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An investigation of coupled natural human systems using a two-way coupled agent-based modeling framework

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ABSTRACT

Improving the understanding of coupled natural human systems (CNHS) can better inform environmental policymaking. We investigated the co-evolution (*i.e.*, bidirectional interactions) issues in CNHS via two-way coupling RiverWare (RW; a river-reservoir routing model) with agent-based models (ABMs, human decision models) in the Yakima River Basin in Washington, US. Results show that coupled models can better capture the historical irrigation diversion (human) and streamflow (nature) dynamics. We further demonstrated the effect of social norms (*i.e.*, the influence of neighbors) among farmers and tested a "water reallocation" scenario to evaluate the influence of water policies on irrigation diversion behaviors. Detailed model structure and parameter uncertainty analysis are suggested to further quantify the benefit of CNHS models in multi-level water resources governance.

1. Introduction

Most of the major basins involve some degree of human activity in this anthropogenic era, indicating the significance in investigating the co-evolution (i.e., bidirectional interactions) between natural and human systems, so-called the coupled natural human systems (CNHS; An, 2012; Giuliani et al., 2016; Hyun et al., 2019; Liu et al., 2007; Yang et al., 2020) or socio-environmental systems (SES; Elsawah et al., 2020). While the social-hydrology communities (Sivapalan and Blöschl, 2015) actively study the co-evolution mechanism emphasizing human influences on the water cycle, we focus more on the water resources management problem from a CNHS point of view, where the hydrological response is one of the indicators for making decisions (Brown et al., 2015; Reuss, 2003).

An additional human complexity layer has been claimed can improve environmental planning and policy (Zellner, 2008). To that, the co-evolution mechanism is the foundation to generate more holistic information for policymaking, especially for revealing the offsetting behavior (Campbell et al., 2004; Fielding et al., 2012), where the feedback of human behaviors toward the changing policy jeopardizes the original intention or the effectiveness of that newly introduced policy, and multi-level governance application (Cash et al., 2006; Di Gregorio et al., 2019), which tend to address co-management issues across power-imbalanced governance levels (or human actors). This study aims to tackle the abovementioned management issues by improving the understanding of the co-evolution mechanism in CNHS modeling. More specifically, we would like to explore the influence of policy rules (*e.g.*, water reallocation; Du et al., 2021; Hillman et al., 2012; Yang et al., 2012) on human behaviors (*e.g.*, irrigation diversions and risk attitudes) and discuss how CNHS model can potentially benefit multi-level water resources governance.

To model the co-evolution mechanism in CNHS, a human layer is required in addition to the natural systems (*e.g.*, hydrological model). For constructing the human system, agent-based modeling (ABM) is often used for its capability of describing emergent and heterogeneous human behaviors. The flexibility of the ABM framework allows various designs of decision-making processes, including factors such as people's past experiences, future expectations, risk attitudes, availability of resources, and interaction with the environment and neighbors (Hu et al., 2006; Niles and Mueller, 2016). However, the social norm effect, defined as the informal rules that govern behavior in groups and societies (Bicchieri and Muldoon, 2011), are often missing in CNHS models with only a few exceptions (Abebe et al., 2020; Nhim et al., 2019). Groeneveld et al. (2017) pointed out social influences are one of the least

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considered factors among 134 agent-based land-use change models' literature. Kremmydas et al. (2018) also indicated that over 70% of concerned agents' interactions in the review of ABM for agricultural policy evaluation studies referred to a land market that the agents' interactions are a shared database for sending/getting bidding information instead of agent-to-agent interactions. The theoretical foundation of the social norm effect is still actively developing (Gelfand et al., 2017), and many studies have shown the social norm effect is an essential factor influencing human behavior (Ajzen, 1991; Bicchieri and Muldoon, 2011; Cedeno-Mieles et al., 2020; Chen et al., 2012; Epstein, 2012). For example, studies of groundwater management (Castilla-Rho et al., 2017), adoption of field practice innovation (Baba et al., 2021), and weather forecast utilization (Hu et al., 2006) have shown farmers' behaviors can be significantly affected by neighbors' opinions. These motivate us to explore how the social norm effect influences the CNHS modeling results.

Consequently, this study aims to improve our understanding of the co-evolution mechanism in CNHS through a case study. We adopt the Yakima River Basin (YRB) in Washington, US, as our study area, where the RiverWare model (a river system model), YAKRW, developed by the U.S. Bureau of Reclamation (USBR), is available (Malek et al., 2018; USBR, 2011) to us. For the human model, we develop two diversion ABMs to represent farmers' heterogeneous irrigation diversion behaviors with and without the social norm effect. The objectives of this paper are (1) coupling YAKRW (natural model) and diversion ABMs (human model), (2) comparing coupled models with the original YAKRW (baseline) to explore streamflow and irrigation diversion dynamics in CNHS, (3) investigating the social norm effect with a local sensitivity analysis (LSA) on a directed social network (*i.e.*, information flow among human actors), and (4) demonstrating the impact of changing policy rules (*e.g.*, water reallocation) on human behaviors (*e.g.*, diversion and calibrated ABM parameters).

The paper is structured as follows. We introduce the technical background of RiverWare, ABM, and coupling technique in Sect. 2. Then, Sect. 3 describes the case study information for the YRB. After that, we show the detailed coupled model design and experimental setup in Sect. 4. The results are presented in Sect. 5. Next, we discuss the multi-level governance application and model limitations in Sect. 6, which is followed by the conclusions in Sect. 7.

2. Background

2.1. RiverWare

RiverWare (RW) is a licensed water resource engineering model developed in 1986 by the University of Colorado, Boulder. It is a process-based model that simulates river and reservoir routing (*e.g.*, reservoir operational scheduling) and other natural processes (*e.g.*, return flow) in a basin with policy rules, such as water rights and the canal capacity to fit the legal and physical constraints. The graphical interface enables modelers to build the model using a node-link structure. Each node is defined as an object (*e.g.*, storage reservoir or water diversion district) with a unique set of attributes. It contains various slots to store data (*e.g.*, series slots for storing time-series data). Each link connects different objects to facilitate information flow. We refer to Zagona et al. (2001) and their official website: http://www.riverware.org/for more technical details of the RW model. RiverWare has been used internationally to evaluate real-world water allocation issues and assist reservoir operation (Abudu et al., 2018; Basheer et al., 2020; Biddle, 2001; Everitt, 2020; USBR, 2011, USBR, 2012; U.S. DOE, 2019; Wheeler et al., 2020; Witt et al., 2017). Its popularity in academia and public sectors is one reason that RiverWare is adopted as our coupling target despite its being a licensed standalone software. In addition, we would like to leverage existing RW models' credibility for our case study area (*i.e.*, YAKRW).

2.2. Agent-based modeling

Agent-based modeling (ABM) is a bottom-up modeling approach known for its capability of describing the emergent and heterogeneous agents' behaviors, where an agent is a decision-making unit of actors. Each agent is controlled by a set of rules and attributes, and they can interact with other agents in a shared physical environment. Moreover, the adaptive learning mechanism of agents, defined as the adaptive capacity herein, enables agents' decision rules to co-evolve with a changing environment (Axelrod and Tesfatsion, 2006; Epstein, 2012; Miller and Page, 2007). Many fields have successfully adopted the ABM framework to explore CNHS, such as land-use change (Brown et al., 2004; Groeneveld et al., 2017; Zellner and Reeves, 2010), groundwater management (Al-Amin et al., 2018; Castilla-Rho et al., 2015; Reeves and Zellner, 2010), and water resources allocation (Li et al., 2017; Tesfatsion et al., 2017; Yang et al., 2009; Zhou et al., 2015).

2.3. Model coupling

Studies have adopted a two-way coupling technique, a technique to create feedback loops among models, to organize information flow (*e.g.*, real-time information exchange) and illustrate potential system responses between natural models and ABM (Giuliani et al., 2016; Hyun et al., 2019; Jaxa-Rozen et al., 2019; Khan et al., 2017; Reeves and Zellner, 2010). With a more extensive scope, modeling frameworks have been developed to alleviate potential technical barriers (Robinson et al., 2018). For example, some studies emulated nature models (*e.g.*, groundwater model or land-use decision model) into well-developed ABM platforms (*e.g.*, NetLogo) (Castilla-Rho et al., 2015; Sun and Müller, 2013), some established a new modularized ABM framework integrating vegetation models (Murray-Rust et al., 2014; Schreinemachers and Berger, 2011), and some developed a two-way coupling Python package to fully utilized an external simulation model with NetLogo (Jaxa-Rozen and Kwakkel, 2018). More broadly speaking, several communities (*e.g.*, CSDMS, CoMSES Net, AIMES, etc.) have initiated generic coupling/integrating frameworks and model development standards to advance the open science and system-of-systems research. Some examples include OpenMI (Gregersen et al., 2007; Moore and Tindall, 2005), Basic Model Interface (BMI; Hutton et al., 2020; Peckham et al., 2013), Earth System Modeling Framework (ESMF; Hill et al., 2004), and Object Modeling System (OMS; David et al., 2013).

We attempt to follow the same coupling philosophy. However, the abovementioned frameworks might not be applicable in this study due to the licensed (closed source) RiverWare software that has limited modifiability. Therefore, we developed a Python package of RiverWare and Agent-based Modeling Interface for Developers (Py-RAMID) to achieve two-way coupling between RiverWare and ABMs for our numerical experiments. The technical details for Py-RAMID coupling framework are provided in the supplementary materials (Text S1). Py-RAMID and its user manual are available at https://github.com/philip928lin/Py-RAMID.

3. Case study - the Yakima River Basin

The Yakima River Basin (YRB, Fig. 1) is located in central Washington, US, where agriculture significantly contributes to the economy (USBR, 2010). According to the 2017 agriculture census from the USDA, the main crops are orchards (127,934 acres, 29.6%), small grains (67,434 acres, 15.6%), and corns (63,163 acres, 14.6%). The basin-wide annual precipitation is approximately 680 mm, and most precipitation accumulates in the mountain area as snow (Mastin and Vaccaro, 2002). Therefore, the irrigation water supply for downstream croplands relies heavily on five major reservoirs, Keechelus, Kachess, Cle Elum, Bumping, and Rimrock (Fig. 1). These reservoirs capture melting snow in the spring and redistribute water across the growing season (April to October; USBR, 2002). The six major irrigation districts in the YRB are

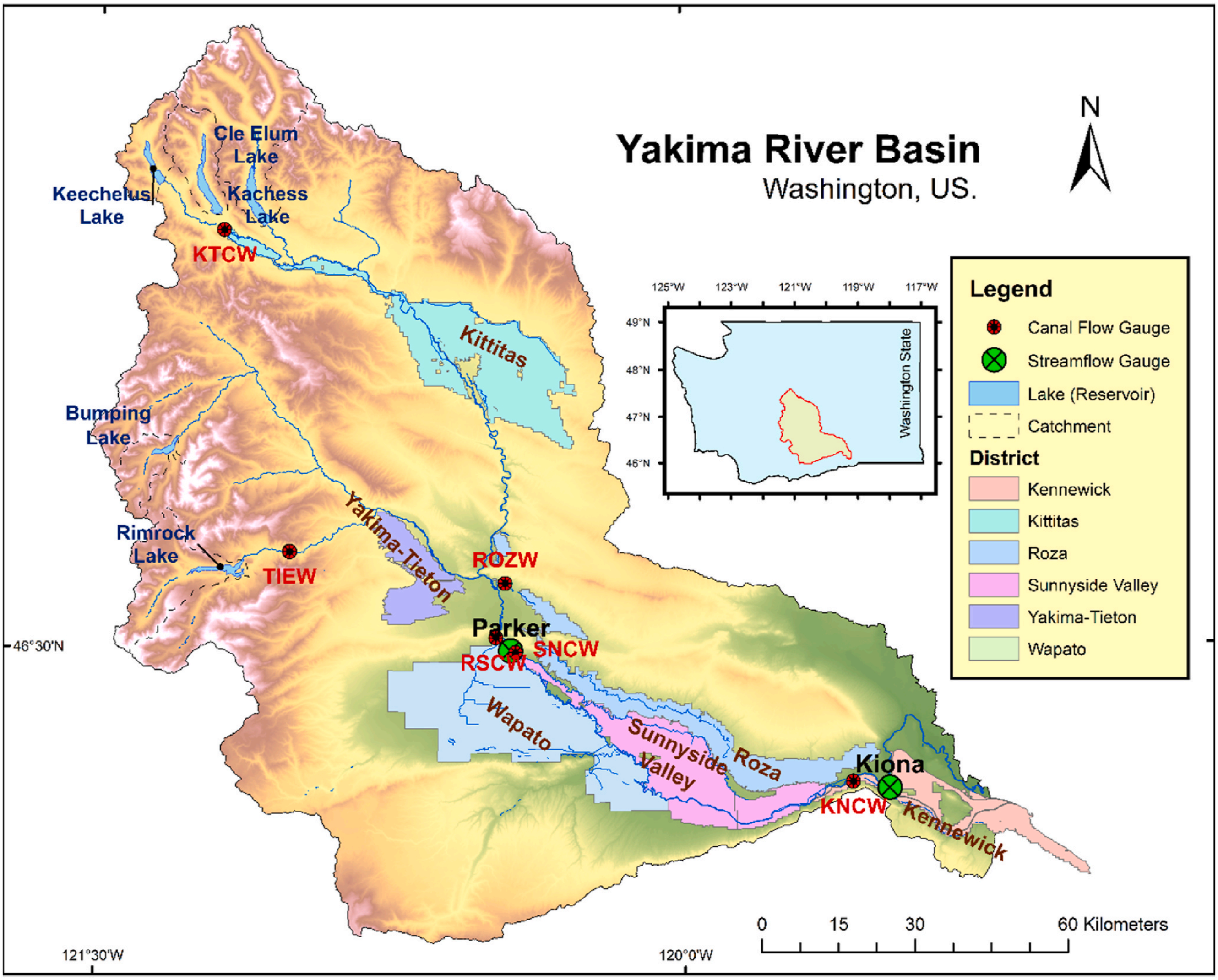

Fig. 1. Yakima River Basin. The map shows five major reservoirs, six major irrigation districts with corresponding canal flow gauges, and streamflow gauges used as model calibration targets.

Kittitas, Yakima-Tieton (Tieton), Wapato, Sunnyside Valley (Sunnyside), Roza, and Kennewick. They have different compositions of water rights (*e.g.,* junior and senior water rights). Allocated by the priority order (first in time, first in right) (USBR, 2002), proratable (receive a reduced or prorated portion of their entitlements during droughts period) and nonproratable (receive full entitlements during droughts period) water rights are given to junior and senior water right holders, separated by the date of May 10, 1905 (USBR, 2002), respectively. The six districts' water rights, average water diversion, district area, and corresponding canal gauges are summarized in Table 1.

Building on previous local studies (Givens et al., 2018; Malek et al., 2018; Qiu et al., 2019), we further explored the YRB from a CNHS's viewpoint by two-way coupling diversion ABMs with the existing Yakima RiverWare model (YAKRW; Malek et al., 2018; USBR, 2011).

Table 1
Canal gauges, water rights, average water diversion, and district area of six irrigation districts.

District	Gauge	Water rights (acre-feet)[a]			Avg. Diversion in 2001–2010 (cfs)[b]	District area (acre)
		Non-proratable[c]	Proratable[c]	Total		
Wapato	RSCW	305,613	350,000	655,613	705.22	190,862
Sunnyside	SNCW	289,646	157,776	447,422	549.03	111,067
Roza	ROZW	0	393,000	393,000	371.56	94,876
Kittitas	KTCW	0	336,000	336,000	411.67	143,383
Tieton	TIEW	75,865	30,425	106,290	103.46	42,150
Kennewick	KNCW	18,000	84,674	102,674	128.00	54,386

[a] (USBR, 2012).
[b] Hydromet.
[c] Proratable water right holders will receive a reduced or prorated entitlement during the droughts period, while nonproratable water right holders will receive full entitlements all the time.

4. Model and experimental setup

4.1. Models and simulation schema

To start the numerical experiments exploring CNHS in the YRB, we first constructed the coupled model, Coupled-YAKRW, by coupling YAKRW and a diversion ABM. Then, we applied Coupled-YAKRW to simulate the dynamics of historical river discharge and irrigation diversions in the six major water use districts. Each irrigation district was defined as a decision-making agent to make annual diversion requests. The general simulation schema is shown in Fig. 2.

First, we used observed irrigation diversions as agent diversion requests and sent them to the RW model in the initial year (y_{t_0}). Then, the RW model outputs the simulated diversion and river discharge. Next, the simulated river discharge was sent to the ABM model (grey boxes in Fig. 2) to update agents' decision rules. Then, ABM used the new observations (*e.g.*, precipitation or reservoir storage) to evaluate the water supply conditions of the coming year (y_t) and calculate diversion-request-adjustment ratios ($R_{g,\,y_t}$) through the updated decision rules (yellow boxes in Fig. 2; formulation details are shown in Sect. 4.1.2). Finally, the diversion-request-adjustment ratios were applied to update the annual mean diversion request values, which were calculated by the annual diversion request records from y_{t_0} to y_{t-1} for each agent and then disaggregated into daily irrigation diversion requests for y_t simulation.

4.1.1. The baseline model – YAKRW

We use the original YAKRW (Malek et al., 2018; USBR, 2011) as our baseline model. All the input data, such as initial reservoir storages, historical reservoir inflows, water rights information, etc., are embedded inside YAKRW. YAKRW runs on a daily scale, and we can output time-series data (*e.g.*, daily streamflow and diversions) of any given RW objects (i.e., water users or reservoirs). The diversion requests of six irrigation districts are calculated using both water entitlement and fixed values computed by historical diversion measurements. YAKRW will first compute conventional diversion requests by combining dry-year (the 50th percentile diversion from historical dry years in 1991–2010) and wet-year (the 50th percentile diversion from historical wet years in 1991–2010) historical diversion sequences for a 365-day period based on the flow conditions at Parker gauge on a daily basis. Then, YAKRW picks the minimum of conventional diversion requests and prorated entitlement calculated according to their water rights (Table 1) to determine the final diversion requests.

We substitute conventional diversion requests with our diversion ABM outputs for coupling purposes. Namely, the diversion decisions made by the ABM are still constrained by water rights. Note that there is an additional policy rule further updates the diversion requests for the Kennewick agent. To that, Kennewick's diversion requests can be dominated by this highly customized policy rule. We refer readers to USBR (2011) for more details about the baseline model's settings.

4.1.2. Diversion ABM

For the ABM model (yellow boxes in Fig. 2), we adopted the Theory of Planned Behavior (TPB, Ajzen, 1991) as a guideline. TPB states that the behavior of an actor (*e.g.*, agent) is built upon its intention (*e.g.*, diversion requests), the social norm it experienced, and reality constraints (*e.g.*, water rights, canal capacity). In this case study, every district acquires the attributes of two state variables and eight parameters, which must be calibrated (Table 2). The decision-making process includes six steps, shown as numbered circles in Fig. 2. In **step 1**, agents will evaluate water supply conditions based on the Empirical Cumulative Distribution Function (ECDF) value of the observation of the coming year (y_t) on the selected *InfoSource* (Table 2, Equation S3.1). The ECDF is constructed from the historical records of selected *InfoSource* from y_{t_0} to y_{t-1}. In **step 2**, agents adjust their perceived beliefs of water supply based on neighbor opinions, so-called the social norm effect (Fig. 3) quantified by Equation (1),

$$p^{adj}_{g,y_t} = \left(1 - Sw_{g,g}\right) \times P_{g,y_t} + Sw_{g,g} \sum_{i=1,\ i\neq g}^{N_{agents}} S_{g,i} \times P_{i,y_t} \tag{1}$$

where p^{adj}_{g,y_t} is the adjusted perceived belief on the water supply conditions considering the social norm effect, p_{g,y_t} is the original perceived belief of the agent at year y_t, and N_{agents} denotes the total number of agents. The social network matrix (*S*, Fig. 3a) that represents agents' interaction networks, and the weight vector (*Sw*, Fig. 3b) that balances neighbor opinions and the agent's evaluation are used to describe the impact of neighbor opinions on their decision, which we label the social norm effect in this study. In the social network matrix, each row of the matrix is a social network connection of an agent. "0" means the agent in that row is not affected by the opinion of the agent in that column. "1" indicates an influence from the opinion of the agent in that column. Also, the social network is directed. For example, agent 2 is affected by agent 1, but agent 1 is not affected by agent 2, as shown in Fig. 3a. Lastly, *P* is a vector collecting all agents' perceived beliefs on water supply conditions (Fig. 3c). Note that all perceived beliefs mentioned in this paper are represented as probabilities, where values closer to 1 indicate an agent is more likely to have a positive belief in water supply conditions. The subscript *g* is the index of an agent.

In **step 3**, agents will update their decision rules by updating a state variable, Center (C_{g,y_t}), which will minimize the average difference between the simulated and observed river discharges (v_{g,y_t}) at their downstream area. We adopted a generalized form of the Bush-Mosteller

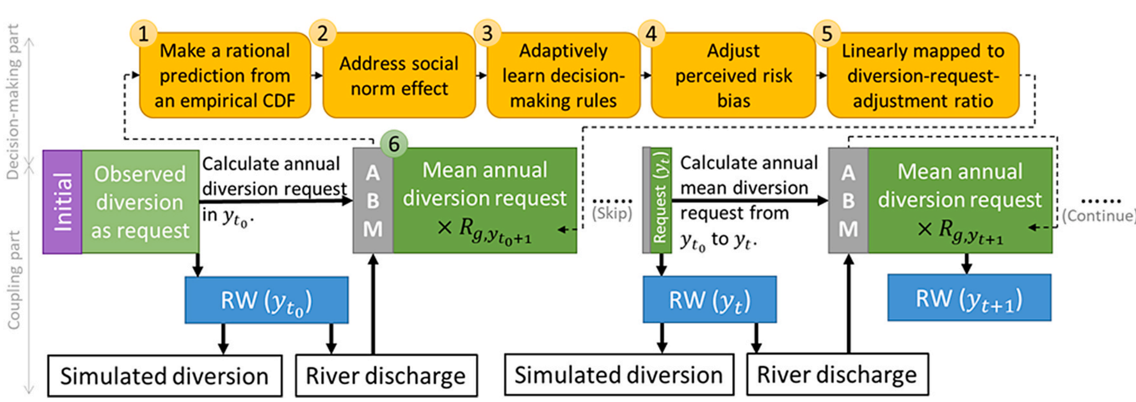

Fig. 2. Coupled-YAKRW simulation schema. Yellow boxes are agent decision-making processes (dotted thin arrows), which output the ratio ($R_{g,\,y_t}$) that is used to adjust the mean annual diversion request (circle number 6) and to simulate the next year by RW. Annual mean diversion request is computed using all historical annual diversion request records before the current year. Solid arrows connecting diversion requests (green boxes) and RW model (blues boxes) show information flow in the coupling process.

Table 2
Agent attributes that affect their decision-making processes.

Attribute	Name	Type	Description
N	Record's length	State	The length of the agent's memory record, where we set it to be the length from the initial year (y_{t_0}) to y_{t-1} in the study.
C	Center	State	C is a state variable distinguishing the positive and negative perceived beliefs on the water supply conditions that result in increasing or decreasing irrigation diversion requests, respectively. It is updated annually using the RL algorithm (Equation (2)).
InfoSource[a]	Information source	Parameter	Information that a particular agent uses to evaluate the coming year's water supply conditions. Sources include the deviation of (1) winter (Oct–Mar) precipitation in each of five reservoir catchments, (2) storage in each of five reservoirs in March, (3) total winter precipitation (Oct–Mar), and (4) total reservoir storage in March. The deviation is the difference between the current value of the selected *InfoSource* and its historical average.
γ[a]	Learning rate	Parameter	γ is the learning rate for reinforcement learning (RL) algorithm (Equation 2) to update the state variable, C, based on the average difference between the simulated and observed river discharges.
Sc[a]	Scale	Parameter	Sc is a scale factor to scale the average difference between the simulated and observed river discharges. It is used to adjust the agent's sensitivity to this difference. (Equation (3)).
α[a]	Alpha	Parameter	α is a prospect function parameter to adjust for positive beliefs about water supply conditions.
β[a]	Beta	Parameter	β is a prospect function parameter to adjust for negative beliefs about water supply conditions.
R_{max}[a]	maximum diversion-request-adjustment ratio	Parameter	R_{max} is the maximum diversion-request-adjustment ratio.
S[a]	social network matrix	Parameter	S is the social network matrix (Fig. 3a), which defines the directed social network among agents. Each row of the matrix is the social network of the agent in that row.
Sw[a]	weight vector	Parameter	Sw is a weight vector for the social norm effect (Fig. 3b), showing the proportion of each agent's belief to the neighbors' opinions.

[a] Denotes parameters involved in the calibration.

model (Brenner, 2006), a type of reinforcement learning model, to achieve the agent's adaptive learning behavior shown in the following equations:

$$C_{g,y_t} = \begin{cases} C_{g,y_{t-1}} + h_{g,y_t} \times \gamma_g \times \left(1 - C_{g,y_{t-1}}\right) & \text{if } h_{g,y_t} \geq 0 \\ C_{g,y_{t-1}} + h_{g,y_t} \times \gamma_g \times C_{g,y_{t-1}} & \text{if } h_{g,y_t} < 0 \end{cases} \tag{2}$$

where the strength (h_{g,y_t}) defining the updating magnitude of C is

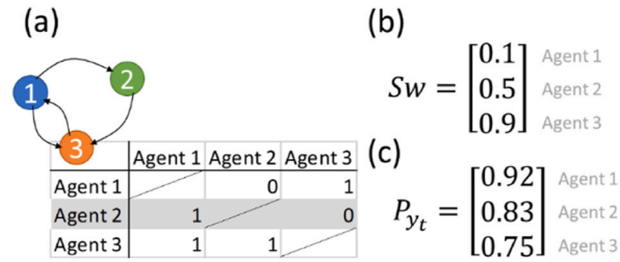

Fig. 3. (a) S is a social network matrix. Each row of the matrix is the social network of the agent in that row, which is affected by the agent in the column with cell's value 1. (b) Sw is a weight vector to balance between neighbor opinions and the agent's own beliefs. (c) P_{y_t} is a collection of agent's evaluations of water supply conditions in y_t.

calculated by Equation (3). In Equation (3), v_{g,y_t} is equal to the observed river discharges minus the simulated discharges. v_{g,y_t} is scaled by a scale factor (Sc_g) and then transformed into a value between 0 and 1 through a sigmoid function (Equation (4)). A "0.5" downshift defines the strength as positive or negative. The range of the strength becomes −0.5 to 0.5.

$$h_{g,y_t} = \begin{cases} \sigma\left(\frac{v_{g,y_t}}{Sc_g}\right) - 0.5 & \text{if } v_{g,y_t} \geq 0 \\ 1 - \sigma\left(-\frac{v_{g,y_t}}{Sc_g}\right) - 0.5 & \text{if } v_{g,y_t} < 0 \end{cases} \tag{3}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

The logic of Equation (2) and Equation (3) is that if we have a positive strength (positive v_{g,y_t}), which implies the observed river discharge is greater than the simulated discharge; then the agent will divert less water achieved by increasing C_{g,y_t}. The state variable C_{g,y_t} is used in **step 4** and **step 5** to distinguish the positive and negative perceived beliefs about water supply conditions, resulting in increasing or decreasing irrigation diversion requests, respectively. Therefore, higher C_{g,y_t} indicates a greater chance the agent will divert less water. This enhancement in C_{g,y_t} will result in attenuating the positive v_{g,y_t} mentioned above. In **step 4**, we address the agent's personal bias according to their risk attitude through a prospect function (Kahneman and Tversky, 2013) with a small modification. The modified prospect function includes two nonlinear convex or concave curves split by C_{g,y_t}. These curves represent the agent's risk attitude toward positive belief (more available water) and negative belief (less available water). For a positive belief (larger than C_{g,y_t}), the convex function indicates the agent is risk-seeking, while the concave function indicates a risk-averse attitude. On the contrary, the convex function indicates risk-seeking and the concave function means risk-averse for the agent's attitude toward negative beliefs. The agent's perceived belief (P^{bias}_{g,y_t}) is then updated by Equation (5),

$$P^{bias}_{g,y_t} = \begin{cases} \left(\frac{p - C_{g,y_t}}{1 - C_{g,y_t}}\right)^{\alpha_g} \times \left(1 - C_{g,y_t}\right) + C_{g,y_t} & \text{if } p \in P^{adj}_{g,y_t},\ p \geq C_{g,y_t} \\ \left(\frac{p - C_{g,y_t}}{C_{g,y_t}}\right)^{\beta_g} \times C_{g,y_t} + C_{g,y_t} & \text{if } p \in P^{adj}_{g,y_t},\ p < C_{g,y_t} \end{cases} \tag{5}$$

where α_g and β_g are the curvatures of nonlinear curves for the positive and negative beliefs, respectively, and P^{adj}_{g,y_t} is a vector of values of a discretized beta probability distribution computed from p^{adj}_{g,y_t} and N (Table 2, Equation S3.6). In **step 5**, the diversion-request-adjustment ratios are generated by mapping perceived beliefs (P^{bias}_{g,y_t}) into diversion-request-adjustment ratios (R_{g,y_t}) through a linear mapping function (Equation (6)).

$$R_{g,y_t} = \left(\left(\mathrm{ECDF}^{-1}_{P^{bias}_{g,y_t}}(u_{g,y_t}) \times 2 - 1\right) - (C_{g,y_t} - 0.5) \times 2\right) \times R_{g,\,max} \quad (6)$$

where u_g is a random number from a Uniform$(0, 1)$ distribution.

In this study, the $R_{g,\,y_t}$ is represented by the expected value (R_g^{Exp}) for enhancing the calibration converging speed.

$$R^{Exp}_{g,y_t} = E_u\left[R_{g,y_t}\right] \quad (7)$$

In addition, to prevent the numerical error, the R^{Exp}_{g,y_t} is forced to be greater than −0.9. If it is below −0.9, the algorithm will replace it with −0.9. Finally, we complete the decision-making process by using the ratios to update mean annual diversion requests and disaggregate them into daily diversion requests (**step 6,** Equation S3.10). The ODD + D description (Müller et al., 2013) for the ABM model (Text S2) and a complete mathematical description of the decision-making algorithm (Text S3) are provided in the supplementary materials.

4.2. Models' calibration and validation

To calibrate the model, we separated a single simulation into three periods: (1) warm-up period (1960–1965), (2) calibration period (1966–1995), and (3) validation period (1996–2005). The objective function for the calibration is to maximize the mean annual Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970) of six diversions (i.e., Kittitas, Tieton, Wapato, Sunnyside, Roza, and Kennewick) and two river discharges (i.e., Parker and Kiona) as the RW is updated by the diversion ABM with an annual frequency (Sect. 4.1).

Coupled-YAKRW contains 72 parameters that require calibration, including six parameters (Table 2) for each district, a social network matrix, a weight vector. To reduce the searching space, we first calibrate Coupled-YAKRW without a social network matrix (Coupled-YAKRW w/o S.); namely, 36 parameters from the social network matrix and the weight vector are removed. Then, we calibrate Coupled-YAKRW with a fixed *InfoSource* parameter from the calibrated Coupled-YAKRW w/o S. model for each agent.

4.3. Experimental setup

We design the following numerical experiments to compare coupled models with the YAKRW (baseline), investigate the social norm effect, and assess the impact of changing policy rules on human irrigation behaviors.

4.3.1. Model comparison for testing different ABM structures

We first calibrate and validate two coupled models (Coupled-YAKRW and Coupled-YAKRW w/o S.). Then, we compare them with the baseline model (YAKRW) to exam whether coupled models can better capture both the hydrological responses (system viewpoint) and irrigation diversion dynamics (the local viewpoint).

4.3.2. LSA on a directed social network

The social norm effect is argued to be a significant factor affecting farmer decisions in the western U.S. (Hu et al., 2006). Therefore, in addition to the model comparison in Sect. 4.3.1, we further explored the sensitivity of social network structure to local or system-wide model performance (*i.e.*, NSE) using local sensitivity analysis (LSA) on the directed social network. In the experiment, we slightly perturbed connections inside the network of the calibrated network of Coupled-YAKRW. This means we randomly selected one or two agent pairs and reversed their calibrated network connections. For example, if the pair of agents had no connection (*e.g.*, cells in the social network matrix (Fig. 3a) with value 0), then we added a connection (changed 0 to 1) or vice versa. For a single perturbation, we had 30 combinations in social networks. For two perturbations, we had 435 combinations. Consequently, we ran a total of 465 simulations in the LSA.

4.3.3. Water-reallocation-induced behavior changes

The third experiment is performed as a proof-of-concept to demonstrate how the two-way coupled model can be applied to inform potential human behavior changes through a "what-if" water reallocation scenario. We would like to show how agents' risk attitudes will change if their water rights are all proratable, meaning they share the water deficiency during the drought years. To clarify, we are not proposing the implementation of such top-down water rights changes. Instead, we want to use the scenario to test the hypothesis that agents originally with nonproratable water rights will be more sensitive to the environmental changes (i.e., toward risk-averse) as there is no guarantee water supply during drought years. In reality, water rights change is an extremely complicated issue involving political debate, government negotiation, and multiple level stakeholder engagements, which is out of the scope of our paper focus and beyond the limit of our current ABM structure. Therefore, we can only show the results of "what will happen" if water can be reallocated in the YRB, but we will not explore "how it might happen" in this paper. To test the abovementioned changing behavior hypothesis, we recalibrated the coupled model with the all-proratable water rights setup and compared the recalibrated agents' parameters with the original one.

5. Results

5.1. Model comparison and adaptive capacity

We show how coupled models can better capture both long-term (overall trends) and short-term (year to year variations) hydrological and irrigation diversion dynamics in this section. We also discuss the impacts of the social norm effect, namely, the impact of the ABM model structure as well. In this case study, the NSEs resulting from the annual diversion of six major irrigation districts are considered as local level model performances. In contrast, the NSEs from the annual discharge of the Parker and Kiona flow gauges near the basin outlet represent system-wide performances.

Table 3 shows both Coupled-YAKRW and Coupled-YAKRW w/o S. can better capture local and system-wide dynamics of the observed data compared to the baseline model (YAKRW) in terms of NSE values. For system mean NSEs, the two coupled models and the baseline model are similar. However, the coupled models show significantly better local NSEs (Table 3). Kennewick's performances are dominated by RW's policy rule (Sect. 4.1.1), as we can also see in Fig. 4. Fig. 4 reveals the annual diversion time series data for six agents. The grey lines are the observed data. The validation results (after the vertical dashed lines in Fig. 4) indicate the calibrated models are not overfitted. Similar results are provided for Parker and Kiona flow gauges in Figs. S4–2. These results suggest that coupled models better catch diversion dynamics induced by human activities through adaptive decision-making.

We quantify how adaptive capacity benefits by capturing long-term trends in irrigation diversions with the state variable C in Fig. 5. State variable C contributes to steps 3, 4, and 5 of the agent's decision-making process as a parameter in decision rules (Fig. 2). As mentioned in Sect. 4.1.2, C distinguishes the positive and negative perceived beliefs about water supply conditions, leading to increasing (above C) or decreasing (below C) irrigation diversion requests, respectively. Therefore, although a bit counterintuitive, if we observe C value is continuously higher than 0.5, then we can anticipate a long-term decreasing diversion trend and vice versa. For the Roza, Wapato, and Tieton districts in Fig. 5, the C value fluctuates at approximately 0.5 before 1980 and remains greater than 0.5 after 1980. This corresponds to an observed decreasing diversion trend after 1980 (Fig. 4). Following the YRB's history, there was only one major drought between 1960 and 1980, which provided fewer incentives to alter diversion behaviors. However, the YRB experienced about one drought every five years after 1980 (Malek et al., 2018; Pellicciotto et al., 2012), which may have influenced the competition dynamics of water. This affected the overall cooperative or

Table 3
NSE values of YAKRW, Coupled-YAKRW, and Coupled-YAKRW w/o S. models.

Models	Local NSEs						System NSEs	
	Roza	Sunnyside	Tieton	Kennewick	Kittitas	Wapato	Kiona	Parker
YAKRW	−0.08	−5.87	−1.66	−0.69	−2.78	−0.12	0.97	0.91
Coupled YAKRW	0.60	0.34	−0.42	−0.68	0.55	−0.16	0.95	0.98
Coupled-YAKRW w/o S.	0.56	−0.60	0.54	−0.73	0.81	0.13	0.96	0.99

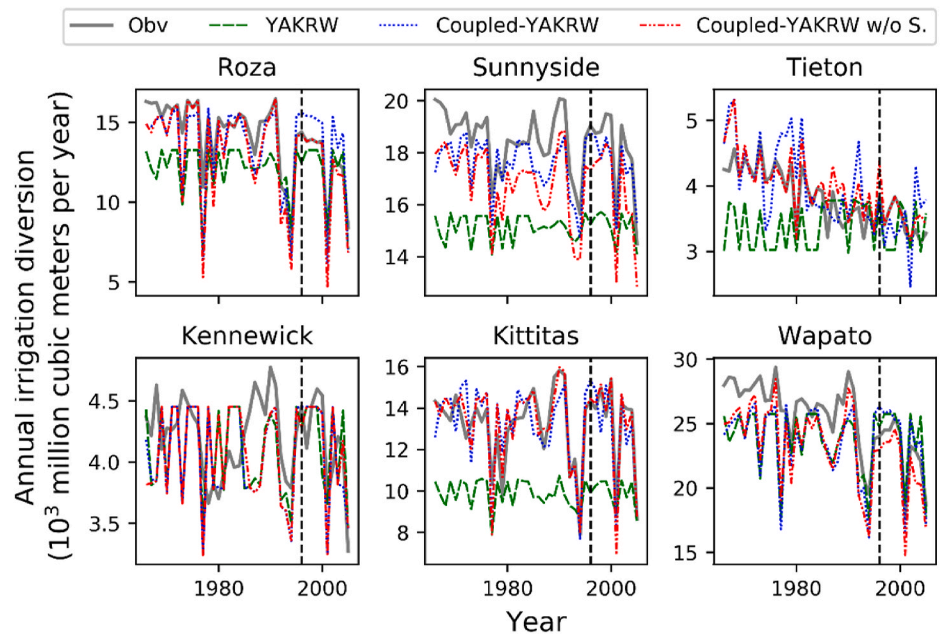

Fig. 4. Model comparison of annual diversions. Grey lines are the observed annual irrigation diversions. Green dashed lines are outputs of the original YAKRW model. Blue and red dotted lines are simulated results from coupled-YAKRW and coupled-YAKRW w/o S., respectively.

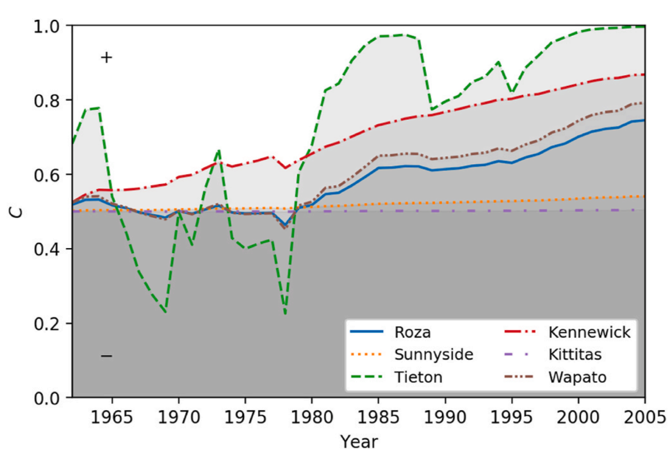

Fig. 5. Timeseries plot of the state variable, Center (*C*), for six agents in the Coupled-YAKRW model. Colored regions have negative perceived beliefs of water supply conditions. Note: higher *C* values indicate agents will divert less water.

defective structure in the basin, which motivates some districts to initiate water conservation measures (*e.g.*, changing crop types and improving irrigation efficiency). These long-term changes in diversion behavior can be combined and implicitly captured by state variable *C*. For Sunnyside and Kittitas, *C* values remained approximately 0.5 during the entire simulation period, suggesting no noticeable long-term trend in diversions. These results also corresponded to the observations in Fig. 4. For the Kennewick agent, due to dominant policy rules inside the YAKRW model (Sect. 4.1.1), our ABM model showed a minor influence on Kennewick's behavior. Therefore, neither the simulated diversion value nor the *C* value captured the observed dynamic.

5.2. LSA of social network structure

The social norm effect is suggested as a significant factor in farmer decision-making processes in the western U.S. (Hu et al., 2006). However, in this case study, both Coupled-YAKRW and Coupled-YAKRW w/o S. models provided a similar level of mean NSE, where Coupled-YAKRW w/o S. generated a slightly higher mean NSE (Table 3). One explanation is model equifinality, where the over-parameterized model obtains a set of parameters (Figs. S4–4) or structures that result in similar model performance. In Table 4, we show how calibrated agent-unique parameters (i.e., agent attributes) were changed from Coupled-YAKRW to Coupled-YAKRW w/o S to compensate the absence of the social norm effect (*S* and *Sw*). Although judging the correctness of different model settings is not the target of this paper, a further investigation can

Table 4
Percentage of difference between Coupled-YAKRW and Coupled-YAKRW w/o S. with regard to calibrated range of each parameter. Raw parameter values of Coupled-YAKRW and Coupled-YAKRW w/o S. are given in Tables S4–1 and Tables S4–2, respectively.

Parameter	Roza	Sunnyside	Tieton	Kennewick	Kittitas	Wapato
γ	−17%	−96%	21%	−7%	−63%	18%
Sc	31%	30%	20%	−12%	34%	4%
α	−29%	−24%	−64%	29%	−80%	45%
β	−15%	−54%	23%	21%	−81%	14%
R_{max}	−48%	−74%	28%	−7%	−17%	−31%

advance our understanding of the role of the social norm effect and help us evaluate model equifinality issues in the coupled models for future CNHS studies.

To further examine the impact of the social network structure on model performance, local sensitivity analysis (LSA) was performed by perturbing the calibrated social network matrix (Tables S4–3) as described in Sect. 4.1.2. The LSA results (Fig. 6) show that the mean diversion NSE over six agents was similar to the calibrated Coupled-YAKRW model (red cross). However, perturbation of the social network could affect the local performance of individual agents (*e.g.*, Tieton, Kittitas, and Sunnyside). Our original hypothesis is that agents with larger weights for the social norm effect will be more sensitive to social network perturbations. However, the Tieton district, with a lower weight value (0.09), showed a more significant variation in NSE values compared to other agents with higher weights (*e.g.*, Roza and Wapato). This was due to predefined policy rules inside the YAKRW model, described in the next paragraph. For the Kittitas district, the perturbation results had higher NSE values in the irrigation diversion outputs. This phenomenon was caused by the system-wide calibration objective function, in which local parameters might not be optimized for each agent. For the Sunnyside district, the variance among LSA simulations was small (*i.e.*, insensitive), but there was a noticeable decrease in NSE values. One possible reason is that Sunnyside has the highest calibrated learning rate (γ; Tables S4–1) and maximum diversion-request-adjustment ratio (R_{max}; Tables S4–1), meaning its decisions may be greatly influenced by the environment feedback (*e.g.*, streamflow, v). Therefore, other agents' behaviors may implicitly affect Sunnyside's diversion decisions through changing the streamflow (*e.g.*, upstream diversions) during the social network perturbation.

Agents such as Roza, Sunnyside, Kennewick, and Wapato were not sensitive to the social network structure. However, those insensitive results do not imply that the social norm effect is not essential, where the predefined policy rules in the YAKRW might cause such results. Policy rules, including water rights or maximum/minimum diversion constraints (Sect. 4.1.1), could limit the utility of ABM outputs. Therefore, the social norm effect might seem limited using RW outputs. To illustrate this complexity, we plotted the standard deviation of 465 simulations with respect to calibrated Couple-YAKRW results in Fig. 7, where blue circles represent actual diversion (RW output) and orange triangles indicate the diversion requests sent from ABM to RW (RW input). In general, larger *Sw* values have greater standard deviations since the agent relies more on the neighbor's opinions. However, those trends are limited by RW policy rules (Sect. 4.1.1), where the standard deviations

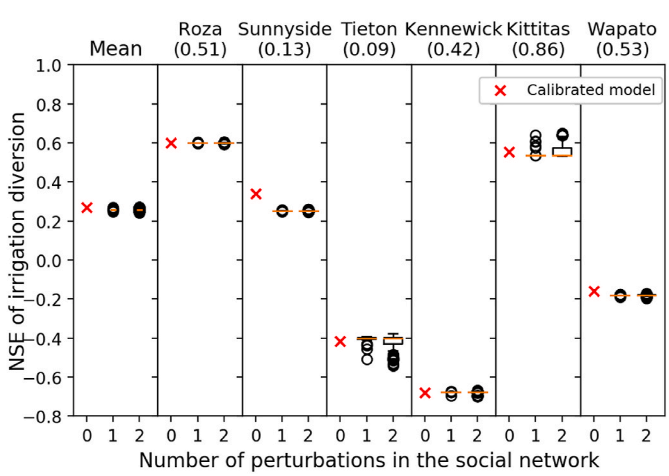

Fig. 6. NSE of irrigation diversions in LSA. The weight of the social norm effect of each agent is shown by bracket. The red cross indicates calibrated Coupled-YAKRW model results, and orange lines are median values. Black circles are NSE values outside the range of 25% and 75% quantiles shown as boxes.

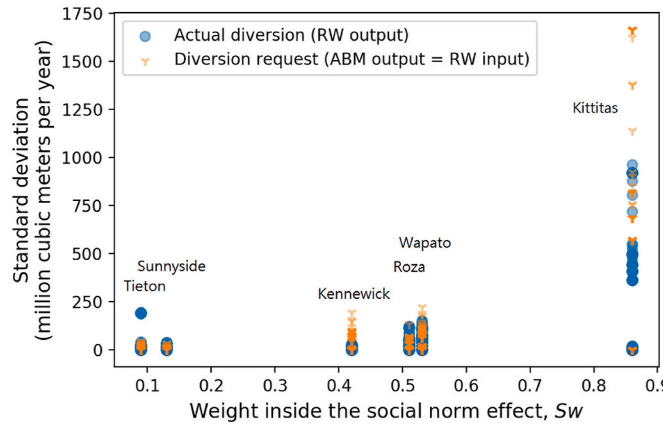

Fig. 7. Standard deviations of 465 LSA simulation results with respect to calibrated Coupled-YAKRW outputs. The x-axis is the weight inside the social norm effect. Blue circles represent actual diversion (RW output), and orange triangles indicate diversion requests sent from ABM to RW (RW input).

of RW outputs are less than RW inputs. This phenomenon becomes clear at larger *Sw*. Such a limitation is acceptable because individual human behaviors are indeed restricted by policy rules (*e.g.*, water rights) in the real world.

5.3. Impact of policy rules on the human behavior

Studies have shown evidence in offsetting behaviors (Campbell et al., 2004; Fielding et al., 2012), where the feedback of human behaviors toward the changing policy jeopardizes the original intention or the effectiveness of that newly introduced policy. For example, Fielding et al. (2012) indicated that the policy of giving people water-saving hardware might result in higher water consumption, which was opposite to the goal of their water conservation programs. This offsetting behavior motivates us to explore the impact of changing policy rules (*e.g.*, water reallocation) on human behavior (*e.g.*, diversions and risk attitudes).

In the comparison of Coupled-YAKRW w/o S. between original and all-proratable water rights, we found that Wapato, Sunnyside, and Tieton divert much less water during the drought years since their original non-proratable water rights are set to all-proratable water rights. Then, when those senior water rights holders divert less water, more water becomes available to junior holders. This is more obvious in normal and wet years. Therefore, we observed larger diversion fluctuations in those agents (Figs. S4–3). We ignore Kennewick in the latter analysis due to dominant policy rules in the YAKRW (Sect. 4.1.1), leading to minor influence from the diversion ABM.

To further investigate the potential changes in human behaviors, we recalibrated the Coupled-YAKRW w/o S. (with fixed *InfoSource*) under the all-proratable water rights setup. The results indicate that agents become more sensitive to the changing environment (*i.e.*, toward risk-averse), as shown in Fig. 8. Fig. 8 presents the prospect functions (Equation (5)) of agents' perceived beliefs on the water supply conditions. The curvatures (α and β in Equation (5)) are agents' risk attitudes. For example, concave shapes in the upright corner in each subplot of Fig. 8 means that agents are risk-seeking and insensitive to the belief of the positive water supply conditions (*e.g.*, more available water), while convex shapes represent risk-averse attitudes and sensitive characteristics to the belief of the positive water supply conditions. On the contrary, the concave and convex shapes have opposite meanings for the lower-left corner in the subplots (Fig. 8), which indicates the agents' risk attitudes to the belief of the negative water supply conditions (*e.g.*, droughts). The prospect functions of the recalibrated Coupled-YAKRW w/o S. are shown in dotted lines, where the solid lines are from the original model. Comparing solid and dotted lines, we can see that most

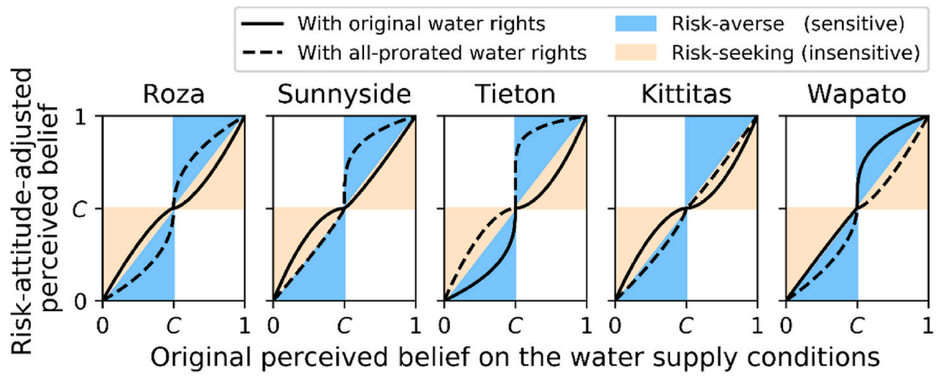

Fig. 8. Prospect functions (*e.g.*, mapping agents' risk attitudes; Equation (5)) under original (solid lines) and all-proratable (dotted lines) water right scenarios. Upper right corners are the risk attitudes toward the beliefs of positive water supply conditions, while lower left corners are to negative conditions (*e.g.*, droughts).

of the lines curve toward risk-averse regions (blue area) in Fig. 8 except parts of Tieton and Wapato. Namely, agents become more willing to adjust their diversion behaviors according to the changing environment. This flexibility could potentially benefit the instream flow control (*e.g.*, adjusting their diversions to meet target flow) and enhance the efficiency in water uses, where efficiency is defined as maximizing productivity without wasting. It has been shown that the value associated with instream flow (*e.g.*, recreational and esthetic uses) are greater than the value made from irrigation of low-value crops (Watts et al., 2001). However, the unstable irrigation supply could also impact the investment in high-value perennial crops such as orchards and grapes (Feinerman and Tsur, 2014), which requires several preparing years before making profits.

6. Discussion

6.1. Cross-scale CNHS modeling for multi-level governance application

This study investigates the co-evolution mechanism in the CNHS modeling via a case study in the YRB. The results show that the coupled models can better capture both system (*e.g.*, streamflow) and local (*e.g.*, irrigation diversions) dynamics. Also, we demonstrate the influences of the social norm effects and the impact of the changing water allocation policy. We would like to further discuss how to link the coupled models proposed in this study to potential multi-level water resources governance applications.

Multi-level water resources governance naturally occurs in many managements problem in solving water conflicts. For example, the Yakima River Basin Integrated Water Management Plan (Office of Columbia River, 2020) began in the 1980s, involving federal (*e.g.*, USBR), Washington state, Yakama Nation, counties, cities, and farmers to collaboratively offer a long-term vision and a management plan for water allocation under the changing climate and environment. To that, the coupled model provides a quantification method to model the cross-scale responses supported individually customized actors' behaviors and interactions (*e.g.*, federal policy to the reservoir operations, water allocation policy to the farmers' behaviors, and ecological conditions to the drought responses) under a decentralized modeling framework (*e.g.*, ABM). Such properties of coupled models create a unique niche for informing multi-level water resources governance via modeling results. Furthermore, according to an entire Columbia River Basin (CRB)-wide survey results (Zhang et al., 2021), reservoir operations in the CRB gradually shifted to improve the aquatic environment (USBR, 2020) and people were most supportive of sustainability policies impacting the food and water sectors instead of energy sectors. The YRB situations and our modeling results align with the survey findings. This implies that the model structure of Coupled-YAKRW (*e.g.*, reservoir operation rules in the RW and the diversion ABM) has the potential to be scaled up and applied to the entire CRB.

More importantly, we would like to discuss the motivation of how water agencies might consider adopting coupled models, which could help them resolve possible water conflicts under different policy scenarios (with explicit human decisions quantified). Here are some historical events for water conflicts associated with water resources multi-level governance in the CRB region. In 2006, a water rights fight between a power company and the Idaho State government occurred at the Snake River, US, where ongoing water rights dispute with the Nez Perce Indians has been last for decades (Miller, 2006). In 2016, the armed fights over the water rights and land resources in the Malheur National Wildlife Refuge, Oregon, US, between the federal government and the local people led to several casualties (Wiles, 2016). We vision that coupled models can analyze and broaden policies and management strategies, which provide a higher chance of finding a smoother path to ease those water conflicts. However, such a hypothesis cannot be solely proved by our current modeling experiments. It requires vigorous involvement of social science to establish the theoretical foundation for model setup and continuous communication among stakeholders.

6.2. Limitations

To explore water management challenges in CNHS, we tested different ABM models for different human behavior assumptions and built the coupled model on top of existing process-based models (*e.g.*, YAKRW in our case study), which were developed by USBR. These existing models are used by authorities to assist in real-world operations. Therefore, policy constraints are included in the modeling structure to reflect reality as much as possible. These inclusions are most likely present due to legal issues around water rights and minimum stream flows constraints, as examples. Therefore, our case study might not fully demonstrate the utility of the ABM. As shown in the Result section, we encountered limited flexibility in the YAKRW model. Nonetheless, these results do not mean that we should not couple with these existing models; we would like to leverage their credibility and use the coupled model to demonstrate some potential policy changes via modeling results.

Also, the current ABM model design limits our capability to further explore the water reallocation experiment. As a result, we only demonstrate "what will happen" but not "how will it happen." A possible way to facilitate the discussion of water reallocation, in reality, is through water banking or water market mechanisms (Du et al., 2021; Yang et al., 2012). For example, with economic incentives, Du et al. (2021) and Yang et al. (2012) showed the possible transition of a non-proratable water right holder might become a proratable water right holder in a water market. Note that the water market setting will drive farmers' behaviors in a different way as we presented in this paper and require a different ABM model design (*i.e.*, a decentralized optimization algorithm to drive agent's behavior is needed in the water market setup). Nevertheless, this topic will be a perfect future study applying the two-way coupled model.

Another limitation is the model equifinality issues (*e.g.*, multiple models result in similar calibrated outcomes) along with the potentially over-parameterized coupled models. Namely, due to the unknown of true process, modelers will encounter the trade-offs between narrative complexity (*e.g.*, how detail is the human behavior modeling design?) and model complexity (Grimm and Railsback, 2012a), which leads to greater equifinality (Figs. S4–4). We further refer readers to Beven (2006), Khatami et al. (2019), and Lin and Yang (2022) for a more comprehensive introduction to equifinality issues. To address this limitation, we plan to conduct uncertainty and sensitivity analysis (Yen et al., 2014) and add these features in the next version of Py-RAMID to help modelers identify dominant policy rules in the RW and model equifinal parameter sets of coupled models. Also, instead of a single mean NSE value, we can calibrate the coupled models with pattern-oriented modeling (Grimm and Railsback, 2012b; Wiegand et al., 2003), which focuses more on the adaptive capacity of the system. For example, the adaptation of an agent's behaviors (*e.g.*, crop types and crop area) as responses to the changing environment or extreme events (*e.g.*, droughts).

Finally, even though we put the effort of developing python-based Py-RAMID package for embracing the Open Science by Design concept (NASEM, 2018; U.S. DOE, 2019) through improving coupled models' reproducibility (Goodman et al., 2016) and extensibility (Lacroix and Critchlow, 2003), we understand Py-RAMID has its limitation to fully meet the idea due to the licensed RiverWare. Moreover, similar coupling concepts like co-simulation, multi-modeling, multi-formalism modeling, and multi-model ecologies have also been explored in energy and system control domains (Bollinger et al., 2018; Gomes et al., 2018; Plessis et al., 2014; Vangheluwe, 2000; Vaubourg et al., 2015), as well as the integration frameworks like High-Level Architecture (HLA; Dahmann et al., 1997) in the technology context. Therefore, we do not claim that Py-RAMID is a novel contribution to the Open Science by Design concept. Instead, we hope this study can help our readers to be aware of this concept and further contribute to it in the future.

7. Conclusions

This study aims to improve our understanding of CNHS, which has been shown to ameliorate environmental planning and policy (Zellner, 2008), through the YRB case study. We designed three numerical experiments investigating different facets of CNHS. First, we compare coupled models (*e.g.*, Coupled-YAKRW and Coupled-YAKRW w/o S.) with the baseline model (*e.g.*, YAKRW) and demonstrate that coupled models can better capture both irrigation diversion (human behaviors) and streamflow dynamic. Second, we analyzed the role of the social norm effect through a local sensitivity analysis. The similar simulation results between coupled models with or without social norm effect are caused by the dominant RW policy rules and the potential model equifinality issue. Separate research on quantifying the model complexity and equifinality are required before further demonstrating the effect of the social norm in CNHS modeling. Third, we show human behaviors (*e.g.*, diversions and risk attitudes) could be affected by policy rules, where agents become more sensitive (*i.e.*, risk-averse) to the changing environment under the all-proratable-water-rights scenario in the YRB. In sum, this study explores the co-evolution in CNHS from different facets such as model structures (*e.g.*, social norm effect) and the reciprocate influence between policy rules (*e.g.*, water allocation) and human behaviors (*e.g.*, diversions and risk attitudes). However, a more detailed model uncertainty analysis is needed to further quantify the benefit of CNHS in informing policymaking for future multi-level water resources governance applications.

Software availability

The Py-RAMID package is designed to run under Python 3.7 in the Windows system. The package and its user manual are freely accessible at https://github.com/philip928lin/Py-RAMID.

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.envsoft.2022.105451.

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