Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-555
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 2 January 2019
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Develop a coupled agent-based modeling approach for uncertain water management decisions

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Abstract

Managing water resources in a complex adaptive natural-human system is subject to a challenging task due to the difficulty of modeling human behavior and decision uncertainty. The interaction between human-engineered systems and natural processes needs to be modeled explicitly, and a formal approach is required to characterize human decision-making processes and quantify the associated uncertainty caused by incomplete/ambiguous information. In this study, we "two-way" coupled an agent-based model (ABM) with a river-routing and reservoir management model (RiverWare) while ABM uses a bottom-up approach that allows individual decision makers to be defined as agents – each able to make their own decisions based on their objectives and confidence in the acquired information. The human decision-making processes is described in the ABM using Bayesian Inference (BI) mapping joined with a Cost-Loss (CL) model (BC-ABM). Incorporating BI mapping into an ABM allows an agent's internal (psychological) thinking process to be specified by a cognitive map between decisions and relevant preceding factors that could affect decision-making. The associated decision uncertainty is characterized by a risk perception parameter in the BI mapping representing an agent's belief on the preceding factors. Integration of the CL model addresses an agent's behavior caused by changing socioeconomic conditions. We use the San Juan River Basin in New Mexico, USA to demonstrate the utility of this method. The calibrated BC-ABM-RiverWare model is shown to capture the dynamics of historical irrigated area and streamflow changes. The results suggest that the proposed BC-ABM framework provides an improved representation of human decision-making processes compared to conventional rule-based ABMs that does not take uncertainties into account. Future studies will focus on modifying the BI mapping to consider direct agents' interactions, up-front cost, joint human and natural uncertainty evaluation, and upscaling the watershed ABM to the regional scale.

Keywords: Risk perception, Bayesian Inference Mapping, Cost-Loss Model, Coupled natural-human systems, Energy-Water Nexus

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1. Introduction

Managing water resources for growing demands of energy and food while sustaining the environment is a grand challenge of our time, especially when we are dealing with a complex adaptive natural-human system that subject to various sources of uncertainties. Nowadays, almost every major basin in the world can be considered as a coupled natural-human system (CNHS) where heterogeneous human activities are affecting the natural hydrologic cycle and vice versa (Liu et al., 2007). The interaction between human activity and the natural environment needs to be explicitly addressed, and the uncertainty within this complex system characterized according to a formal approach if benefits toward improved water resource management (Brown et al., 2015) are to be realized.

Recently, agent-based modeling (ABM) has become a commonly used tool in the scientific community to address CNHS issues. An ABM framework identifies individual actors as unique and autonomous "agents" that operate according to a distinct purpose. Agents follow certain behavioral rules and interact with each other in a shared environment. By explicitly representing the interaction between human agents (e.g., farmers) and the environment (e.g., a watershed) where they are located, ABM provides a natural "bottom-up" setting to study transdisciplinary issues in CNHS. Applying ABM approach in water resources management began a decade ago and became a popular topic in CNHS analyses (Berglund, 2015; Giuliani et al., 2015; Giuliani and Castelletti, 2013; Hu et al., 2017; Khan et al., 2017; Mulligan et al., 2014; Schlüter et al., 2009; Yang et al., 2009; Yang et al., 2012; Zechman, 2011).

However, one major challenge of applying ABM approach to water management decisions arise from the difficulty of adequetly characterizing human decision-making processes and meet real-world management intuition. The traditional approach through, for example, survey or

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interview with local decision makers is extremely limited (e.g., Manson and Evans, 2007) in space and time. Therefore, this study introduces the Theory of Planned Behavior (TPB), a well-known theory in psychology used to predict human behavioral intention and actual behavior (Ajzen, 1991), into ABM framework to quantify human decision-making processes. The TPB states that an individual's beliefs and behaviors can be expressed in terms of a combination of attitude toward behavior, subjective norms, and perceived behavioral control. Attitude toward behavior and subjective norms specify an individual's perceptions of performing a behavior affected by its internal thinking processes and social normative pressures, while perceived behavioral control describes the effects from external uncontrollable factors (e.g., socioeconomic conditions). If an individual has high belief about making a specific decision, then it has an increased confidence that s/he can perform the specific behavior successfully. On the other hand, the tendency of a person for making a specific decision increases/decreases if social normative pressures decrease/increase.

Implementating the TPB into ABM requires that all the three components to be modeled explicitly. In this study, we adapt the Bayesian Inference (BI) mapping (Pope and Gimblett, 2015) and the Cost-Loss model (CL) (Thompson, 1952) for this task. The BI mapping (also called Bayesian networks, belief networks, Bayesian belief networks, causal probabilistic networks, or causal networks), built on the Bayesian probability theory and cognitive mapping, calculates the likelihood that a specific decision will be made (Sedki and de Beaufort, 2012 via Pope and Gimblett, 2015) while sequentially updating beliefs of specific preceding factors (model parameters) as new information is acquired (Dorazio and Johnson, 2003). By applying the BI mapping, an individual's beliefs affected by its internal thinking processes and perceptions of social normative pressures can be described as a cognitive map between decisions and relevant

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preceding factors. Ng et al. (2011) developed an ABM using BI to model the farmer's adaptation of their expectations (or belief) and uncertianties of future crop yield, cost, and weather. Yet the preceding factors were assumed to be independent of each other, which is not always true especially if two preceding factors are spatially related (e.g., downstream reservoir elevation and upstream precipitation). More importantly, the internal thinking processes of all farmers were assumed to be the same (i.e., no spatial heterogeneity is modeled). As a result, a more realistic framewok of applying BI to ABM is still needed to improve representation of human decision-making processes.

While BI mapping specifies the human psychological decision-making process, CL model addresses the effect of external socioeconomic conditions on an individual's decision-making (i.e., perceived behavioral control in the TPB). CL model is frequently used as a simple decision-making model in economic analysis to quantify human decision-making according to economic theory (Thompson, 1952). CL modeling has been widely used in estimating the economic value of weather forecasts (Keeney, 1982; Lee and Lee, 2007; Murphy, 1976; Murphy et al., 1985). Tena and Gómez (2008) and Matte et al. (2017) incorporated the Constant Absolute Risk Aversion theory in CL modeling to evaluate risk perception of decision makers since the original CL model assumes a risk-neutral decision maker. They used a parameter, Arrow-Pratt coefficient, to represent "risk-averse" and "risk-seeking" decision makers but did not specify how this parameter could be determined. They also did not clarify what will happen if different decision makers in the system have different perceptions of risk (again, no spatial heterogeneity).

Evaluating uncertainty in CNHS is another challenge. For example, uncertainties involve in the water resources decision making include errors in measurement and sampling of natural systems, environmental variability, or incomplete knowledge of others behavior (Dorazio and

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Johnson, 2003). Previous studies have demonstrated that quantitative information of uncertainty can facilitate water resouce management in terms of selecting strategies, reduce implementation cost, and adapt more effectively to unexpected changes in circumstances (e.g., Singh et al., 2010a). Uncertainty in water resource management can be divided into two basic terms: variability and ambiguity (Vucetic and Simonović, 2011). The variability describes the uncertainty in relation to the inherent physical characteristics of water resources systems (i.e., hydrologic variability), while ambiguity is the uncertainty in human decision-making processes caused by a fundamental lack of knowledge or ambiguous information (Simonović, 2009).

Efforts of quantifying uncertainty in water resources management intensified in the 1980s (Rogers and Fiering, 1986). Given the difficulty of modeling human behavior and decision uncertainty (Loucks, 1992; Schlüter et al., 2012), previous studies have largely focused on characterizing uncertainties associated with hydrologic variability such as climate (Hall et al., 2012), surface water (Herman et al., 2014) and groundwater (Singh et al., 2010b). Optimal management schemes like robust decision making (Lempert and Collins., 2007) and decision scaling (Brown et al., 2012) have been developed to address uncertainties common to the natural environment. In contrast, only a handful of existing studies adequately addresses the human decision uncertianty caused by incomplete or ambiguous information. Quantifying these uncertainties faces the fundamental challenge of understanding how the brain combines “noisy” sensory information with prior knowledge to perceive an act in the natural world (Huang et al., 2012). As a result, the human decision uncertainty caused by ambiguous or incomplete knowledge has been either neglected or simplified and remain a vital issue for sustainable water resources management (Fulton et al., 2011; Schlüter et al., 2017).

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To address all these research gaps aforementioned, we developed an ABM based on the BI mapping and CL model, as an implementaiton of the TPB, and referred to as the BC-ABM. The BC-ABM is "two-way" coupled with a river-routing and reservoir management model (RiverWare) following an emerging research topic in Earth system modeling (Di Baldassarre et al., 2015; Troy et al., 2015) and water resources system analysis (Denaro et al., 2017; Giuliani et al., 2016; Khan et al., 2017; Li et al., 2017; Mulligan et al., 2014) about coupled modeling approach. Utilizing BI mapping in an ABM allows the agents' internal thinking processes and assocaited decision uncertainty to be accommodated in the agent rules as well as explicitly represented in the causal reasoning behind an agent's internal (psychological) decision-making (Kocabas and Dragicevic, 2013) while the CL model informs the agent's actions under changing socioeconomic conditions (Murphy, 1976; Spiegelhalter et al., 1993). The San Juan River Basin in New Mexico, USA is used as the demonstration basin for this effort. The calibrated BC-ABM-RiverWare model is used to evaluate impacts of uncertain risk preception from all agents in this basin. In this study, multiple comparative experiments of conventional rule-based ABM (i.e., without using the BL and CL) are conducted to demonstrate the advantages of the proposed BC-ABM framework in modeling human decision-making processes. We also evaluate the effect of changing external economic conditions on an agent's decisions.

The paper is structured as follows. We introduce our methodology in Section 2. The background of the case study area: the San Juan River Basin is presented in Section 3. We show the calibration and different scenario results of the coupled BC-ABM-RiverWare model in Section 4 (Results). The institutional context as well as model limitation and future work are discussed in Section 5 (Discussion) followed by the Conclusion Section.

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2. Methodology

2.1. Develop a "two-way" coupled ABM-RiverWare model

River-routing and reservoir management modeling is designed to simulate the deliveries of water within a regulated river system (Johnson, 2014). Many river-reservoir management models have been developed to address different objectives within a geographic region such as MODSIM, RiverWare, CALSIM (Draper et al., 2004), IQQM (Hameed and O'Neill, 2005), and WEAP (Yates et al., 2005). These models use a "node-link" structure to represent the entire river network where "nodes" are important natural (sources, lakes, and confluences) or human (water infrastructures and water withdrawals) components and "links" represent river channel elements.

RiverWare, developed in 1986 by the University of Colorado Boulder, is a model of water resource engineering system for operational scheduling and forecasting, planning, policy evaluation, and other operational analysis and decision processes (Zagona et al., 2001). It couples watershed and reach models that describe the physical hydrologic processes with routing and reservoir management models that account for water use for water resources assessment. RiverWare has a graphic user interface and uses an object-oriented framework to define every node in the model as an "Object." Each object is assigned a unique set of attributes. These attributes are captured as "Slots" in RiverWare. There are two basic types of slots: Time Series and Table Slots for each Object to store either time series or characteristic data. Details of RiverWare structure and algorithm can be found at Zagona et al. (2001) and its website: http://www.riverware.org/.

Coupling an ABM with a process-based model has been done before but mostly focused on groundwater models such as Hu et al. (2017) and Mulligan et al. (2014). One of the few examples that involve coupling with a surface water model, Khan et al. (2017) developed a simple

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ABM that coupled with a physically-based hydrologic model, Soil and Water Assessment Tool. In this paper, we perform a two-way coupling (data transfer back and forth between ABM and RiverWare) between an ABM and RiverWare, where selected Objects in RiverWare are defined as agents. To facilitate the two-way coupling, we utilize a convenient built-in tool within RiverWare: the data management interface (DMI) utility which allows automatic data imports and exports from/to any external data source (RiverWare Technical Documentation, 2017, see also Figure S1).

2.2.Quantify planned behavior with BI mapping and CL model

The ABM developed in this paper, as an implementation of the TPB, consists of two components: the Bayesian Inference (BI) mapping and the Cost-Loss (CL) modeling. This unique setting allows us to explicitly describe human decision-making processes and asscociated uncertainty casued by information ambiguity in water management decisions. We describe the details in this section.

2.2.1. The Bayesian Inference (BI) Mapping

In this study, the Bayesian Inference (BI) mapping is applied to specify a decision maker's (or agent's) internal thinking processes by building a cognitive map (also called a causal structure) between decisions (or taking a specific management behaviors) and relevant preceding factors that could affect decision-making (Dorazio and Johnson, 2003; Pope and Gimblett, 2015). In this setting, the goal of an agent is to develop a decision rule (or management strategy) that prescribes management behaviors for each time step that are optimal with respect to its objective function. The uncertainty associated with these management behaviors, arise from ambiguity, is specified by a "risk perception" parameter (Baggett et al., 2006; Pahl-Wostl et al., 2008) representing the

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extent to which decision-makers explicitly consider limited knowledge or belief about (future) information in their decision-making process (Müller et al., 2013; Groeneveld et al., 2017). This is the definition of Knightian uncertainty which comes from the economics literature where risk is immeasurable or the probabilities are not known (Knight, 1921).

In the field of water resource management, a decision is often made based on whether the preceding factor is larger (or less) than a prescribed threshold (i.e., exceedance). A simple example is that a farmer' belief of changing the irrigation area will be affected by the forecast of water stored in an upstream reservoir at the beginning of the growing season (i.e., water availability). In this study, both the forecast of a certain preceding factor f (a random variable) and an agent's belief of taking a specific management behavior (or making a decision) θ can be represented as probabilities shown in Equations (1) and (2):

$$P(f) = \frac{\#\ of\ events\ that\ a\ preceding\ factor\ exceeds\ threshold}{\#\ of\ total\ events\ \ in\ modeling\ period} \tag{1}$$

$$P(\theta) = \frac{\#\ of\ events\ of\ taking\ a\ management\ action\ (=make\ decision)}{\#\ of\ total\ events\ \ in\ modeling\ period} \tag{2}$$

The conditional probability as represented in Equation (3) describes the probability of a preceding factor exceeding its threshold given a specific decision was made.

$$P(f|\theta) = \frac{P(f \cap \theta)}{P(\theta)} \tag{3}$$

The conditional probability obtained in Equation (3) is then used to calculate the joint probability of both the preceding factor exceeding its threshold and a particular decision being made (Equation 4).

$$P(\theta \cap f) = P(f|\theta) \times P(\theta) \tag{4}$$

Alternatively, the joint probability can be computed with Equation (5).

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$$P(f \cap \theta) = P(\theta|f) \times P(f) \tag{5}$$

Since the left-hand side of Equation (4) and (5) are mathematically equivalent, we can write their right-hand side as

$$P(f|\theta) \times P(\theta) = P(\theta|f) \times P(f) \tag{6}$$

Rearranging Equation (6) provides a solution to $P(\theta|f)$ by Equation (7)

$$P(\theta|f) = \frac{P(f|\theta) \times P(\theta)}{P(f)} \tag{7}$$

The marginal probability can be written as:

$$P(f) = P(f \cap \theta) + P(f \cap \theta^c) \tag{8}$$

where θ^c means that the management behavior was not made. $P(f \cap \theta)$ is the probability of the preceding factor exceeding its threshold when the decision was made, while $P(f \cap \theta^c)$ is the probability of the preceding factor exceeding its threshold when the decision was not made. Substituting Equation (8) into Equation (7):

$$P(\theta|f) = \frac{P(f|\theta) \times P(\theta)}{P(f \cap \theta) + P(f \cap \theta^c)} \tag{9}$$

Equation (9) can be rewritten by expanding $P(f \cap \theta)$ and $P(f \cap \theta^c)$,

$$P(\theta|f) = \frac{P(f|\theta) \times P(\theta)}{P(f|\theta)P(\theta) + P(f|\theta^c)P(\theta^c)} \tag{10}$$

where $P(\theta^c) = 1 - P(\theta)$ is the probability of not taking the management behavior θ. In our case, the information of f is coming from RiverWare to ABM and θ is the result the ABM sends back to RiverWare.

Equation (9) represents the probability of θ being made when the preceding factor exceeds the given threshold. Similarily, θ being made when the preceding factor does not exceed the threshold (f^c) may be expressed as

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$$P(\theta|f^c) = \frac{P(f^c|\theta) \times P(\theta)}{P(f^c|\theta)P(\theta) + P(f^c|\theta^c)P(\theta^c)} \tag{11}$$

The overall probability of taking a management behavior $P(\theta)$ relying on the preceding factor f can be written using the law of total probability

$$P(\theta) = P(\theta|f) \times P(f) + P(\theta|f^c) \times P(f^c) \tag{12}$$

A solution of $P(\theta)$ can be obtained by substituting Equations (10) and (11) into (12)

$$P(\theta) = \frac{P(f|\theta) \times P(\theta)}{P(f|\theta)P(\theta) + P(f|\theta^c)P(\theta^c)} \times P(f) + \frac{P(f^c|\theta) \times P(\theta)}{P(f^c|\theta)P(\theta) + P(f^c|\theta^c)P(\theta^c)} \times P(f^c) \tag{13}$$

A general form of Equation (13) can be written as (Shafiee-Jood et al., 2017)

$$P(\theta) = \sum_i P(\theta|F_i) \times P(F_i) = \sum_i \frac{P(F_i|\theta)P(\theta)}{\sum_j P(F_i|\Theta_j)P(\Theta_j)} \times P(F_i) \tag{14}$$

where $F_i \in [f, f^c]$, $\Theta_j \in [\theta, \theta^c]$. In this study, we re-name the variables in Equation (13) as follows

$$\begin{cases} \Gamma_{pr} = P(\theta) \\ \Gamma_{pd} = P(f) \\ \lambda = P(f|\theta) \end{cases} \tag{15}$$

where Γ_{pr} represents the decision maker or agent's prior belief of θ, Γ_{pd} the probabilistic forecast of preceding factor f, λ the rate of acceptance of new information which represents a decision maker's belief about the received information from f (belief of the forecast/measurement accuracy representing the degree of ambiguity of f).

By applying the BI theory to Equation (13) with the expressions in Equation (15), the agent's prior belief of θ, Γ_{pr}^t at time t can be expressed as

$$\Gamma_{pr}^t = \frac{\lambda\Gamma_{pr}^{t-1}}{\lambda\Gamma_{pr}^{t-1} + (1-\lambda)\left(1-\Gamma_{pr}^{t-1}\right)}\Gamma_{pd}^t + \frac{(1-\lambda)\Gamma_{pr}^{t-1}}{(1-\lambda)\Gamma_{pr}^{t-1} + \lambda\left(1-\Gamma_{pr}^{t-1}\right)}\left(1-\Gamma_{pd}^t\right) \tag{16}$$

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In Equation (16), the agent's prior belief of θ at timestep t, Γ_{pr}^{t}, is updated based on the prior belief at previous timestep $t-1$, Γ_{pr}^{t-1}, and new incoming information or forecast at time t, Γ_{pd}^{t}. Γ_{pr}^{t} lies in between Γ_{pr}^{t-1} and Γ_{pd}. Two extreme cases are described here. When $\lambda = 1$, Equation (16) reduces to $\Gamma_{pr}^{t} = \Gamma_{pd}^{t}$, which indicates that the agent's belief of taking management behavior is purely based on the new incoming information, which corresponds to a risk-seeking decision maker. In contrast, when $\lambda = 0.5$, Equation (16) becomes $\Gamma_{pr}^{t} = \Gamma_{pr}^{t-1}$ suggesting that a decision is made based on an agent's previous experiences alone (i.e., the decision maker's most recent experience). This means that we have a risk-averse decision maker who totally ignores the new incoming information (or no information arrived) and strictly makes his/her decision based on his/her previous belief. In this study, the Γ_{pr}^{t} in Equation (16) at each time step is updated by applying the Bayesian probability theory to Γ_{pr} between two consecutive time steps to take the temporal causality between the two decisions into account.

In most water resources management cases, multiple preceding factors affect the probability of a single management decision. In this paper, we assume that agents will make a decision based on the most "highly recognized" preceding factor following the suggestion from Sharma et al. (2013). The fundamental assumption is that a decision-maker will pay the closest attention to the most abnormal of any preceding factors, such as the severity of droughts or floods, historic low or high water levels of an upstream reservoir or an extreme upstream water diversion. The way we represent this tendency is by calculating the "extremity" factors (V) of preceding factors

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \tag{17}$$

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where θ_i is the i^{th} preceding factor and θ_{max} is the maximal value of θ_i. After the extremities of all preceding factors have been calculated, agent will select the preceding factor with the highest V_i to update the prior belief of management actions based on Equations (16).

2.2.2. The Cost-Loss (CL) Model

The BI mapping method described in Section 2.2.1 characterizes an agent's behavioral intentions related to its internal (psychological) decision-making processes. According to the TPB, a real-world management decision or action also depends on external uncontrollable factors such as socioeconomic conditions. The CL model is applied in this study to address this concern. The CL model measures the tendency of an adverse event affecting the decision of whether to take costly precautionary action to protect oneself against losses from that event. Based on the theory of Cost-Benefit Analysis, if such event does not occur, the expected cost of taking action is "C" and the expected loss of not taking action is "L". On the other hand, if such event does occur (with a probability of p), the expected cost of taking action is still "C" and the expected loss ("L") of not taking action is "$p \times L$." It follows that for one to take precautionary action, the expect cost of taking that action should be less than the expected loss:

$$C \leq pL \tag{18}$$

Where Equation (18) can be rewritten as

$$z = \frac{C}{L} \leq p \tag{19}$$

where z is defined as the Cost-Loss (CL) ratio and only when this value is less the probability of the event occurring, the precautionary action will be taken.

To fit the CL model into the proposed ABM framework, we modify the above CL model following the concept of Tena and Gómez (2008) and Matte et al. (2017) which added the

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perception of risk into the decision-making process. We define "C" as the expected cost of taking management action that will potentially increase the gross economic profit and "L" as the expected opportunity loss of not taking such management action. The ratio of C to L (CL ratio z), as a measure of tendency, can be compared with the prior belief of an agent's for taking a management decision (Γ_{pr}^{t} in Equation 16). When Γ_{pr}^{t} is greater than z, this decision will become real world management action since it makes economic senses.

$$\Gamma_{pr}^{t} \geq z = \frac{C}{L} = \frac{the\ expected\ cost\ of\ taking\ management\ action}{opportunity\ loss\ of\ not\ taking\ management\ action} \tag{20}$$

When z increases, it means the cost of taking management action goes up or the opportunity loss of not taking management action goes down. In either case, agents are less likely to take action due to reduced profits. When z decreases, following the same logic, agents are more likely to take action.

Figure 1 summarizes the methodology in Section 2.2 applied to this study. Agent's decision-making and action process will start when receiving information (Γ_{pd}^{t}) from RiverWare and the conditional probability of its decision Γ_{pr}^{t} will be computed after the most "highly recognized" preceding factor is decided by the V_i values. This probability of an agent's decision will be compared with the CL ratio (z) to account for the external economic conditions where the agent is located. The final management action from the agent will depend on whether the probability of making a decision for an agent's is greater (take the action) or smaller (do not take the action) than the CL ratio. This process is repeated annually throughout the entire simulation period.

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3. Case Study

3.1. Study Area

The San Juan River Basin (Figure 2) is the largest tributary of the Colorado River Basin with a drainage area of 64,570 km^2. Originating as snowmelt in the San Juan Mountains (part of the Rocky Mountains) of Colorado, the San Juan River flows 616 km through the deserts of northern New Mexico and southeastern Utah to join the Colorado River at Glen Canyon. Most water use activities are located in the upper part of the San Juan River Basin inside the States of New Mexico and Colorado. There are sixteen major irrigation ditches, four cities and two power plants (Figure 2) located in this basin and the water for which the San Juan River is the primary source. Major crops grown in the basin include hay, corn, and vegetables and the main planting season runs from May to October (Census of Agriculture – San Juan County, New Mexico, 2012). Navajo Reservoir, located 70 km upstream of the City of Farmington, NM is the main water infrastructure in the basin (Figure 2) which is used for flood control, irrigation, domestic/industrial water supply and environmental flows. The reservoir is designed and operated by the U.S. Bureau of Reclamation (USBR) following the rules in Colorado River Storage Project (Annual Operating Plan for Colorado River Reservoirs, 2017). The active storage of the reservoir is 1.3 million acre-ft (1.6 billion m^3). The maximum release rate is limited to 5000 cfs.

Beside the 16 major irrigation ditches, the Navajo Indian Irrigation Project (NIIP) is one another major water consumption within the basin that provides water to tribal communities in the region. San Juan-Chama Project manages transbasin water transfers into the Rio Grande Basin augmenting supply for Albuquerque, NM, irrigation and instream flow needs. Finally, the San Juan River Basin Recovery Implementation Program (SJRIP) implemented by the Fish and Wildlife Service, manages environmental flows within the basin, dictating timing and magnitude

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of releases from Navajo Reservoir and maintainance of a daily 500 cfs minimum streamflow requirement (Behery, 2017). Water rights within the San Juan River Basin in New Mexico have not been completely adjudicated (see more details in Section 5.1). To address this gap, ten of the largest water users have cooperated to develop a shortage sharing agreement to keep Navajo Reservoir from drawing down the reservoir pool elevation below 5990 ft, which is the elevation required for NIIP diversion. The agreement stipulates that all parties share equally in shortages caused by drought (2013-2016 shortage agreement is available at: https://www.fws.gov/-southwest/sjrip/DR_SS03.cfm).

3.2. The Coupled ABM-RiverWare Model Setup

USBR developed a RiverWare model for the San Juan River Basin to support water management and resource planning efforts. RiverWare includes 19 irrigation ditches objects, 21 domestic and industrial use objects, two power plant objects and three reservoir objects. Input data for the RiverWare model include historical tributary inflows, evapotranspiration rates for each irrigation ditches limited by the crop water requirement, historic water diversion for NIIP and the San Juan-Chama Project, and reservoir operations rules. Ungaged local inflows were determined by the simple closure of the local water budget. The model operates on a daily time step from 10/01/1928 to 09/30/2013 (85 years) with four “cycles” of simulation. Each cycle is a complete model run for the entire modeling period to fulfill part of the necessary information (e.g., some downstream water requirements need to be pre-calculated for Navajo Reservoir to set up the release pattern). Shortage sharing is handled at Cycle 3 and Cycle 4 of the model run. In Cycle 3, if the water level in the Navajo Reservoir at the end of a water year (23:59:59 at September 30th) is lower than the threshold (5990 ft above sea level) , RiverWare will mark the coming year as a “water shortage year.” Then, in Cycle 4, shortage sharing rules dictate Navajo Reservoir

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-555
Manuscript under review for journal Hydrol. Earth Syst. Sci.
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Operations and water deliveries to basin water users. Effectively, Cycles 1 to 3 determine the volume of water available for use such that environmental flows are achieved and Navajo Reservoir levels are maintained above 5990 ft. Where the available supplies are less than the desired use, all users share equally in the shortage.

In this study, the 16 major irrigation ditch objects in RiverWare are defined as agents. At the end of every water year, each of the 16 agents decided whether to expand or reduce their irrigated area for the coming year. We categorized the 16 agents into three groups based on their location (colored in Figure 2). Agents in Group 1 (light blue) were located upstream of the Navajo Reservoir; Group 2 (light green) were located on the Animas River (a major tributary of the San Juan River), and Group 3 (orange) were located downstream of the Navajo Reservoir.

The BI mapping was applied to each group with different causal structures. The preceding factors that affected Group 1 agents' decisions are: (Navajo) upstream winter precipitation, the water level in Navajo Reservoir and flow violations at the basin outlet (days below 500 cfs in a water year). Group 2 agents consider local (Animas River) winter precipitation, upstream winter precipitation, the water level in Navajo Reservoir and flow violations at the basin outlet. Group 3 agents consider local (downstream of Navajo Reservoir) winter precipitation, upstream winter precipitation, the water level in Navajo Reservoir, flow violations at the basin outlet, and NIIP diversions. The agents' information is listed in Table 1. In this study, flow violation at the basin outlet and water level of Navajo Reservoir are two representative factors of social normative pressures as it is considered by all the three groups of agents. In contrast, other factors reflect the diverse internal thinking processes among agent groups due to their geographical locations. Note that the information of winter precipitation was not taken from RiverWare; rather, was gathered from NOAA ground-based rainfall monitoring gauges where we used the coming year's winter

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-555
Manuscript under review for journal Hydrol. Earth Syst. Sci.
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precipitation as a proxy for the snowpack forecast in the causal structure. Agents that participated in the shortage-sharing plan are also considered if a shortage had been declared. If a shortage were declared, the RiverWare model would reduce the targeted streamflow at the basin outlet to 250 cfs. The participating six agents adjust their water diversion to achieve this newly targeted streamflow under these extreme drought conditions. Under the current setting, agents follow the "backward-looking, forward-acting" mode, which means that agents make decisions based on their own past/current experiences (water level in Navajo Reservoir, stream flow violations at the basin outlet, NIIP water diversion, and the previous decision on the irrigated area) and their belief of the winter precipitation forecast in the coming year.

The detailed causal structure of BI mapping for each type of agent are given in the supplemental material where a standard "Overview, Design concepts, and Details" (ODD) protocol for ABM development is followed as suggested by Grimm et al. (2010). Finally, the data transfer from RiverWare to ABM at the end of a water year included 1) irrigation areas for the 16 irrigation agents, 2) the basin outflow, 3) water level in the Navajo Reservoir and 4) the NIIP water diversion. Following the ABM simultaion, data transfer from ABM to RiverWare included 1) updated irrigated areas and 2) the corresponding water diversion of each agent.

3.3. ABM-RiverWare Model Calibration

One of the major criticisms of ABM development is that ABM results are difficult to verify or validate (Parker et al., 2003; An et al., 2005, 2014; National Research Council, 2014). In this study, we address this concern by calibrating the coupled BC-ABM-RiverWare model to match the historical patterns of 1) individual agent's irrigated area and 2) San Juan River discharge. USBR provides the observed irrigated acreage for all 16 ditches and the flow measurements at two

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different locations along the San Juan River (at the outlet of the San Juan River Basin and directly downstream of the Navajo Reservoir) for calibration purpose.

The calibrated parameters related to an agent's decision-making processes are the risk perception parameters (λ) and CL ratio (z) of each individual agent. In this study, each agent has four λs characterized by the relative geographical location with considered preceding factors. Unique values of λ are assigned to each preceding factor for each agent (through calibration) as different agents should have different levels of risk tolerance for each preceding factor. Different values of z are assigned to each agent representing the spatial heterogeneity of socioeconomic conditions. z is assumed to be constant for each agent throughout the model period as relative up-front cost information is unavailable. We also calibrate the irrigated areal increment of each agent to quantify the capability of different farmers for expanding or reducing their farmland. The actual irrigation area change at each year for each farmer is specified by the calibrated irrigated areal increment with an added uncertainty of 30% representing the execution uncertainty of farmers. The thresholds of each preceding factor are also calibrated for calculating the extremities. A total of 102 parameters (Table 1) are manual calibrated ("trial-and-error") for this specific case in this study and further explained in the supplement materials. In general, we calibrated the parameters sequentially from upstream and tributary agents (i.e. Groups 1 and 2) to downstream (i.e. Group 3). Within a group, we calibrated agents with larger irrigated area first to capture a better system-wide result.

4. Result

4.1. BC-ABM-RiverWare Model Diagnostics

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The BC-ABM calibration results for individual agent's irrigated area from 1928 to 2013 are given in Figure 3 and arranged by group (region). The blue curves are the historical irrigated area. The red curves are the best-fit result among multiple (30) modeling runs (shown by the gray curves, which represents the stochasticity) of each agent. In general, BC-ABM captures the pattern and trend of irrigated area for all agents, and we particularly focus on agents with the largest irrigated areas since their decision can dominate the basin. A figure showing the time variations of extremity values for each group of agents is given in the Supplementary Materials (see Figure S2) to illustrate the preceding factors adopted by different groups of agents for making decision at each time step.

The overall (area) weighted Nash-Sutcliffe Efficiency (NSE) of the best-fit result is 0.55 which represents a reasonable calibration result. There are a few cases where structural changes occurred with some of the ditches that the model does not capture. Specifically, construction of Navajo Reservoir in the 1960 inundated the New Mexico Pine River Ditch, while construction of the dam made it possible to expand the Hammond Irrigation Ditch (located directly downstream of Navajo Reservoir). Similar structural changes are evident with the Echo, New Mexico Animas and Fruitland-Cambridge Ditches. The model limitation associated with the use of BI mapping in ABM is discussed in the Discussion Section.

To demonstrate the enhanced performance of the proposed BC-ABM framework in representing human decision-making processes, we conducted comparative experiments with conventional rule-based ABMs, which exclude the BI mapping and CL ratio, referred to as the Non-BC-ABMs. In the Non-BC-ABMs, agents make decision based on either past experience (e.g., flow violation or NIIP diversion) or future forecast (winter precipitation) alone implying that agents have a perfect foresight in received information. Using precipitation as an example, an agent

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will expand irrigation area if the precipitation forecast is greater than the given threshold, and vice versa. Excluding BI mapping implies that the agents make decision purely based on the forecast or new incoming information and fully ignore the information from past experience, while excluding CL model means that the agents do not take socioeconomic factors into account when making decisions.

Multiple Non-BC-ABMs, in terms of considering different preceding factors and including/excluding extremity in decision-making processes, were tested and results are also shown in Figure 3. The black solid curve represents the Non-BC-ABM simulation utilizing extremity for selecting the reference preceding factor, while the black dashed curve is the Non-BC-ABM using only the precipitation in the decision-making processes. The better performance of the proposed BC-ABM framework, compared to the Non-BC-ABMs, is evidenced by the closer agreements between the simulated and historical patterns of irrigated area from BC-ABM as well as weighted NSE (0.55 for BC-ABM vs. -1.25 for the Non-BC-ABM with extremity and -1.39 for the Non-BC-ABM with precipitation alone). Different Non-BC-ABM simulations are also compared with the BC-ABM simulations as shown in Figure S3. The time variations of Γ_{pr}^{t} and calibrated z for each agent are shown in Figure 4 to illustrate the characteristics of different agents, in terms of risk perception. The results show that the agents in Group 1 and 2 have a consistently lower willingness to adjust irrigation area (Γ_{pr} shown in red) compared to the corresponding CL ratio (z shown in black). In contrast, Group 3 agents adjust irrigation area more often as evidenced by the frequent crossover between red and black curves, which suggest that agents in Group 3 are relatively risk-neutral compared to those in Group 1 and 2.

The calibration results of basin outflow and Navajo Reservoir inflow from 1928 to 2013 are given in Figure 5. The results show that the simulated values of both quantities agree closely

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-555
Manuscript under review for journal Hydrol. Earth Syst. Sci.
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with the historical observations evidenced by the NSEs of 0.60 and 0.54, respectively. The multi-objective calibration conducted in this study can capture not only human agents' activities but also the basin level water balance. On the other hand, multi-objective calibration also reduces the potential equifinality (Beven, 2006) resulting from a large number of model parameters and a limited number of observations, especially for a high-dimensional complex system such as CHNS (e.g., Franks et al., 1998; Kuczera and Mroczkowski, 1998; Yapo et al., 1998; Choi and Beven, 2007). We do notice that our coupled BC-ABM-RiverWare simulation misses peaks of streamflow possibly due to the lower input data of RiverWare. However, since our focus is the water-scarce situation in this case study, this underestimation does not significantly affect our following analysis.

4.2. The effect of agents' risk perception

The calibration results in Section 4.1 demonstrate the creditability of the coupled BC-ABM-RiverWare model in representing human psychological, uncertain decision-making process. The encouraging results suggest that we can apply the proposed BC-ABM framework to test some "extreme conditions" to perform different scenario analyses. Different scenarios in terms of risk perception were tested by making stepwise change of all λ values from "0.5" (risk-averse) to "1" (risk-seeking). The basin-wide results are summarized in Figure 6 which shows the key measure quantities including cumulative probability distribution of annual total irrigated area, Navajo Reservoir water level in December, annual total downstream flow violation frequency and volume. The simulations under extreme risk-averse ($\lambda = 0.5$) and risk-seeking ($\lambda = 1$) scenarios are shown in blue and green, while those with calibrated historical risk perceptions for each agent are shown in red, referred to as the baseline simulation. The gray curves lying between blue and green are the estimates of these measured quantities corresponding to different λ values. The total irrigation area

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generally increases with an increase in λ, indicating that the agents become more risk-seeking if they are more confident about new incoming information.

There are two interesting observations. First, it is clear that when all agents become risk-seeking, their actions become more aggressive and result in greater irrigated area in the basin (Figure 6a). Since all agents want to expand their irrigated area, Navajo Reservoir will reserve more water at the end of each year resulting in slightly higher water levels (Figure 6b). Streamflow violations show a somewhat counterintuitive result. The volume of violation under risk-seeking scenario increases as expected (green curve shifts to right in Figure 6d) but the frequency of violation decreases (green curve shifts to left in Figure 6c). This is due to that Navajo Reservoir holds more water for irrigation season to satisfy downstream increased water demand which will result in much fewer streamflow violation days during the irrigation season. Although this operation slightly increases streamflow violation days in the following season, the total violation days still decrease (Figure S4 in the Supplementary Materials). Second, the results of baseline simulation (red curves) are very close to the “all agents risk-averse” scenario results (blue curves). This is consistent with the findings from previous studies (e.g., Tena and Gómez, 2008), which suggest that farmers are commonly risk-averse when the stakes are high (Matte et al., 2017).

We also look at the time variations of individual irrigated area changes for characterizing risk perceptions of different agents. Figure 7 shows the simulated irrigation area changes for four selected large irrigated areas since they are the major “players” in the basin. It again characterizes different agents’ behavior (see also Figure 3). The results clearly show that Jicarilla (Group 1) and NMAnimas (Group 2) are historically risk-averse agents. In contrast, Hammond and Hogback (Group 3) are relatively risk- neutral, compared to agents in Group 1 and 2, as the red curves lie in between green and blue curves. Group 3 agents are located downstream of Navajo Reservoir, and

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their decision-making process considers the water level in the reservoir (reflected by their BI mapping). Most of Group 3 agents consider Navajo Reservoir as a steady water source so they can have relatively more aggressive attitudes toward risk compared to their upstream counterparts. Also, note that Jicarilla, Hammond, and Hogback under the risk-seeking scenario eventually reach their maximum available irrigated area. Therefore, their irrigated area flattens out at the end of the simulation. The gray curves in Figure 7 represent the simulated irrigation area changes for agents corresponding to different agents' risk perceptions. It shows that the irrigation area generally increases with an increase in λ for all the four agents.

4.3. The effect of socioeconomic condition

The proposed BC-ABM framework allows us to quantify the influences of external socioeconomic factors on human decision-making processes by adjusting the CL ratio. In this study, we conducted a sensitivity analysis on the cost-loss ratio to test "*what if economic conditions change and it becomes more expensive or cheaper to expand the irrigated area*" by systematically increasing (+10% and +20%) or decreasing (-10% and -20%) all z values. When the z value goes up, it means that the cost of increasing irrigated area goes up, or the opportunity loss of not increasing irrigated area goes down. In either case, the situation should become harder for agents to expand their irrigated area. When the z value goes down, following the same logic, the economic conditions become easier for agents to expand their irrigated area. The modeling results shown in Figure 8 fit with this intuition quite well. All blue and cyan curves (increasing z values) are located below, and purple and magenta curves (decreasing z values) are located above red curves (baseline simulations). Modeling results also show that in the basin, Groups 1 and 2 are less sensitive to the changes in economic conditions but agents in Group 3 are more sensitive to the economic conditions. Of course, individual differences exist inside each group.

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According to the San Juan River Basin regional water plan, several strategies and constructions such as on-farm and canal improvements and municipal and irrigation pipeline from Navajo Reservoir, will be authorized for meeting future water demand (State of New Mexico Interstate Stream Commission, 2016). These strategies and constructions could lead to a change of future socioeconomic conditions, in terms of the cost of water usage and changing irrigated area (e.g., up-front cost) for stakeholders. In this study, we quantify the effects of up-front cost on the changes of irrigation area (i.e., irrigation water demand) using the proposed BC-ABM framework. According to the proposed ABM framework, up-front cost could affect human decision-making processes from two perspectives. First, it directly changes the socioeconomic condition of an agent (change of CL ratio). Second, it influences an agent's decision-making processes by introducing more information (change of causal network in BI mapping). As a result, the proposed BC-ABM framework can take up-front costs into account without theoretical and technical difficulties if related information is available. Two scenarios assuming a general increasing and decreasing up-front cost for agents over time, are tested in the study, respectively. For each agent, a time varied z is generated by adding a positive/negative trend with a small random fluctuation to the calibrated z to mimic the spatial and temporal heterogeneity of up-front costs. Note that we did not include up-front cost into current BI mapping as it requires real data from all stockholders to re-calibrate all the model parameters.

The time variation of irrigated area for all 16 agents under different economic scenarios are shown in Figure 9. The cyan and green curves are the irrigated area change under an increasing and decreasing z, respectively, while red curves are the simulations from baseline case using calibrated z values. The results show that Group 1 and Group 2 agents are not affected by the changing z significantly. The influence of changing z on Group 3 agents is relatively significant.

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A consistently higher (lower) green (cyan) curve as compared to the baseline simulation is found. The preliminary results are expected as they fit the economic intuition. In this specific case, farmers tend to expand their irrigation area earlier (by comparing cyan and red curves) if they expect a corresponding increased cost in the future. In contrast, if the cost of expanding irrigation area in the future is expected to go down, farmers will defer the actions to pursue a lower cost.

5. Discussion

5.1 Water policy implementation in the San Juan River Basin

The method proposed in this paper is intended to be a generalizable approach to explicitly characterize human decision-making processes and quantify the associated uncertainty due to information ambiguity in watershed management. The real-world decisions regarding irrigated area change and water management are often more complex than the proposed BC-ABM, especially for a watershed like San Juan River Basin that has a complex institutional context. To illustrate the potential application and broaden the impact of this case study, we summary the policy implementation in the San Juan River Basin in this section.

To improve water planning and management in San Juan River Basin, a steering committee constitute of several state and federal agency representatives was established with the main responsibility of overseeing the institutional complexity for the water plans operated under the 1922 Colorado River Compact and 1948 Upper Colorado River Basin Compact. Although a regional water plan report (RWP) was updated in 2016 (State of New Mexico Interstate Stream Commission, 2016) by interested stakeholders, issues still exist under the terms of 1948 Upper Colorado River Basin Compact. For example, New Mexico's entitled 642,380 acre ft. consumptive use is substantially greater than the corresponding consumptive use.

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The RWP summarizes the related information of water planning such as water rights, future water supply and demand projections, and newly available data. The analysis states that the total water demand in the San Juan Basin is expected to increase due to the authorized expansion of NIIP irrigation area, while a reduction of future water supply due to climate change is anticipated based on the regional assessments conducted by the U.S. Global Change Research Program. A San Juan Navajo Water Rights Settlement was executed in December 2010 for confirming the provisions of the related water supply contract for the Navajo Nation. Even so, several pending adjudications still exist. For example, the current water rights settlements are based upon existing irrigation projects, which may potentially displace the existing non-Navajo water uses. Additionally, part of water supply information is less reliable (e.g., tributary diversion). The RWP also identified several key issues (e.g., stream restoration, water quality protection, irrigation conveyance efficiencies, water banking, and land use.) and strategies (e.g., water system infrastructure upgrade and improvement) for the improvement of water resource management within the region.

Since irrigation activities are the most consumptive components of water demand among others, (74.8% of total water demand, State of New Mexico Interstate Stream Commission, 2016), collective adaptive actions of farmers will significantly affect the water planning and management in San Juan by e.g., changing the water diversion and reservoir release. The BC-ABM results presented in Section 4 have shown that farmers react to changing climatic and socioeconomic conditions. Understanding and accounting for the adaptive capacity of regional water resources in response to farmer's behaviors is critical to the management of scarce water resources. For example, the sensitivity analysis (see Figure 8) suggests that the collective action of farmers has potential to influence the irrigation of 4.5×10^4 to 6.1×10^4 acres of cropland with 9000 to 12000 ac-

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ft of water demand, which is about 30 to 39% of average annual water usage under changing economic conditions (i.e., 20% increase or decrease of up-front cost). A potential increase/decrease of future irrigation cost could also influence farmers' decisions. Understanding such behavior is also critical to future water resource planning and management in the San Juan as (1) threat of climate change will lead to shift in timing of flows associated with a mean decrease in future water supply resulting from an anticipated reduced precipitation and/or increased evaporation, and (2) there are several settlement agreements with the tribal communities along the San Juan where their committed allotment of water has yet to be put to full use (e.g., Navajo Gallup Pipeline and Navajo Indian Irrigation Project that both require construction and/or expansion of existing water delivery infrastructure to make full use of water rights).

5.2 Limitation and future study

Here we discuss several limits or aspects that we did not fully cover in this paper and potential future research directions. First, we focus on the methodologies of model development (i.e., parameter calibration of BC-ABM) specifically, rather than the precise causal structure of BI mapping (Cheng et al., 2002; Premchaiswadi et al., 2010). We aim to demonstrate that the proposed BC-ABM framework can effectively capture agent's risk perception. In general, an accurate causal structure of BI mapping can be obtained by a detailed interview with decision makers (O'Keeffe et al., 2016) or learned from a dataset (Sutheebanjard and Premchaiswadi, 2010). Missing information of factors associated with individual decision making could impact the calibration reuslts. A typical example is that our model does not capture the abrupt change of historical irrigation area change (e.g., Hammond in Figure 3) caused by the missing of key factors in addition to climate conditions (Navajo Reservoir came online implying a change in the irrigation system).

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Second, the external socioeconomic condition (z) for each agent is treated as a calibrated parameter in current ABM framework. The value of z can be estimated directly by acquiring relevant data, if available. For example, the farm production expense data provided by U.S. Department of Agriculture could be used as an approximation of the expected cost of changing irrigation area (C in Equation 20), while the farm income and wealth statistics estimated from crop production may be considered as a major part of opportunity loss (L in Equation 20). Third, the up-front cost is not included in the current BC-ABM framework and performed analysis due to lack of information as mentioned in Section 3.3 and 5.1. A potential solution, upon further tests, is to include up-front cost in the current BI mapping and add the up-front cost to CL ratio whenever it appears as the preceding test presented in Section 5.1.

Fourth, other than the extremity used in this study to be the reference of agent's decision, techniques and methods for multi-criteria decision analysis such as the Analytical Hierarchy Process (AHP, Saaty and Vargas, 2001) or Analytic Network Process (ANP, Saaty and Vargas, 2006), also has potential to be incorporated into current ABM framework as a tool of integrating multiple source of information. These methods are usually served as decision-support tools by evaluating the relative merit among different alternatives (e.g., preceding factors in this study). Finally, the current method does not explicitly consider direct interaction among agents. We do model agents as interacting indirectly through irrigated water withdrawal (i.e., upstream agents' water uses will affect downstream agents' water availability). However, effects like "peer-pressure," "word-of-mouth" and potential water markets are not currently considered in the model. Future work is planned toward methodology development to include direct agent interaction into the BI mapping. Agents' decisions can be affected by observing its neighbor's actions, and this

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information will always be treated with $\lambda = 1$. This means agents will always believe their own observations (i.e. "to see is to believe").

6. Conclusion

Managing water resources in a complex adaptive natural-human system subject to uncertainty is a challenging issue. The interaction between human and natural systems needs to be modeled explicitly with associated uncertainties characterized and managed in a formal manner. This study applies a "two-way" coupled agent-based model (ABM) with a River-Reservoir management model (RiverWare) to address the interaction between human and natural systems using Bayesian Inference (BI) mapping joined with Cost-Loss (CL). The advantage of ABM is that by defining different agents, various human activities can be represented explicitly while the coupled water system provides a solid basis to simulate the environment where these agents are located.

Joining BI mapping and CL modeling has allowed us to 1) explicitly describe human decision-making processes, 2) quantify the associated decision uncertainty caused by incomplete/ambiguous information, and 3) examine the adaptive water management in response to changing natural environment as well as socioeconomic conditions, which extends previous research where treatment of uncertainty has been largely limited to the natural system alone. Calibration results for this coupled ABM-RiverWare model, as demonstrated for the San Juan River Basin, show that this methodology can capture the historical pattern of both human activities (irrigated area changes) and natural dynamics (streamflow changes) while quantifying the risk perception of each agent via risk perception parameters (λ). The scenario results show that the majority of agents in the basin are risk-averse which confirm the conclusion of Tena and Gómez

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(2008). The improved representation of the proposed BC-ABM is evidenced by the closer agreement of BC-ABM simulations against observations, compared to those from an ABM without using BI mapping and CL ratio. Changing economic conditions also yield intuitive agent behavior, that is, when crop area expansion is more expensive/cheaper, fewer/more agents will do it.

The current method does not focus on obtaining an accurate causal structure of the BI mapping, which can be improved via survey or interview with local decision makers. Up-front cost can be incorporated in current ABM framework by modifying the causal network of BI mapping and adjusting the CL ratio whenever up-front cost appears. Considering different types of agents and addressing the direct agents' interactions are other two future research directions.

7. Acknowledgement

This research was supported by the Office of Science of the U.S. Department of Energy as part of the Integrated Assessment Research Program. Special thanks are given to Ms. Susan Behery in USBR for providing historical data in the San Juan Basin. And Mr. Majid Shafiee-Jood in the University of Illinois who discussed the methods of BI mapping and CL modeling with us in the earlier version of the draft. All data used for both the RiverWare model (inflow, crop ET, and water diversion, etc.) and the Agent-based Model (winter precipitation, historical basin outflow, and historical irrigated area, etc.) are explicitly cited in the reference list.

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Tables

Table 1. Name of agent groups, number of agents in each group and the factors considered in decision-making processes for each group of agents in this study

Group	Number of agents	Factors considered in decision-making processes
1. (upstream of the Navajo Reservoir)	2	Upstream Precipitation, Water Level in the Navajo Reservoir, Flow Violation at the outlet, Cost-loss ratio
2.a (Animas River without shortage sharing)	5	Animas Precipitation, Upstream Precipitation, Water Level in the Navajo Reservoir, Flow Violation at the outlet, Cost-loss ratio
2.b (Animas River with shortage sharing)	1	Animas Precipitation, Upstream Precipitation, Water Level in the Navajo Reservoir, Flow Violation at the outlet, Shortage Sharing, Cost-loss ratio
3.a (downstream of the Navajo Reservoir without shortage sharing)	3	Downstream Precipitation, Upstream Precipitation, Water Level in the Navajo Reservoir, Flow Violation at the outlet, NIIP Diversion, Cost-loss ratio
3.b (downstream of the Navajo Reservoir without shortage sharing)	5	Downstream Precipitation, Upstream Precipitation, Water Level in the Navajo Reservoir, Flow Violation at the outlet, NIIP Diversion, Shortage Sharing, Cost-loss ratio

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Figures

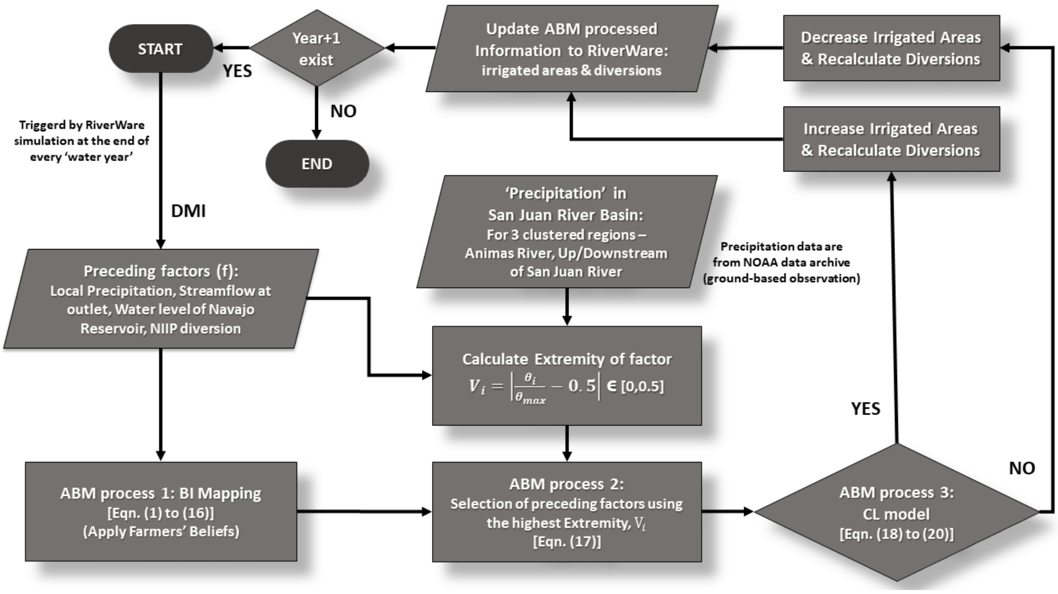

Figure 1. The flow chart of agent decision-making process inside the two-way coupled ABM-RiverWare model (ABM.exe in Figure S1). Agents make their decisions with uncertainty based on the method developed by this paper (joint BI mapping and CL model), and RiverWare will run the simulation based on these decisions.

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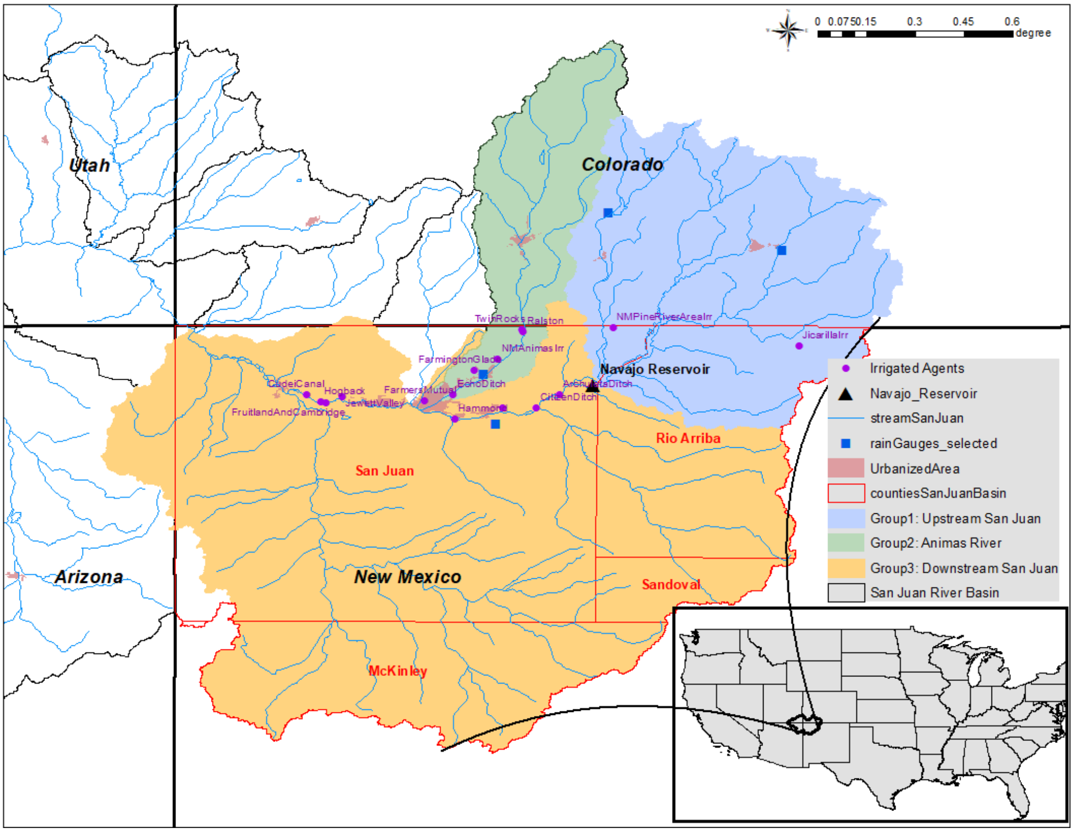

Figure 2. The upper San Juan River Basin. Different colors of the basin represent the geographical regions that this paper used to group major irrigation districts (agents, marked as dots). The location of Navajo Reservoir is marked as a triangle.

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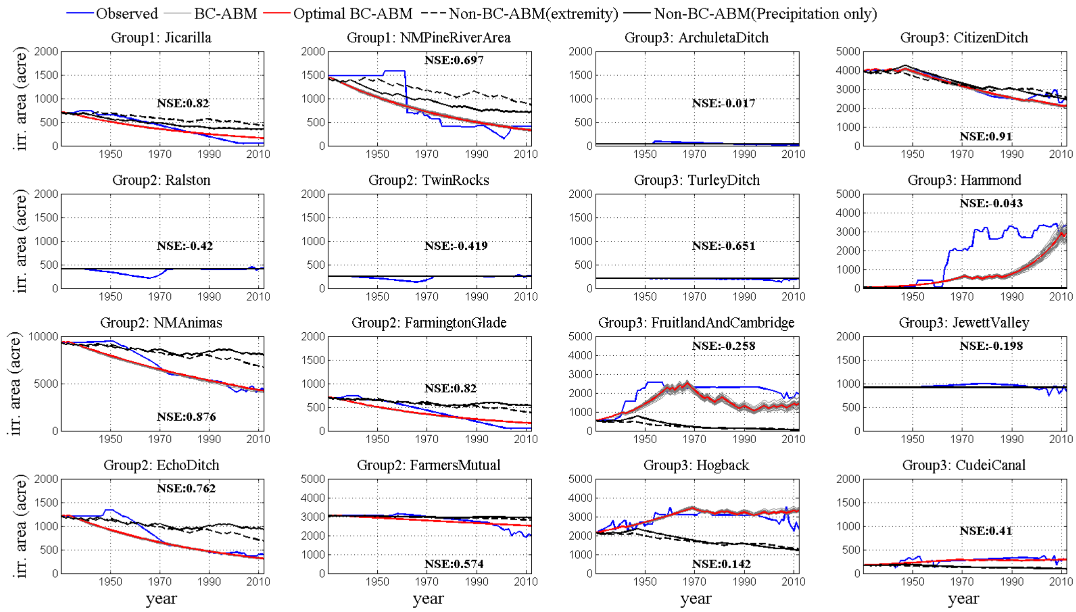

Figure 3. The calibration results of the ABM-RiverWare model: Individual agents' irrigated area changes from 1928 to 2013 organized by irrigation ditch and region (see groups in Figure 3). Each figure includes the simulated irrigated area change from the best-fit BC-ABM (solid red) and the corresponding Nash-Sutcliffe Efficiency (NSE), multiple runs of BC-ABM (solid gray) to visualize the stochasticity (30 runs) of agents' random behavior, Non-BC-ABM with extremity (dashed black), Non-BC-ABM using precipitation only (solid black) against historical record (solid blue).

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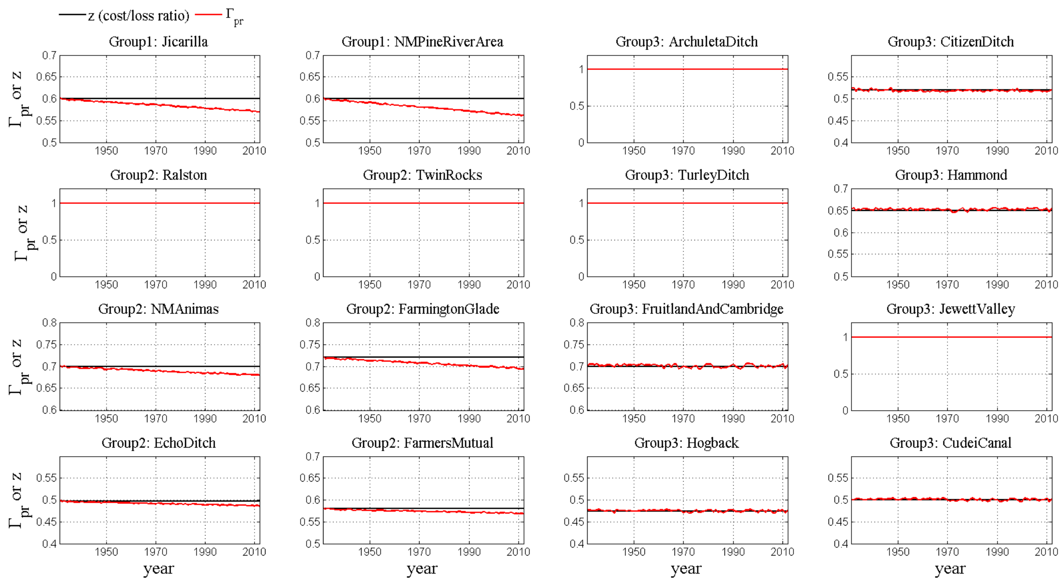

927

928 Figure 4. Calibrated probability of expanding area (Γ_{pr}) and cost-loss ratio (z) for each agent

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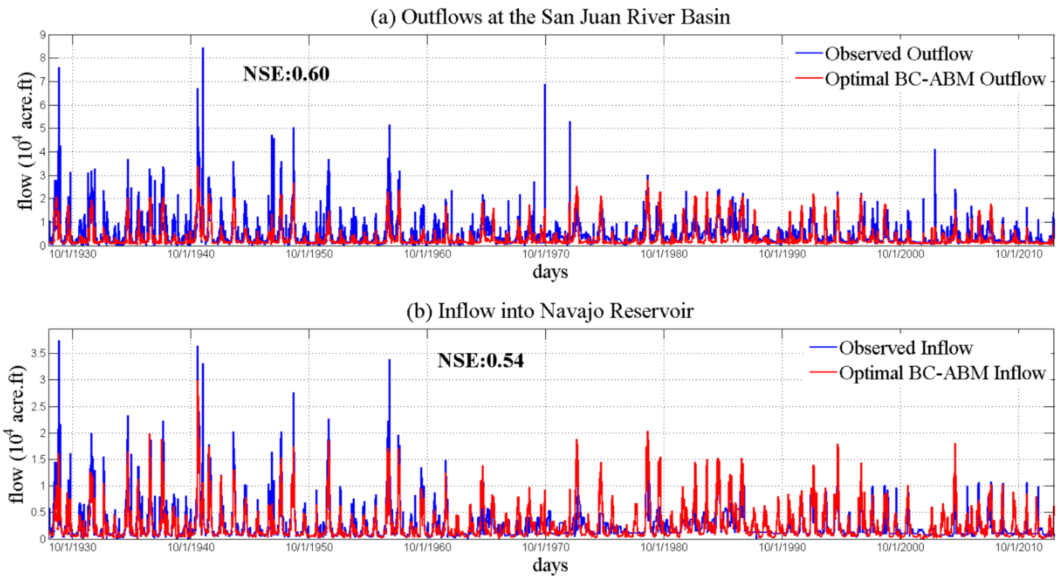

Figure 5. The calibration results of the ABM-RiverWare model: (a) the basin outflow to Colorado River; (b) inflow to Navajo Reservoir. Blue lines are historical data and red lines are modeling results.

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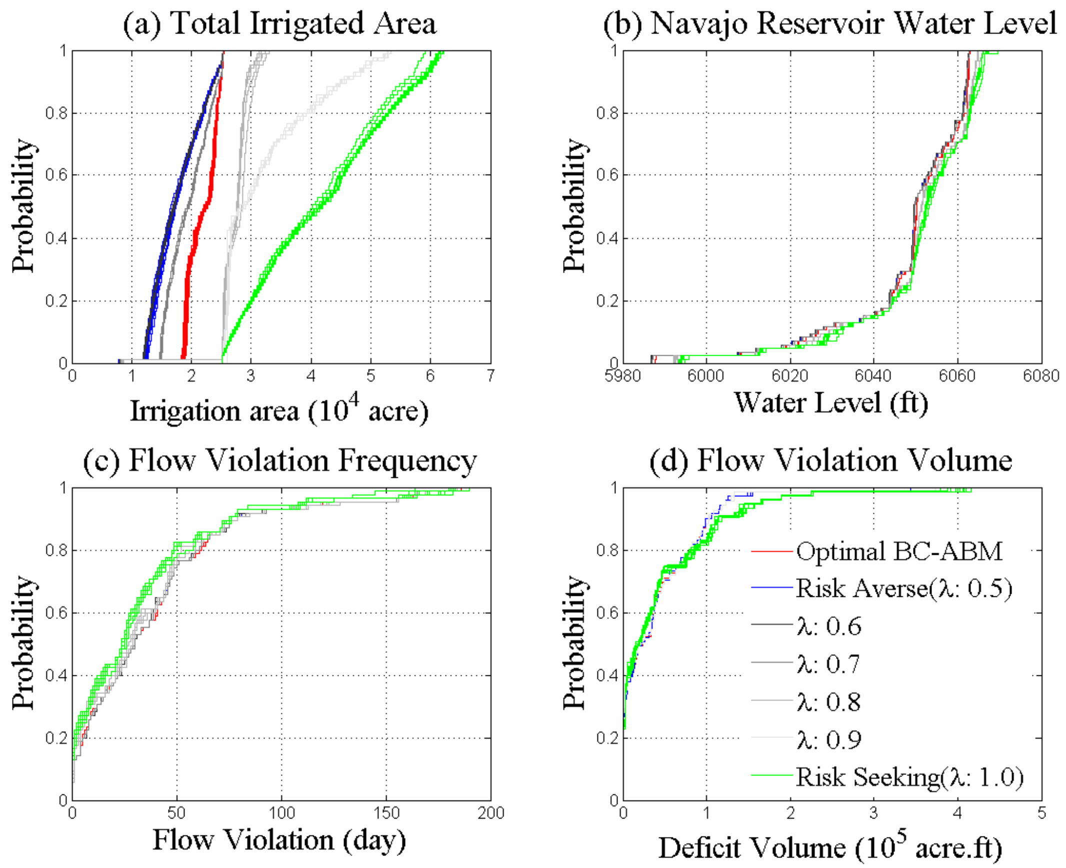

Figure 6. The cumulative density frequency throughout the entire simulation period of (a) basin-wide irrigated area; (b) Navajo Reservoir end of the year water level; (c) basin outlet annual streamflow violation days; (d) basin outlet annual streamflow violation volume. Results are given for the calibrated (green curves), risk-averse (blue curves) and risk-seeking (red curves) cases. The simulation results with different values of agents' risk perceptions (λ) between 0.5 and 1 are shown in gray.

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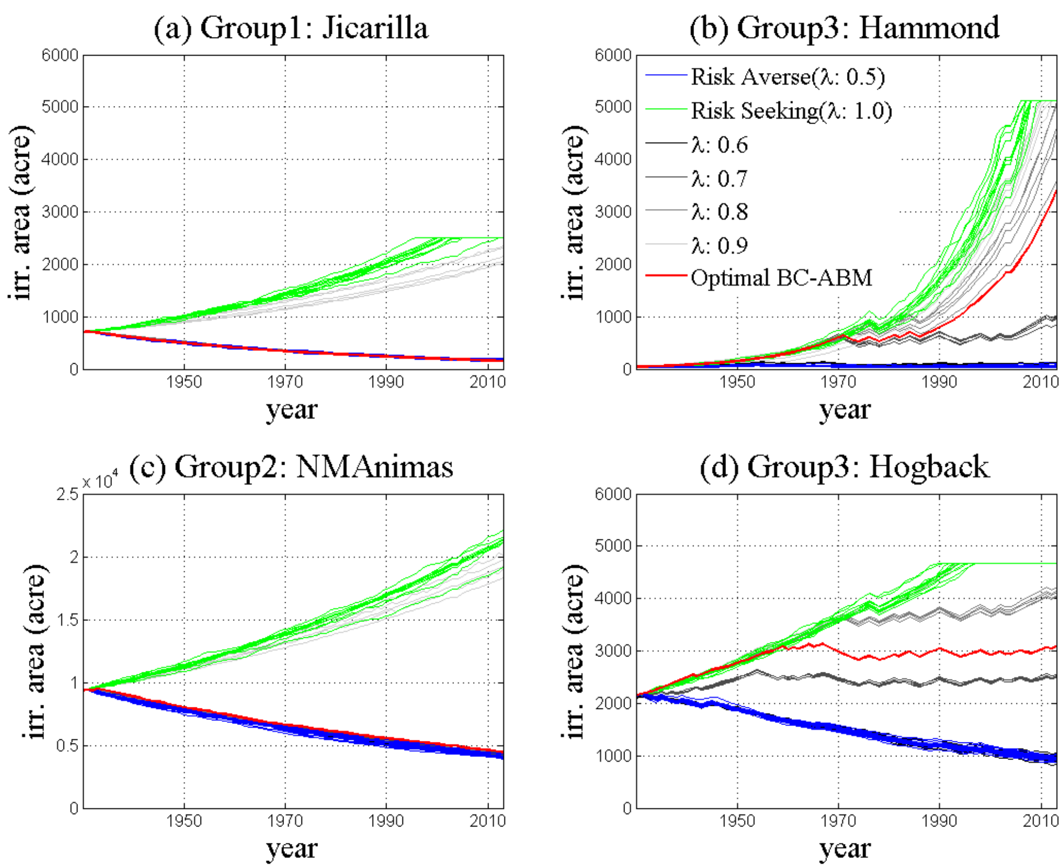

Figure 7. Individual agents' irrigated area changes under calibrated (green curves), risk-averse (blue curves) and risk-seeking (red curves) scenarios. The simulation results with different values of agents' risk perceptions (λ) between 0.5 and 1 are shown in gray.

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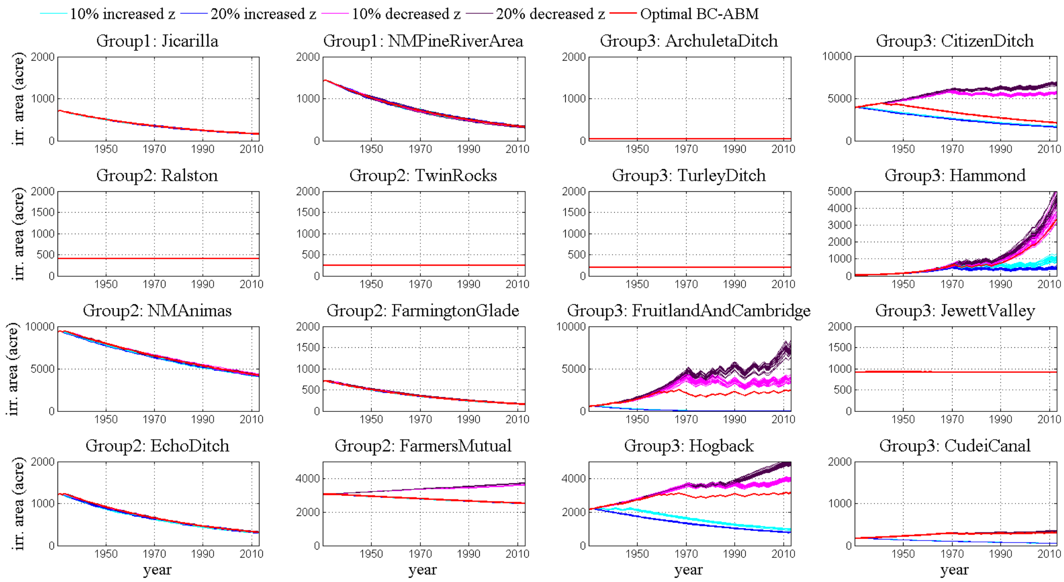

Figure 8. The sensitivity analysis of changing economic conditions on an agent's decision on irrigated areas. Blue (+20%) and cyan (+10%) curves represent increasing z values which make area expansion more expensive. Purple (-20%) and magenta (-10%) lines represent decreasing z values which make area expansion cheaper.

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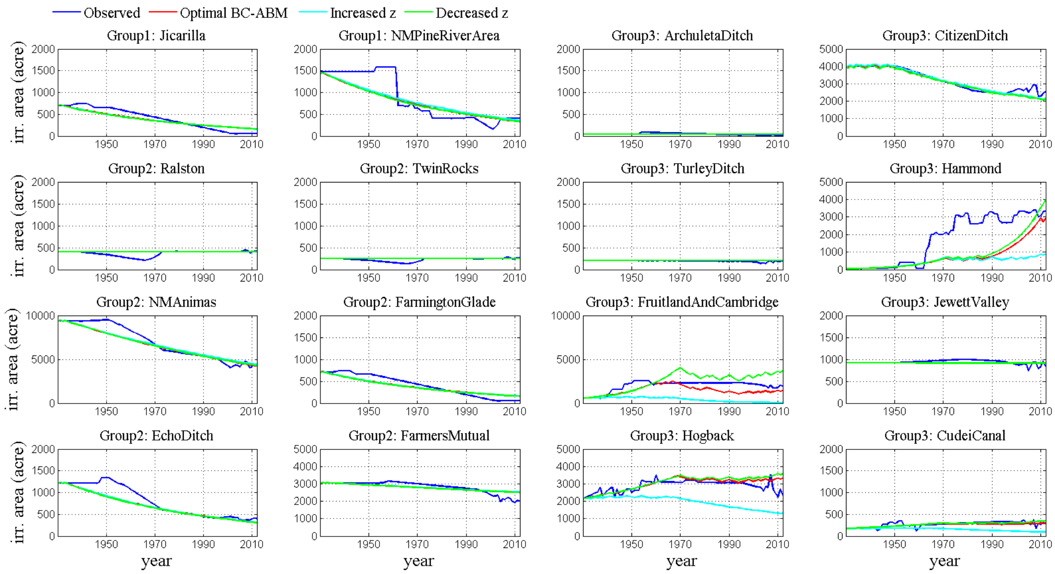

954
955 Figure 9. Irrigation area changes of each agents under the scenario of increasing (cyan) and
956 decreasing (green) z. The calibrated results (baseline simulation) are shown in red and
957 observations are shown in blue.
958