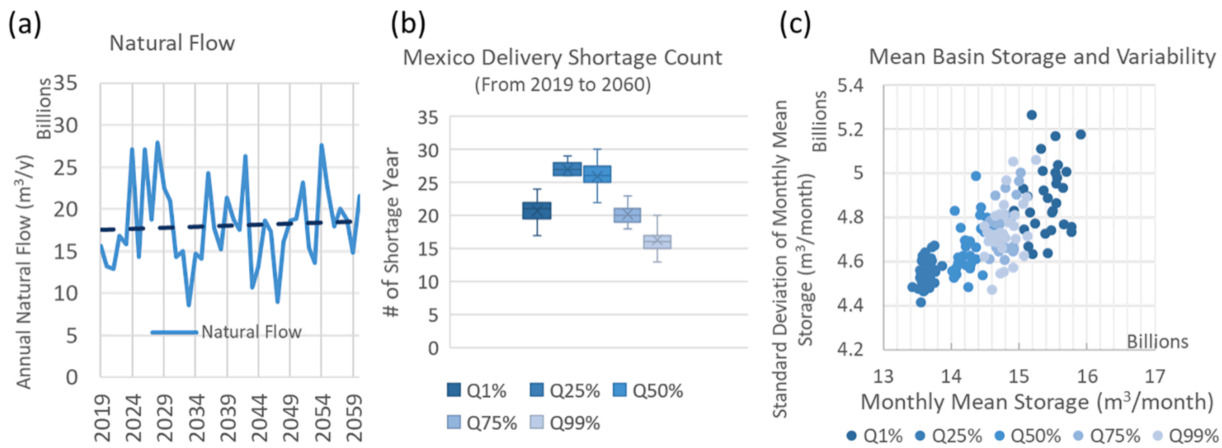


Fig. 2. (a) The future natural flow for the coupled model simulation; (b) the counts of shortage years (the annual water flow to Mexico below 1.9 billion m^3 is a shortage year); and (c) the mean and standard deviation of the total CRB storage. Each scenario is simulated repeatedly 30 times to generate the shortage year counts and mean basin storage results.

Fig. 2b shows the Mexico delivery shortage years of the five scenarios (each has 30 simulations), which range from 13 (the lower limit of the Q99% scenario) to 30 years (the upper limit of the Q50% scenario). We can see a trend that the higher percentile scenario is more likely to have a lower number of shortage years, except for the Q1% scenario. Interestingly, the Q1% scenario (the dark blue circles in Fig. 2c) is more likely to have a higher mean basin storage (larger x-axis values) than the other scenarios, even though the predicted shortage years (median) is higher than scenarios Q75% and Q99% (Fig. 2b). This result can be partially attributed to the Q1% scenario's higher inter-annual variability in the basin storage (larger y-axis values), resulting from the farmer characteristics (i.e., agent parameter values).

To further investigate human impacts on basin storage variability, we compare the water consumption of scenarios Q1% and Q99%, aggregated to sub-basin and basin levels, as Fig. 3 shows. Moreover, we highlighted three time periods in Fig. 3 by the orange boxes, separated by the 2033 and 2047 droughts to facilitate the discussion.

In period (a), from 2019 to 2032, the water stored in the reservoirs is sufficient to satisfy water demands, so agents continue to exploit water resources (Fig. S4, Supplementary Information). Until 2033, the excessive water uses in period (a) and the significantly lower natural flow depletes water storage in the basin, resulting in a deep plunge in the basin and sub-basin water consumption. Because the reservoirs are depleted, agents have to adapt to the reduced water supply in period (b) to restore basin storage. We named this period (b) the adaptation period for the substantial changes in the water system, although agents in the three periods are active learning either for exploiting or conserving water resources. In both scenarios, the water consumption in the sub-basins shows different patterns: the UB consumption gradually recovers to the pre-adaptation level, while the LB consumption recovers to a lower-than-pre-adaptation level. The LB agents mainly rely on water flow release from Lake Mead, which will be low in water storage after the 2033 drought, so they need to restrain their water uses. Whereas many UB agents have access to the natural flow and can return to their

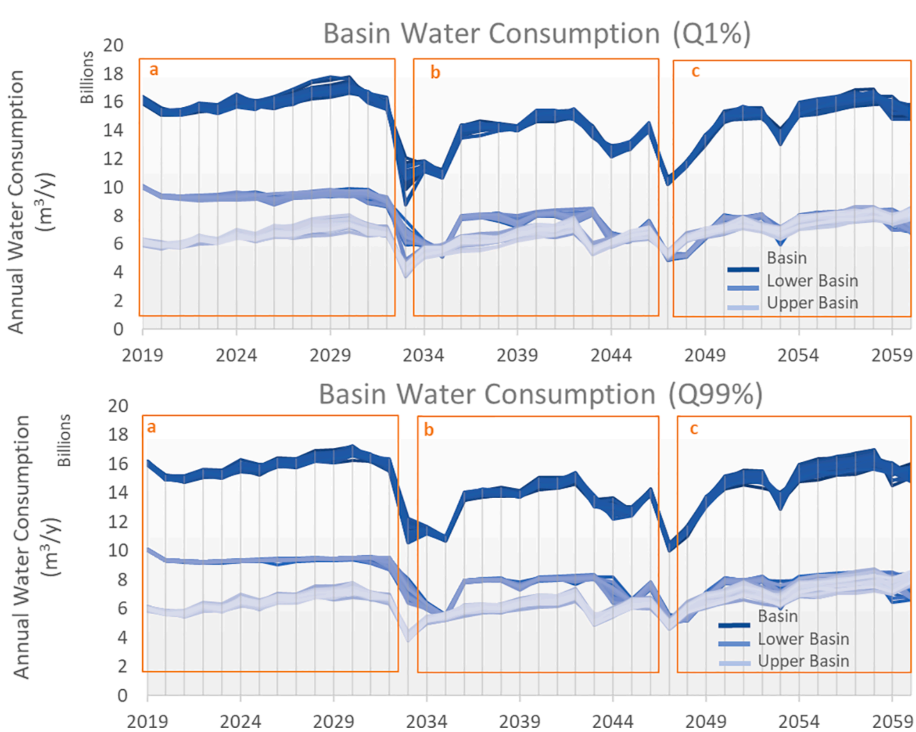


Fig. 3. Water consumption results of scenarios Q1% (top) and Q99% (bottom). The figures show the annual consumption time series lines of the Upper Basin (UB, light blue lines), the Lower Basin (LB, blue lines), and the total CRB (dark blue lines). Each line represents one of the 30 simulations and is stacked to represent the uncertainty band. Three periods are highlighted by the orange boxes: (a) pre-adaptation, (b) adaptation, and (c) post-adaptation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

normal water uses as long as the precipitation is within the normal conditions. Furthermore, although the UB consumption patterns are much alike in the two scenarios, we can see that the UB consumption in the Q1% scenario has a higher recovering rate (i.e., the slope of the water consumption) than in the Q99% scenario besides the wider band.

When another severe drought occurs in 2047, it triggers another round of adaptation in the CRB and announces the arrival of the post-adaptation period (c). Given the experience of the adaptation period (b), agents are in a better position to cope with the shortage. Consequently, the CRB and the sub-basin water consumption can quickly recover to the adaptation period level or higher. The results of the two scenarios are very similar in this period, except that the uncertainty (measured by the range, i.e., maximum-minimum) is higher in the Q99% scenario. This implies that agents in both scenarios may have similar water use strategies when the natural flow returns to the normal condition, but some agents of the Q99% scenario may learn more diverse strategies in the simulations for the wider bandwidth. The difference between Q1% and Q99% is due to our assumptions about farmers' characteristics (i.e., agent parameter values). Fig. 4 shows 31 agents' parameter distributions (parameter ranges are normalized to 0–1 range for the ease of reading) in the two scenarios where the main difference lies in ϵ (the probability of taking an exploration action) and *regrets* (a penalty for undersupply). The Q1% scenario's high exploration rate results in the higher consumption variability in periods (a) and (b), whereas the low exploration rate and high regret of the Q99% scenario can explain the diverging trajectories in period (c). Fig. 4 also demonstrates that the scenario generation process can effectively generate distinct agent compositions while maintaining agent heterogeneity.

Our analysis illustrates that the assumptions about farmers' adaptation behaviors can substantially influence system-level water scarcity outcomes. However, farmers' adaptation depends on their perceptions of future water availability after shortages and their willingness to adapt - both are controlled by the ABM parameters. It is important to note that learning and adaptation occur at the farmer (agent) level and can differ from farmer to farmer depending on their local environment and characteristics.

3.2. Clustering and principal component analyses for human behavior uncertainty assessment

Following the uncertainty analysis in Section 3.1, we used the behavioral sets identified by the performance thresholds as the input data for clustering. Each agent has 200 behavioral sets. The analysis includes two steps. First, we mapped the behavioral sets to a 2-dimensional principal component space using principal component analysis (Jolliffe, 1986) for visual presentation and interpretation. The principal components (PCs) are linear transformations of the original parameter space (normalized to the range of 0 to 1) so that the PCs are linear uncorrelated. The PCs are orthogonal directions with the high variance numbered conventionally by order of variance explained. Table 2 shows the coefficients of the linear transformation function of the two PCs: PC1 mainly emphasizes the action parameters (μ and σ) and PC2 is related to the adaptation parameters (α, γ, ϵ and regret). A variable's coefficient close to zero means that the variable has little contribution to the PC. Based on the features of the PCs, we named PC1 "the boldness in action" and PC2 "the willingness to adapt."

Then, we tested the K-means clustering by setting the number of clusters from 2 to 5 and found that three clusters yielded the most meaningful results. The clustering performance results are shown in Figs. S5 and S6, Supplementary Information. Fig. 5 shows the behavioral sets assigned to one of the three clusters: *Prudent*, *Forward-looking*, and *Bold*. The clusters' naming is based on their mean parameter values, which are shown at the bottom of Fig. 5. The Prudent agents (orange circles) are cautious in adjusting amounts of water use (low μ and σ), inclined to conserve water after water shortages (high *regret*), and more willing to explore new strategies (high ϵ). The Forward-looking agents (blue circles) consider the value of future water (high γ) and deliberate in adaptation to environmental changes (low α and ϵ). Whereas the Bold agents (green circles) prefer making substantial adjustments in their water use (high μ, σ, and α) and do not regret nor value future water as much (low γ and *regret*).

Assuming each parameter set is equally likely to be a good representation of an agent's decision-making, we can then calculate the probabilities of an agent being assigned to each cluster (Tables S2 and S3, Supplementary Information). For example, Fig. 6 (right) shows the

Table 2
The 2D principal component axes.

	μ	σ	α	γ	ϵ	regret
PC 1	0.49	0.71	−0.06	0.02	−0.26	−0.43
PC 2	0.07	0.00	0.49	−0.75	0.36	−0.25

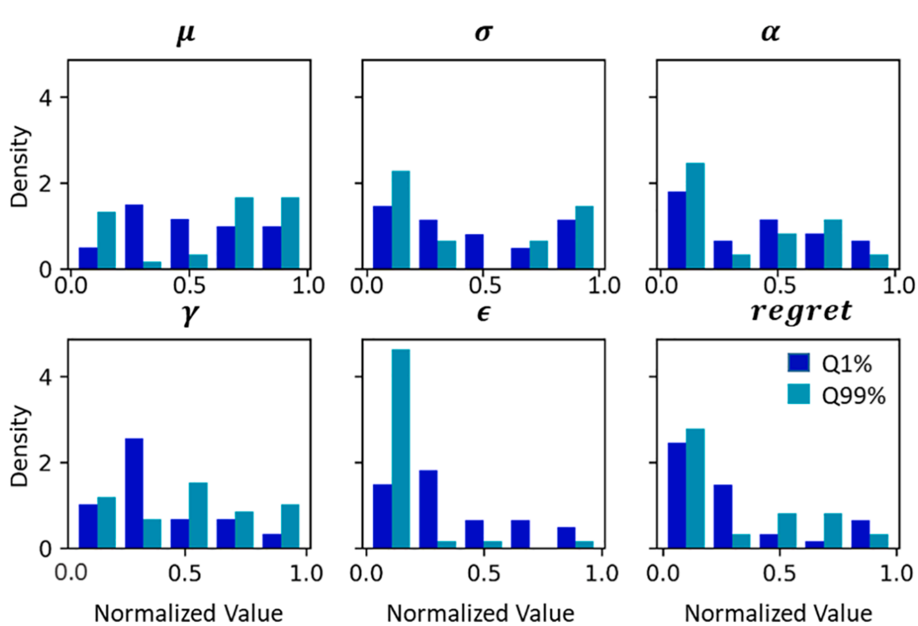
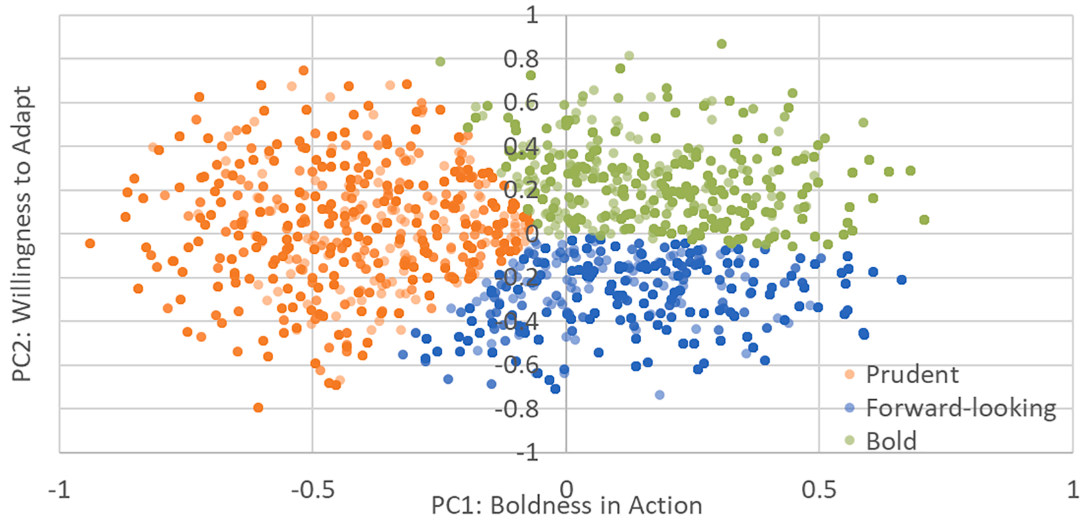


Fig. 4. The comparison of agents' parameter values (normalized to [0,1]) applied in Q1% and Q99% scenarios.



Cluster	Mean: μ	Standard deviation: σ	Learning rate: α	Discount rate: γ	Epsilon: ϵ	*regret*
Prudent	0.29	0.30	0.42	0.42	0.13	2.18
Forward-looking	0.55	1.10	0.25	0.71	0.05	1.23
Bold	0.60	1.24	0.48	0.28	0.10	0.64

Fig. 5. The scatter plot of the clustering results in the 2D principal component space and the mean parameter values of the three clusters. The dark-colored circles are multiple circles stacked together. The mean value fields are colored in blue for low values and yellow for high values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

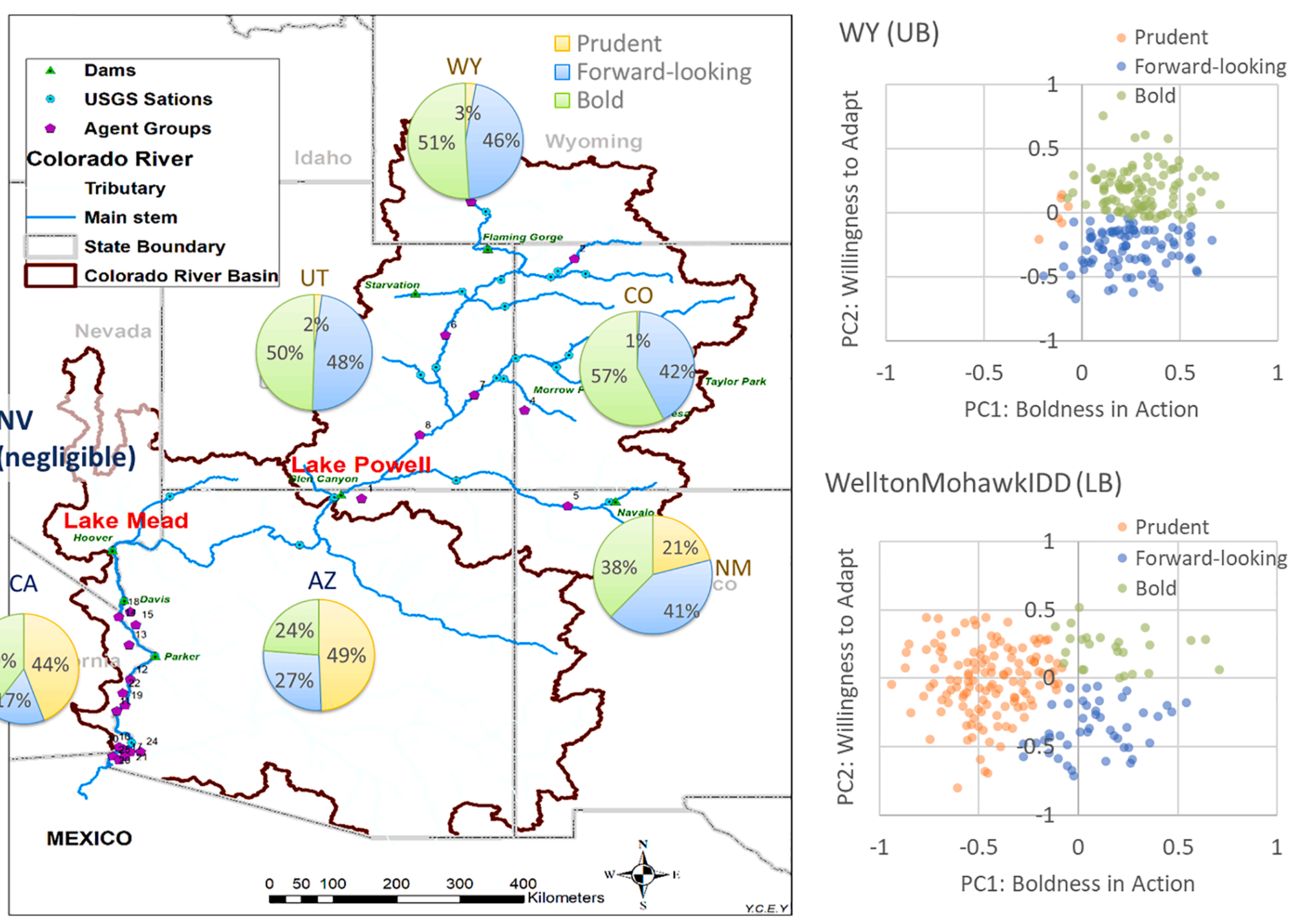


Fig. 6. Pie charts of agent classification aggregated to the state level and weighted by agents' water consumption (left) and two examples of individual agent clustering results (right).

clustering results of two agents: WY in the UB and WelltonMohawkIDD in the LB, and the probabilities are calculated based on the point counts of the clusters. The WY sets are mostly assigned to the *Bold* or *Forward-looking*, while the majority of the WelltonMohawkIDD sets are classified as the *Prudent*. Fig. 6 (left) shows the pie charts of the results, aggregated to the state level and weighted by agents' water consumption in 2018. The agents simulated may consist of many farmers in reality, and therefore, the classification results are weighted by the water consumption when aggregated to the state level. The pie charts show that UB agents are likely to be categorized as either the *Bold* or *Forward-looking* agents, while the LB agents are likely to be assigned to the *Prudent* cluster. The classification and probability analysis of agent type can provide qualitative information about farmers' adaptation behavior. For example, an agent may show "prudent" behaviors due to either the agent's own thinking or the institutional constraints. Explicitly modeling the institutional constraints can eliminate the latter and help us focus on agents' thinking. This will be a future research direction. Additionally, other clustering algorithms may generate different results. The comparison of multiple algorithms for better characterization can be another future research topic.

3.3. Morris and Sobol SAs for human behavior model diagnoses

This section presents the results of two SAs. Due to the high computation cost of the ABM evaluation, we limited the sample size for the SAs to between 1,000 and 2,000 samples. The model output selected for the SAs is the KGE, and the parameters are sampled from the ranges listed in Table S1 in Supplementary Information.

In Morris SA, an insensitive parameter (i.e., a low mean value of EE) means that the ABM's output does not depend on the parameter value – any value (in the parameter range) of that parameter would generate a similar result. Contrarily, a sensitive parameter (i.e., a high mean value of EE) indicates that the ABM performance is sensitive to the parameter value. Fig. 7 shows the Morris SA results on a scatter plot, and each circle represents a parameter's EE of an agent (total 186 circles; 31 agents * 6 parameters). The numerical results are presented in Tables S4 and S5 in Supplementary Information. The circles are colored orange and blue to indicate the UB and LB agents' parameters, respectively. We can see that the EEs of the parameters vary in a wide range which suggests heterogeneity in farmers' characteristics.

To improve our understanding of agents' behaviors, we examined the historical diversion data. Starting from the extremes, we use HopiTribe and Powers as two examples to explain why ABM performance is sensitive or insensitive to the changes in the parameter values. The ABM is designed to simulate changes in behavior through adaptive learning. Since the HopiTribe shows no obvious changes in its water uses, its performance would worsen when the parameters suggest more adaptation or a significant change. HopiTribe's high STD is the result of applying a non-linear ABM to predict a rather linear behavior. In contrast, the Powers has steady water use and a decreasing trend after a significant drop. The ABM training process is to equip an agent with initial strategies. In the case of a simple trend, like the Powers, agents can easily learn good strategies from training and perform well regardless of what the parameter values are. When the ABM performs well in capturing a farmer's adaptation behavior, the parameters generally have moderate EEs (0.2–0.4), as shown by MohaveValleyIDD in Fig. 7.

Moreover, we can see that the circles exhibit a linear relationship between the means and standard deviations (STDs) of the EE values, which implies a scale effect in the parameters' EE distributions. Large STDs also suggest the presence significant non-linear effects (Iooss and Lemaître, 2015). Interestingly, the orange circles (i.e., UB agents) also show a linear relationship, but some of the circles significantly deviate from the linear trend line (Fig. 7). Since performance metric KGE is a composite metric of correlation, mean, and variance ratios between simulated and observed data, parameters deviated from the trend line are indicators of the agents' complex behaviors that require further investigation.

To investigate what ABM parameters may require further attention, we showed the same results color-coded for parameters, instead of sub-basins, in Fig. 8. We can see that *regret* (blue asterisk), ϵ (orange square), and α (light blue diamond) are more likely to deviate from the trend line. This finding suggests non-linear and non-stationary mechanisms in the penalty, exploration, and learning behaviors. In addition, the magnitude of the Mean EE values (y-axis) indicates the potential abrupt twists in the agents' historical water consumption patterns. When the observation data has an evident change, it is crucial for the model to capture the timing of the change. Failure to capture timing can result in a plunge in model performance (measured by KGE) because the trajectory would be very different.

Fig. 9 shows the Sobol SA results of the UB agents and the largest five agents (in terms of water consumption) in the LB. The numerical results are presented in Tables S6 and S7 in Supplementary Information. Since Sobol SA is a variance-based method, σ (the standard deviation of the water use change) and ϵ (the random exploration rate) are expected to have higher first-order Sobol index values. The statement is generally true for the LB agents, but the results show that *regret* and α are also important parameters for many UB agents. This finding implies that

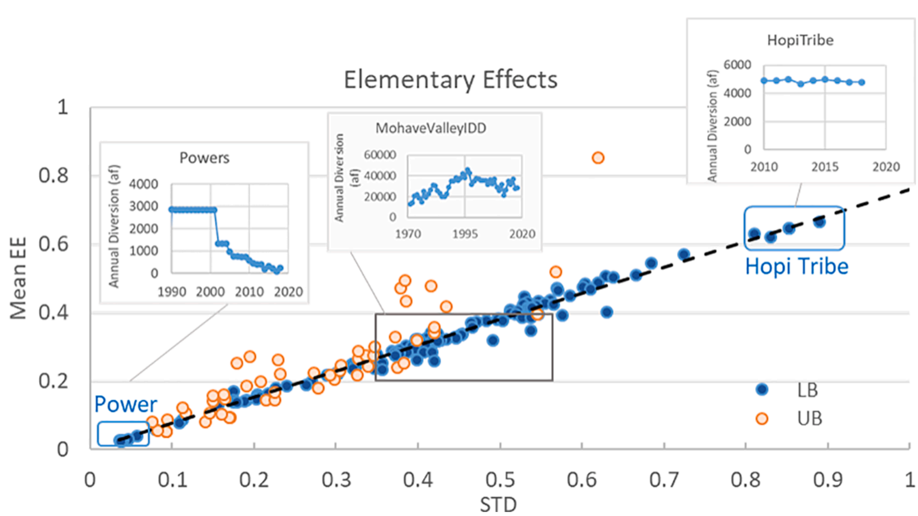


Fig. 7. The mean absolute value and the standard deviation (STD) of agent-parameter EE are colored by sub-basins. The dashed line is the linear trend line of the results. The historical water use patterns of the HopiTribe, MohaveValleyIDD, and Powers are three examples of ABM model diagnoses.

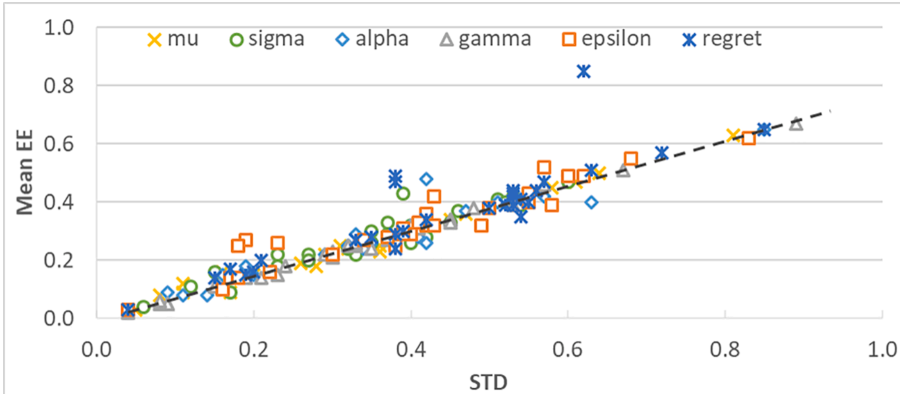


Fig. 8. The mean absolute value and the standard deviation (STD) of agent-parameter EE are colored by parameters. The dashed line is the linear trend line of the results.

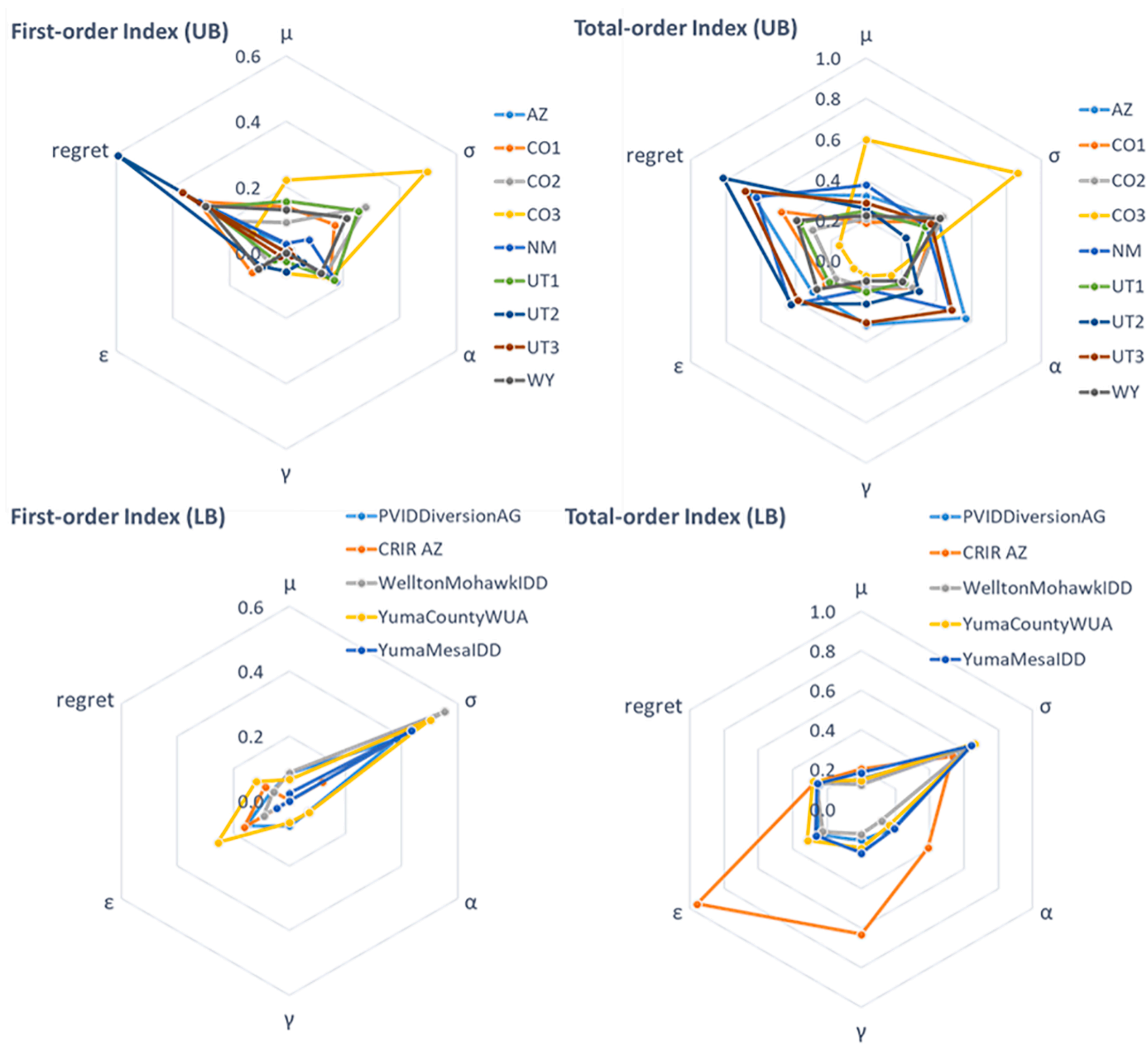


Fig. 9. The first-order (S_1) and total-order (S_T) Sobol indices for the UB agents and the top-five agents in the LB. An agent' parameter values are indicated by connected color lines to highlight the value differences between agents.

being able to adapt may be crucial for simulating UB agents' historical water use patterns. Moreover, suppose the parameters do not have significant interactions (i.e., the higher-order terms are close to 0). In that case, the sum of an agent's first-order indices (and the sum of the total-order indices) should be close to 1. Therefore, the sum of the first-order indices substantially deviates from 1 is an indicator of strong nonlinearity (e.g., UT3 and AZ in the UB and CRIR AZ and YumaMesa IDD in the LB).

The total-order Sobol indices represent the variances contributed by a parameter and its interactions with other parameters. This information can guide research to reduce the uncertainty of an agent's simulation performance. For example, *regret* is the most sensitive parameter (in terms of the total-order Sobol index) for many UB agents, and if we can improve the *regret* estimations by collecting data and evidence of human cognitive thinking, we can significantly reduce the uncertainty in modeling UB agents' adaptation behaviors. For the five LB agents, future research should focus on σ and $\in$ to improve understanding of agents' water consumption variability and reasons to deviate from the agents' normal water consumption patterns. In addition, from Fig. 9, we can see that CO3 and CRIR AZ exhibit very different patterns in both Sobol indices compared to other agents in the sub-basin. Further investigation of these agents' behaviors can be one of the future directions.

When comparing the Morris and Sobol methods results, we observed that the two methods identify different sensitive parameters. The first-order Sobol indices indicate σ and $\in$ as the most influential parameters, the total-order Sobol indices highlight *regret* and α for the UB agents and σ for the five LB agents, and the Morris method predicts the agent's parameter EEs in a cluster. These different results of sensitive parameters confirm that multiple SA methods should be used to investigate ABM efficacy in representing farmers' adaptation behaviors from multiple aspects. Future research can consider exploring the broad spectrum of the SA methods for ABM model diagnosis.

4. Discussion

The results of the three analyses can inform policy development and shed light on future water management and climate adaptation research in the CRB. Below, we discussed the lessons learned from the numerical experiments and the limitations.

4.1. Uncertainty analysis for exploration and improving understanding

Previously in Section 3.1, we have shown that water storage, shortages, and consumption uncertainties at basin level can vary with the scenarios and ABM parameterization (Figs. 2 and 3). To further investigate the adaptation uncertainty effects at the sub-basin level, we summarized the water consumption results of the five scenarios in Figs. 10 and 11 and compared the results with the 2018 water consumption. The boxplots in Fig. 10 indicate the higher water consumption uncertainty in the UB than the LB within and across scenarios. Fig. 11 shows the time series plots of the UB and LB water consumptions in the Q99% scenario stacked on top of the uncertainty band of all five scenarios as an example of the uncertainty propagation through time. In the scenarios (Fig. 10), we can see that the UB water consumption has substantial increases, although in varying degrees, while the LB consumption is always well below the 2018 consumption level. The reasons are twofold. First, the UB water consumption has not yet reached the annual allowance of 9.25 billion m^3, so the UB agents can continue to expand consumption except for the severe drought years (in 2033, 2043, and 2047; Fig. 11). In contrast, the LB consumption in 2018 had already reached the 9.25 billion m^3 allowance, which left limited room for agents to expand their consumption. Second, the severe water shortage in 2033 would deplete the basin storage, which would result in a serious water security crisis for the LB agents for losing the stable water supply from Lake Mead. Moreover, since water in the CRB is originated from the mountain area in the UB, the UB agents will have priority access to the water until its consumption reaches the sub-basin allowance. Consequently, the UB agents can continue to increase water consumption while the LB agents need to curtail consumption due to the limited available water (after 2034, Fig. 11.). However, whether this is an economic and equitable distribution of the water resources under these shortage conditions may require further discussions and renegotiation among the stakeholders in the basin to tackle the water security issues.

4.2. Policy implications for human adaptation and water scarcity

The CRB's first-tier water shortage declaration in August 2021 has stirred discussions on water conservation in the seven states. Consequently, the water supplies to Arizona and Nevada are reduced by 18% and 7% of their total allocations, respectively, starting in 2022, according to the Drought Contingency Plan. Without substantial actions for water conservation, further curtailment would soon be needed, as suggested by the simulation results (Fig. 11). Education programs can be effective tools to promote water conservation by triggering substantial learning that leads to water consumption behavior changes. The coupled model can be applied to assess when we need behavior changes to happen and to what degree. The learning parameters (α, γ, and *regret*) in our ABM control how quickly agents respond to environmental changes. Therefore, we can simulate the desired parameter values and design education programs to facilitate the transition. Moreover, the classification results provide a basis for making assumptions about the evolution of agents' decision-making in response to the policies. The ABM can be applied to assess various policy combinations and assumptions to facilitate the discussion about the evolution in farmers' irrigation behaviors and design policy accordingly to guide and quicken the evolution.

One example could be some education programs that convert *Bold* agents to *Forward-looking* or *Prudent* agents. However, research may be needed to further investigate farmers' attitudes toward climate change to reduce the uncertainties in human behavior modeling (including the model structure and parameter uncertainties) and design education programs to change farmers' perceptions. The coupled ABM-CRSS is suitable for assisting such soft policy designs, as demonstrated in a previous study (Hung and Yang, 2021). Although the soft policy alone

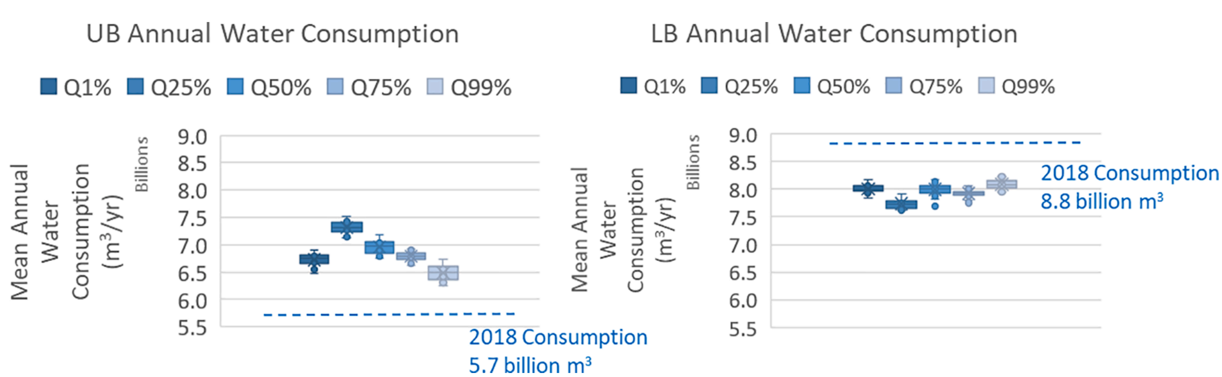


Fig. 10. The UB and LB water consumption uncertainty in the five scenarios. For comparison, the 2018 sub-basin water consumptions (dashed lines) are added to the subfigures as references.

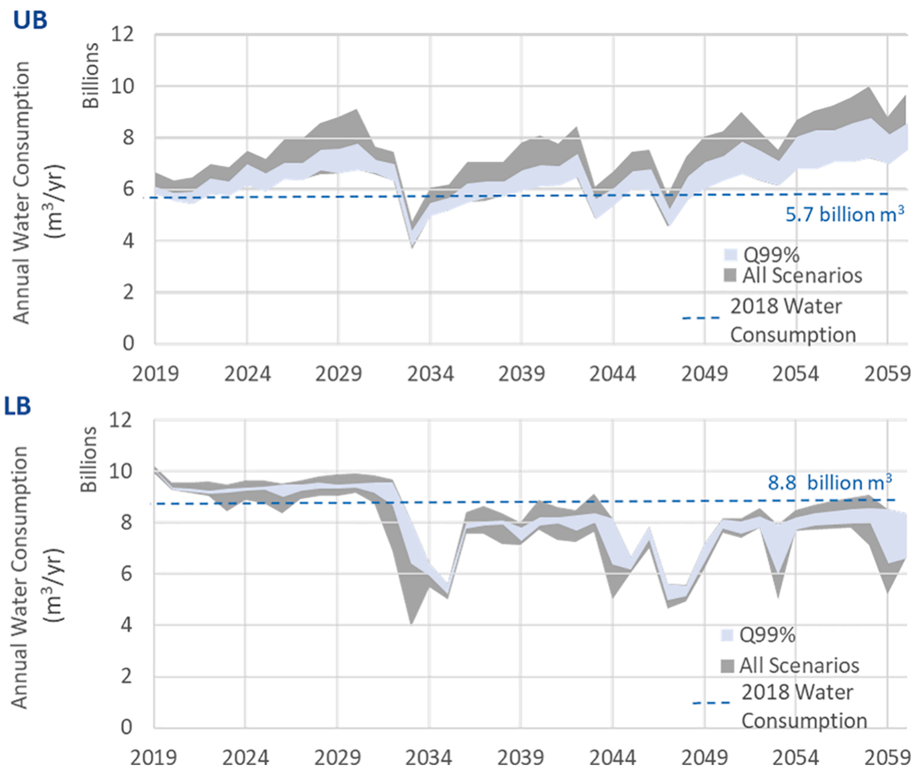


Fig. 11. The annual water consumption uncertainty in the Q99% scenarios stacked on the consumption uncertainty band of all scenarios. The 2018 sub-basin water consumptions (dashed lines) are plotted as references.

may not solve the water scarcity problem, it can delay the decline in water storage for policymakers to generate solutions such as water right allocation renegotiation and water markets.

If the basin continues to stay in drought conditions due to climate change, renegotiation of the water allocation will be needed for adaptation (Gerlak et al., 2021; Udall and Overpeck, 2017). One can only be proactive in tackling the water scarcity problem if one recognizes that the decline in water supply is ongoing and not temporary. Furthermore, the timing of the actions is critical. Early actions to conserve water will help maintain reservoir storage at a more resilient level for climate adaptation and renegotiation. Failing to act promptly will cause an increased risk of depleting reservoirs (as Fig. S4 shows) and drive the basin to intense competition among water users. Our results suggest that it may be time to shift the water management paradigm from "supply-focus" to "risk-focus" to strengthen CRB's adaptation capacity.

4.3. Limitations and future research directions

The ABM applied in this study simulates human decision-making as stochastic processes to account for the inherent randomness and our insufficient knowledge about human behavior. Since the historical data is merely a single realization of many possibilities, the ABM parameterization should be viewed as an assumption of how agriculture irrigation consumption patterns may change in the future. In the uncertainty analysis (Fig. 3), we showed the extent of future water consumption in the CRB could differ from the historical pattern. The results can serve as a basis for future discussions on climate change adaptation and water resources management. Additionally, the modeling results indicate that farmers would actively conserve water after substantial water shortages (box b in Fig. 3). However, in reality, whether the water supply cuts starting in 2022 can trigger farmers' adaptation for water conservation and synchronize the co-evolution of the human and natural systems in the CRB still need to be verified. In fact, studies of human behavioral modeling should be continuous and adaptive. With new data and research findings becoming accessible, we will be able to reduce the water scarcity uncertainty, validate the results, and improve the model's prediction. Regional survey and interview studies can be a complement to the clustering and sensitivity analyses and improve our understanding to reduce epistemic uncertainties.

From the technical perspective, we summarize four future directions for quantifying and managing uncertainties in ABMs. First, sensitivity analyses for coupled ABM-CRSS are computationally expansive for the exponential growth in simulations with the increase of parameters. Future works can consider developing fully integrated models and utilizing High-Performance Computing to improve the accuracy of the sensitivity indices.

Second, many sampled parameter sets performed poorly in the case study due to the model structure uncertainty, and including these parameter sets can obscure the implications of the analysis. Studies suggest applying screening methods to refine behavioral parameter space (Pianosi et al., 2016; Wagener and Pianosi, 2019), yet methods that systematically generate the behavioral parameter space are still not seen in the literature, except for the simple threshold method (Pappenberger et al., 2008). Developing screening methods for sensitivity analyses is one of our future directions.

Third, the results of the clustering analysis may not always be clear-cut. For example, the agents (circles in Fig. 5) located next to the cluster borderlines may exhibit significantly different behaviors than those agents close to the centroid of that cluster. The ambiguity may be partially attributed to the limitations of the K-means clustering method. Future research will apply more sophisticated clustering algorithms, such as Gaussian Mixture Models (Reynolds et al., 2000), to further explore the farmers' characterization.

Finally, our ABM only considers agriculture water use uncertainty and does not include other uncertainties in human systems, such as population growth, crop selections, irrigation practices, agriculture yields, and food preference. Future research may incorporate other decisions and uncertainties in human systems modeling. Additionally, we will consider investigating the impacts of current buy-and-dry practices and water leasing in the CRB on water resources management in the long run.

5. Conclusions

The Colorado River Basin (CRB) is a complex, non-linear, stochastic, and dynamic coupled human-natural system. While those features are recognized in the literature (Sivapalan et al., 2012; Vogel et al., 2015), most modeling studies have focused on the hydrological processes and overlooked the importance of the human counterpart. Such compromises in model development are inevitable due to the presence of high complexity and deep uncertainty (Hadjimichael et al., 2020b; Quinn et al., 2020). With the looming water crisis in the basin, it is critical to incorporate the human response and manage the water scarcity uncertainty in developing climate adaptation policy. This paper complements the existing natural process-focused studies by investigating human-water system interactions and the uncertainties in the human system with three numerical experiments: uncertainty, clustering, and sensitivity analyses. Our contributions include quantifying water scarcity uncertainty in the CRB caused by human adaptation, exploring farmers' decision-making typology based on historical data, and identifying opportunities to reduce model structure and parameter uncertainties in human behavior modeling.

The results of the uncertainty analysis reveal the escalating water scarcity and an urgent need for changes in water management in the basin. The clustering analysis provides probabilistic information on farmers' irrigation behavior characterization in the CRB. Moreover, our results indicate that farmers in the Upper Basin tend to change their water uses in response to climate signals, whereas, in the Lower Basin, farmers are more cautious in adjusting their water uses. Our findings in clustering analysis suggest that water conservation programs can be more effective if we tailor management programs based on farmers' characteristics. The sensitivity analyses highlight the opportunity for future research on human behavioral modeling in the CRB. Findings from the Morris SA indicate a need to review the ABM structure for agents with highly sensitive or insensitive parameters (e.g., HopiTribe and Powers). Whereas the Sobol SA quantifies individual parameters' contribution to the outcome uncertainty, thus signifying the potential for uncertainty reduction. Although the results of these analyses may not be directly applicable to policy-making yet, they form a foundation for policy discussion regarding human response and adaptation.

Furthermore, modeling human adaptation and quantifying the uncertainty of the co-evolution in coupled human-natural systems are critical research fields for coping with water scarcity issues in major river basins. We demonstrated that the uncertainty, clustering, and sensitivity analyses could be applied to coupled human-natural system models to quantify and manage the uncertainty. Our immediate future work will focus on improving human behavior modeling and scenario selection design for water scarcity uncertainty analysis. Another future research direction is to include climate uncertainty to provide a holistic view of water scarcity in the CRB.

CRediT authorship contribution statement

Fengwei Hung: Conceptualization, Methodology, Software, Visualization, Writing – original draft. **Kyongho Son:** Conceptualization, Methodology. **Y. C. Ethan Yang:** Supervision, Writing – review & editing.

Declaration of Competing 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2022.128015.

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