Supporting Information for

Develop a coupled agent-based modeling approach for uncertain water management decisions

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Additional Supporting Information (Files uploaded separately)

None

Introduction

The supplement can be used as a template for Overview, Design Concept and Details (ODD) protocol of the Agent-Based Model (ABM). This standardized protocol provides more understandable and comprehensive account of the ABM. (Grimm et al. 2006)

Text S1 - ODD Protocol of Agent-Based Model

1. Overview

1.1. Purpose

Question: What is the purpose of the model?

The coupled modeling provides a framework to simulate the impact of human decision on water resources management at the watershed scale. In this study, the ABM simulates the action of the agents (humans' decision-making on the annual irrigation plan) to interact with River-Reservoir management model, RiverWare.

1.2. Entities, State Variables, and Scales

Questions: What kinds of entities are in the model? By what state variables, or attributes, are these entities characterized? What are the temporal and spatial resolutions and extents of the model?

This model is composed of 16 irrigation districts (List of Agents) to investigate the humans' decisions of the irrigation area over the river basin. The River-Reservoir management model, RiverWare, operates on a daily time step, for a period of 85 years (October 1, 1928, to September 30, 2013). The ABM operates on an annual time step to interact with the RiverWare.

List of Agents

Agent Name	Sub-Group	Initial Size (acre)
JicarillaIrr	Group1 (Upstream of Navajo Reservoir)	700
NMPineRiverAreaIrr	Group1 (Upstream of Navajo Reservoir)	1420
TwinRocks	Group2 (Animas River – Tributary of San Juan River)	251.3
NMAnimasIrr	Group2 (Animas River – Tributary of San Juan River)	9341.1
FarmingtonGlade	Group2 (Animas River – Tributary of San Juan River)	700
EchoDitch	Group2 (Animas River – Tributary of San Juan River)	1210
FarmersMutual	Group2 (Animas River – Tributary of San Juan River)	3050
Ralston	Group2 (Animas River – Tributary of San Juan River)	407.6
ArchuletaDitch	Group3 (Downstream of Navajo Reservoir)	40
CitizenDitch	Group3 (Downstream of Navajo Reservoir)	3940
TurleyDitch	Group3 (Downstream of Navajo Reservoir)	205
Hammond	Group3 (Downstream of Navajo Reservoir)	40
FruitlandAndCambridge	Group3 (Downstream of Navajo Reservoir)	540
JewettValley	Group3 (Downstream of Navajo Reservoir)	920
Hogback	Group3 (Downstream of Navajo Reservoir)	2140
CudeiCanal	Group3 (Downstream of Navajo Reservoir)	170
Total Number of Agents in San Juan River Basin		**16**
Total Irrigation Area (initial) in San Juan River Basin		**25075**

The state variables in the model include six watershed system parameters that set a foundation for the risk perceived decision-making. The agents have their economic parameters which acts as external threshold during Cost-Loss model. Furthermore, 48 parameters represent the farmer's beliefs regarding a process of Bayesian Inference (BI) mapping (List of Parameters).

List of Parameters

Parameter	Note	# of Parameters
Upstream Precip. Threshold	Apply to all agents: 16 agents in mm	1
Animas River Precip. Threshold	Apply to agents in group 2: 6 agents in mm	1
Downstream Precip. Threshold	Apply to agents in group 3: 8 agents in mm	1
Navajo Reservoir Elevation	Elevation in feet	1
Frequency of flow violation	Number of days which the flowrate is below 500 cfs at the outlet of San Juan River Basin	1
NIIP Diversion threshold	One single parameter will be used for all agents.	1
Cost/Loss Parameter (z)	$z = \frac{Cost\ (Total\ Cost\ due\ to\ expansion)}{Loss\ (Loss\ of\ Earning)}$	16
Irr. Area Increment	Range from -5% ~ 5%	16
Farmers' Belief(λ_i) [$0.5 \leq \lambda \leq 1$]	λ: Upstream Precip. -> Navajo Res. Elev.	16
	λ: Upstream Precip. -> Decision Irr. Area	2
	λ: Animas Precip. -> Decision Irr. Area	6
	λ: Downstream Precip. -> Decision Irr. Area	8
	λ: Flow Violation -> Decision Irr. Area	16
	λ: updating Farmer's belief	16
Total Number of Parameters		**102**

1.3. Process overview and schedule

Questions: Who (i.e., what entity) does what, and in what order? When are state variables updated? How is time modeled, as discrete steps or as a continuum over which both continuous processes and discrete events can occur? Except for very simple schedules, one should use pseudo-code to describe the schedule in every detail, so that the model can be re-implemented from this code. Ideally, the pseudo-code corresponds fully to the actual code used in the pro-gram implementing the ABM.

The ABM is triggered at every end date of the water year, 24:00:00 September 30th by using Data Management Interface which is an in-programmed tool in the RiverWare. The state variables for the ABM are updated from the RiverWare when the ABM interacts with RiverWare annully (discrete steps). After the ABM computation, newly updated irrigation areas and corresponded water diversions are exported to the Riverware (Object/Slot). A pseudo codes are provided below to describe the detailed schedule. The pseudo-code is a simplified algorithm of actual ABM codes.

Pseudo Code: Risk Perception of ABM

Group 1. Upstream of Navajo Reservoir

For year **=** 1928 to 2013 (In the sample code only 20 years of study period was considered.)

For Agent **=** 1 to 16

Bayesian Inference (BI): systematic network

BI_Prec_NElev (Upstream Precipitation|Navajo Elevation);

BI_FlowVio_inner (BI_Prec_NElev|Flow Violation);

BI_UpstreamPrecip (Upstream Precipitation|Irr Area);

BI_FlowVio (BI_FlowVio_inner|Irr Area);

Bayesian Inference (BI) : BI mapping

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

Extremity analysis to build Cost/Loss structure

V = factors which are related to the decision-making process such as Upstream/Animas/Downstream Precipitation, NIIP diversion, and Flow Violation (Shortage Sharing is always located at the highest decision factor);

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \epsilon\ [0,0.5]$$

sort factors ['flow violation' and 'upstream precipitation'] by extremity

BI_High = BI factor with higher extremity;

Bayesian Inference: updating farmer's belief

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

Cost/Loss analysis

If cost/loss ratio factor (z) is smaller than or equal to **BI_High Then**

Agent decreases irrigated area by a certain percentage;

Elseif

Agent increases irrigated area by a certain percentage;

Endif

Next Agent

Next Year

Group 2-1. Animas River without Shortage Sharing

For year **=** 1928 to 2013

For Agent **=** 1 to 16

Bayesian Inference (BI)

BI_Prec_NElev (Upstream Precipitation|Navajo Elevation);

BI_FlowVio_inner (BI_Prec_NElev|Flow Violation);

BI_AnimasPrecip (Animas Precipitation|Irr Area);

BI_FlowVio (BI_FlowVio_inner|Irr Area);

Bayesian Inference (BI) : BI mapping

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

Extremity analysis to build Cost/Loss structure

V = factors which are related to the decision-making process such as Upstream/Animas/Downstream Precipitation, NIIP diversion, and Flow Violation (Shortage Sharing is always located at the highest decision factor);

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \epsilon\ [0,0.5]$$

sort factors [‘flow violation’ and ‘Animas River precipitation’] by extremity

BI_High = BI factor with higher extremity;

Bayesian Inference: updating farmer’s belief

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

Cost/Loss analysis

If **cost/loss ratio factor (z)** is smaller than or equal to **BI_High** **Then**

Agent decreases irrigated area by a certain percentage;

Elseif

Agent increases irrigated area by a certain percentage;

Endif

Next Agent

Next Year

Group 2-2. Animas River with Shortage Sharing

For year = 1928 to 2013

For Agent = 1 to 16

Bayesian Inference (BI)

BI_Prec_NElev (Upstream Precipitation|Navajo Elevation);

BI_SS_inner (BI_Prec_NElev|Shortage Sharing);

BI_FlowVio_inner (BI_Prec_NElev|Flow Violation);

BI_AnimasPrecip (Animas Precipitation|Irr Area);

BI_FlowVio (BI_FlowVio_inner|Irr Area);

BI_ShortageSharing (BI_SS_inner|Irr Area);

Bayesian Inference (BI) : BI mapping

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

Extremity analysis to build Cost/Loss structure

V = variables which are related to the decision-making process such as Upstream/Animas/Downstream Precipitation, NIIP diversion, and Flow Violation (Shortage Sharing is always located at the highest decision factor);

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \epsilon\ [0,0.5]$$

sort factors ['flow violation' and 'Animas River precipitation'] by extremity

BI_High = BI factor with higher extremity;

Bayesian Inference: updating farmer's belief

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

Cost/Loss analysis

If cost/loss ratio factor (z) is smaller than or equal to **BI value of 'shortage sharing' Then**

Agent decreases irrigated area by a certain percentage;

Elseif

If cost/loss ratio factor (z) is smaller than or equal to **BI_High Then**

Agent decreases irrigated area by a certain percentage;

Elseif

Agent increases irrigated area by a certain percentage;

Endif

Endif

Next Agent

Next Year

<u>Group 3-1. Downstream of Navajo Reservoir (San Juan River) without shortage sharing</u>

For year = 1928 to 2013

For Agent = 1 to 16

Bayesian Inference (BI)

BI_Prec_NElev (Upstream Precipitation|Navajo Elevation);

BI_NIIPdiv_inner (BI_Prec_NElev|NIIP Diversion);

BI_FlowVio_inner (BI_Prec_NElev|Flow Violation);

BI_DownstreamPrecip (Downstream Precipitation|Irr Area);

BI_FlowVio (BI_FlowVio_inner|Irr Area);

BI_NIIPdiv (BI_NIIPdiv_inner|Irr Area);

Bayesian Inference (BI) : BI mapping

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

Extremity analysis to build Cost/Loss structure

V = variables which are related to the decision-making process such as Upstream/Animas/Downstream Precipitation, NIIP diversion, and Flow Violation (Shortage Sharing is always located at the highest decision factor);

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \epsilon\ [0,0.5]$$

sort factors [‘flow violation’ and ‘Animas River precipitation’] by extremity

BI_High = BI factor with the highest extremity;

Bayesian Inference: updating farmer’s belief

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

Cost/Loss analysis

If cost/loss ratio factor (z) is smaller than or equal to **BI_High Then**

Agent decreases irrigated area by a certain percentage;

Elseif

Agent increases irrigated area by a certain percentage;

Endif

Next Agent

Next Year

Group 3-2. Downstream of Navajo Reservoir (San Juan River) with shortage sharing

For year = 1928 to 2013

For Agent = 1 to 16

Bayesian Inference (BI)

BI_Prec_NElev (Upstream Precipitation|Navajo Elevation);

BI_NIIPdiv_inner (BI_Prec_NElev|NIIP Diversion);

BI_FlowVio_inner (BI_Prec_NElev|Flow Violation);

BI_SS_inner (BI_Prec_NElev|Shortage Sharing);

BI_DownstreamPrecip (Downstream Precipitation|Irr Area);

BI_FlowVio (BI_FlowVio_inner|Irr Area);

BI_NIIPdiv (BI_NIIPdiv_inner|Irr Area);

BI_ShortageSharing (BI_SS_inner|Irr Area);

Bayesian Inference (BI) : BI mapping

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

Extremity analysis to build Cost/Loss structure

V = variables which are related to the decision-making process such as Upstream/Animas/Downstream Precipitation, NIIP diversion, and Flow Violation (Shortage Sharing is always located at the highest decision factor);

$$V_i = \left|\frac{\theta_i}{\theta_{max}} - 0.5\right| \epsilon\ [0,0.5]$$

sort factors [‘flow violation’, ‘NIIP diversion’ and ‘downstream precipitation’] by extremity

BI_High = BI factor with the highest extremity;

Bayesian Inference: updating farmer’s belief

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

cost/loss analysis: Bayesian Inference (BI)

If cost/loss ratio factor (z) is smaller than or equal to **BI value of 'shortage sharing' Then**

Agent decreases irrigated area by a certain percentage;

Elseif

If cost/loss ratio factor (z) is smaller than or equal to **BI_High Then**

Agent decreases irrigated area by a certain percentage;

Elseif

Agent increases irrigated area by a certain percentage;

Endif

Endif

Next Agent

Next Year

2. Design concepts

Questions: There are eleven design concepts. Most of these were discussed extensively by Railsback (2001) and Grimm and Railsback (2005; Chapter. 5), and are summarized here via the following questions:

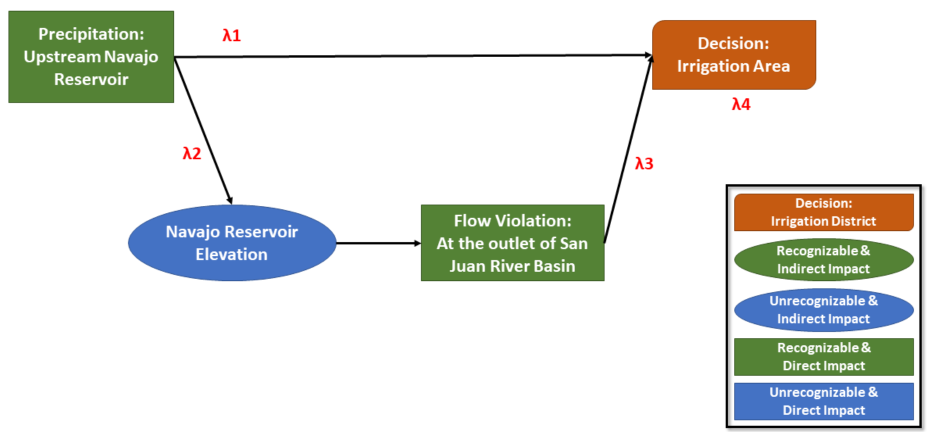
2. 1. Basic Principles

Question: Basic principles. Which general concepts, theories, hypotheses, or modeling approaches are underlying the model's design? Explain the relationship between these basic principles, the complexity expanded in this model, and the purpose of the study. How were they taken into account? Are they used at the level of submodels (e.g., decisions on land use, or foraging theory), or is their scope the system level (e.g., intermediate disturbance hypotheses)? Will the model provide insights about the basic principles themselves, i.e., their scope, their usefulness in real-world scenarios, validation, or modification (Grimm, 1999)? Does the model use new, or previously developed, theory for agent traits from which system dynamics emerge (e.g., 'individual-based theory' as described by Grimm and Railsback (2005) as well as Grimm et al. (2005))?

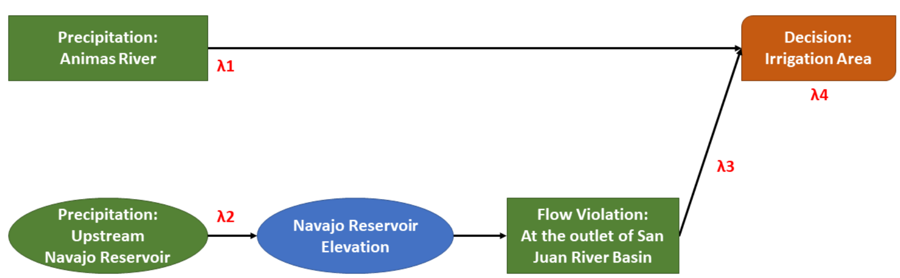
The ABM accepts a theory of the Risk Perception by using Bayesian Inference (BI) mapping to evaluate the uncertainty of the humans' psychological decision-making process. The basic assumption in building the BI network is that decision-makers (farmers) are active parties in the local weather forecast. The decision makers always perceive the locally varied precipitation, reservoir water level, upstream diversion, as well as downstream flow requirements. The agents were clustered into the three groups (Group1: Upstream of Navajo Reservoir, Group2: Animas River, Group3: Downstream Navajo Reservoir) due to the geographic locations and the spatially varied the winter precipitation (snowpack). In particular, the six agents (one in Group2 and five in Group3) are under a shortage-sharing rule in the Riverware rule-based simulation. Furthermore, the ‘individual-based ABM model’ is embodied through applying ‘farmers’ belief’ on new information derived from the basin toward the decision makers to update their belief their belief of the causal relationship in the BI mapping. The pictorial BI mappings which based on the clustering are provided below.

Bayesian Mapping

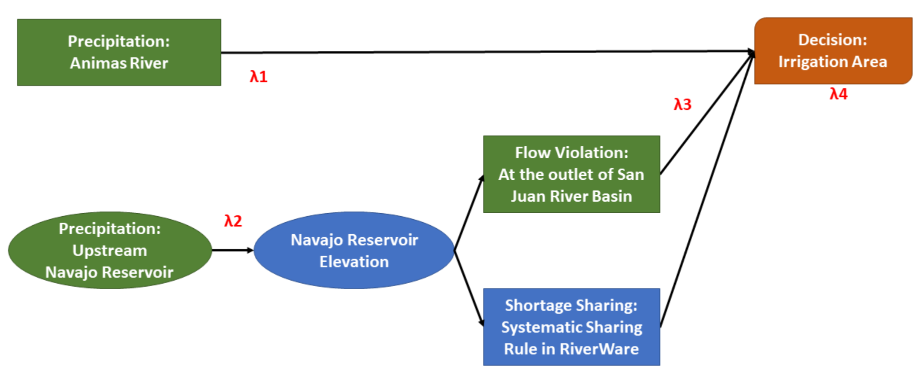
Group1_Upstream of San Juan River (Navajo Reservoir, wet region)



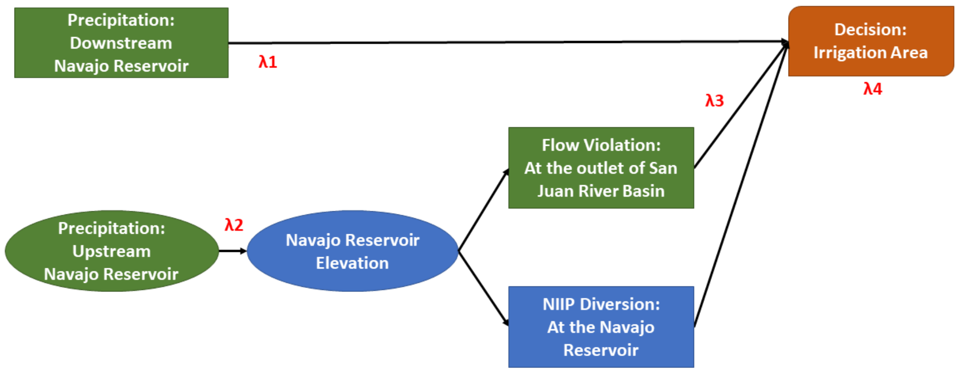
Group2.a_Animas River (dry region) without Shortage Sharing



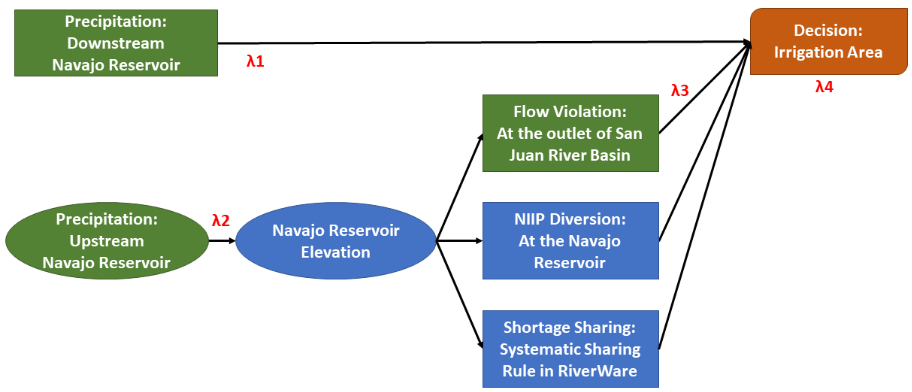
Group2.b_Animas River (dry region) with Shortage Sharing



Group3.a_Downstream of San Juan River (Navajo Reservoir, dry region) without Shortage Sharing



Group3.b_Downstream of San Juan River (Navajo Reservoir, dry region) with Shortage Sharing



2.2. Emergence

Question: What key results or outputs of the model are modeled as emerging from the adaptive traits, or behaviors, of individuals? In other words, what model results are expected to vary in complex and perhaps unpredictable ways when particular characteristics of individuals or their environment change? Are there other results that are more tightly imposed by model rules and hence less dependent on what individuals do, and hence 'built in' rather than emergent results?

The most remarkable result in the risk-perceived ABM is an evaluation of the humans' psychological decision-making process at the agent level by putting the concept of the farmer's belief (λ) in the BI mapping. An individual belief (λ) differentiated credibility of the causal mapping of the decision-making process.

2.3. Adaptation

Question: What adaptive traits do the individuals have? What rules do they have for making decisions or changing behavior in response to changes in themselves or their environment? Do these traits explicitly seek to increase some measure of individual success regarding its objectives (e.g., “move to the cell providing fastest growth rate,” where growth is assumed to be an indicator of success; see the next concept)? Or do they instead simply cause individuals to reproduce observed behaviors (e.g., “go uphill 70% of the time”) that are implicitly assumed to convey success or fitness indirectly?

The agents in the same group share the same system parameters in the BI mapping. However, the trait of an agent’s belief (λ) is unique to adjust the causal probability at the agent level. The BI mapping contains multiple decision-making processes to finalize the following year’s irrigation plan. In the real world, the factors in the decision-making process are not considered parallel but rather hierarchal due to extremities of the factors. An important input to the ABM is identification of variation of precipitation due to the geographic heterogeneity across the river basin.

2.4. Objectives

Question: If adaptive traits explicitly act to increase some measure of the individual's success at meeting some objective, what exactly is that objective and how is it measured? When individuals make decisions by ranking alternatives, what criteria do they use? Some synonyms for ‘objectives’ are ‘fitness’ for organisms assumed to have adaptive traits evolved to provide reproductive success, ‘utility’ for economic reward in social models or simply ‘success criteria.’ (Note that the objective of such agents as members of a team, social insects, organs—e.g., leaves—of an organism, or cells in a tissue, may not refer to themselves but to the team, colony or organism of which they are a part.)

The irrigation agents make the decisions to expand or shrink their cropland on an annual time step, and these decisions derived from the causal probabilities (BI mapping) and following economic decision model, Cost-Loss (CL) model. In a coupled model, Riverware (watershed)-ABM (a human as a user), the two models exchange the information to maximize the human agricultural benefit within the river-managing criteria. This coupled model proposes the smart way to use the water resources in the era of the water scarcity.

2.5. Learning

Question: Many individuals or agents (but also organizations and institutions) change their adaptive traits over time as a consequence of their experience? If so, how?

An agent’s adaptive traits changes over the time. The fundamental decision-making process is based on the timely developing BI probabilities (30 years of window) in the BI mapping. Moreover, the annual extremity has been reset the structural pathway of the Risk-Perceived decisions.

2.6. Prediction

Question: Prediction is fundamental to successful decision-making; if an agent's adaptive traits or learning procedures are based on estimating future consequences of decisions, how do agents predict the future conditions (either environmental or internal) they will experience? If appropriate, what internal models are agents assumed to use to estimate future conditions or consequences of their decisions? What tacit or hidden predictions are implied in these internal model assumptions?

The historical winter precipitation data from November to February in each year are used as a substitute for the snowpack forecast in the ABM model. This historical data assumed to be used as a perfect prediction of the snowpack. Except for this point, the previous data are used in the ABM decision-making process. Grafting with the future climate model is suggested on this part.

2.7. Sensing

Question: What internal and environmental state variables are individuals assumed to sense and consider in their decisions? What state variables of which other individuals and entities can an individual perceive; for example, signals that another individual may intentionally or unintentionally send? Sensing is often assumed to be local, but can happen through networks or can even be assumed to be global (e.g., a forager on one site sensing the resource levels of all other sites it could move to). If agents sense each other through social networks, is the structure of the network imposed or emergent? Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?

The actual decision made via the cost/loss problem and the cost/loss ratio (z) is a considerable state variable (threshold) that senses the decision. It merely represents the external (economic) factor in the decision-making process.

2.8. Interaction

Question: What kinds of interactions among agents are assumed? Are there direct interactions in which individuals encounter and affect others, or are interactions indirect, e.g., via competition for a mediating resource? If the interactions involve communication, how are such communications represented?

Agents interact both directly and indirectly. Agent interact directly through their decision on the water usage by changing their cropland. The agents' decisions change the managing plan in the RiverWare due to the dynamic change of the agricultural water usages.

2.9. Stochasticity

Question: What processes are modeled by assuming they are random or partly random? Is stochasticity used, for example, to reproduce variability in processes for which it is unimportant to model the actual causes of the variability? Is it used to cause model events or behaviors to occur with a specified frequency?

Stochasticity is included in the agent-based model regarding the increasing or decreasing rate of the irrigation area. The percentile change with the 2% of maximum limitation is applied after the binary decision (0: decreasing and 1: increasing).

2.10. Collectives

Question: Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Such collectives can be an important intermediate level of organization in an ABM; examples include social groups, fish schools and bird flocks, and human networks and organizations. How are collectives represented? Is a particular collective an emergent property of the individuals, such as a flock of birds that assembles as a result of individual behaviors, or is the collective simply a definition by the modeler, such as the set of individuals with certain properties, defined as a separate kind of entity with its own state variables and traits?

In the watershed used as case studies for this modeling framework, the agents are grouped into three different regions. The spatial variation of the precipitation (snowpack) is critical in this region due to the orographic effect. Thus, the irrigation agents are aggregated into the geo-precipitation group. Within a group, the agents share the same systematic parameters and BI structure. Collectives in the model represented the different dependencies of the agent's decision by a primary reservoir's (Navajo Reservoir) operation. For instance, the agents in the Group 3: Downstream Navajo Reservoir, are sensitively react with the upstream reservoir release schedule. Meanwhile, the agents in the Group 1: Upstream Navajo Reservoir, have little reference to the reservoir operation.

2.11. Observation

Question: What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected? Are all output data freely used, or are only certain data sampled and used, to imitate what can be observed in an empirical study ("Virtual Ecologist" approach; Zurell et al., 2010)?

The simulated irrigation areas are validated by the historically observations of the irrigation area from the Bureau of Reclamation. The output data from the ABM decisions, the areal increments and the actual water diversions, are freely used for updating the corresponding Object/Slow values in the RiverWare.

3. Details

3.1. Initialization

Questions: What is the initial state of the model world, i.e., at time t = 0 of a simulation run? In detail, how many entities of what type are there initially, and what are the exact values of their state variables (or how were they set stochastically)? Is initialization always the same, or is it allowed to vary among simulations? Are the initial values chosen arbitrarily or based on data? References to those data should be provided.

The RiverWare, simulates the river-basin operation rules from October 1, 1928, to September 30, 2013 (water-year cycle). Before the rule-based simulation in the RiverWare, the model initialized all input flows (derived from hydrologic models – VIC and StateMob) and constant parameters (given by the river basin regulations and the reservoir operation) for internal calculations. The initialization is always the same during the simulation because the initialization performed once before the beginning of the RiverWare simulation. The ABM begins to interact with RiverWare at the end of water year (September 30th, 1929). The initial sizes of the irrigation areas are taken from the historical observations from the Bureau of Reclamation.

3.2. Input Data

Question: Does the model use input from external sources such as data files or other models to represent processes that change over time?

Most of the input data-including data regarding the flow at the outlet of the basin, the Navajo Reservoir elevation, the irrigation areas and the water diversion for Indian Reservation district (NIIP) for the ABM-are retrieved from Riverware. On the other hand, the precipitation data are taken from external sources: ground-based rainfall observatories (rain-gauges) operated by National Oceanic Atmospheric Administration (NOAA).

3.3. Sub-models

Questions: What, in detail, are the sub-models that represent the processes listed in 'Process overview and scheduling'? What are the model parameters, their dimensions, and reference values? How were sub-models designed or chosen, and how were they parameterized and then tested?

The details of the ABM sub-models are presented completely in the ODD supplement. The model parameters which includes definitions and units is presented in the table. We expect ODD descriptions to include appropriate levels of explanation and justification for the ABM decisions, but the complete description of sub-models is likely to be provided in the relevant references.

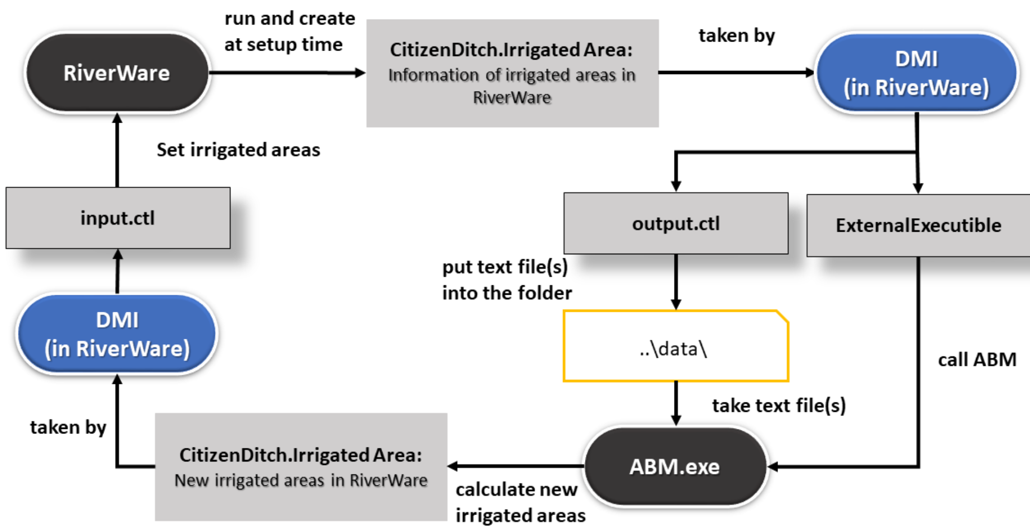


Figure S1. An illustration of the two-way coupling process between an agent-based model (ABM) and a RiverWare using a built-in function of RiverWare: the data management interface (DMI). The figure uses a Water Use Object in RiverWare as an example. The DMI retrieves data from targeted Slots (e.g., irrigation area and water demand in CitizanDitch irrigation area) in RiverWare and exports the data (text files) to the ABM with the path assigned by the “output.ctl” control file. By using exported data and other inputs, the ABM makes the necessary calculations for simulating the human decision-making process (determine the new irrigation are and water demand for the coming year). The updated irrigation area and water demand are then input back to the same RiverWare Slots designated in the “input.ctl” control file. This process is repeated at the end of each water year throughout the model period.

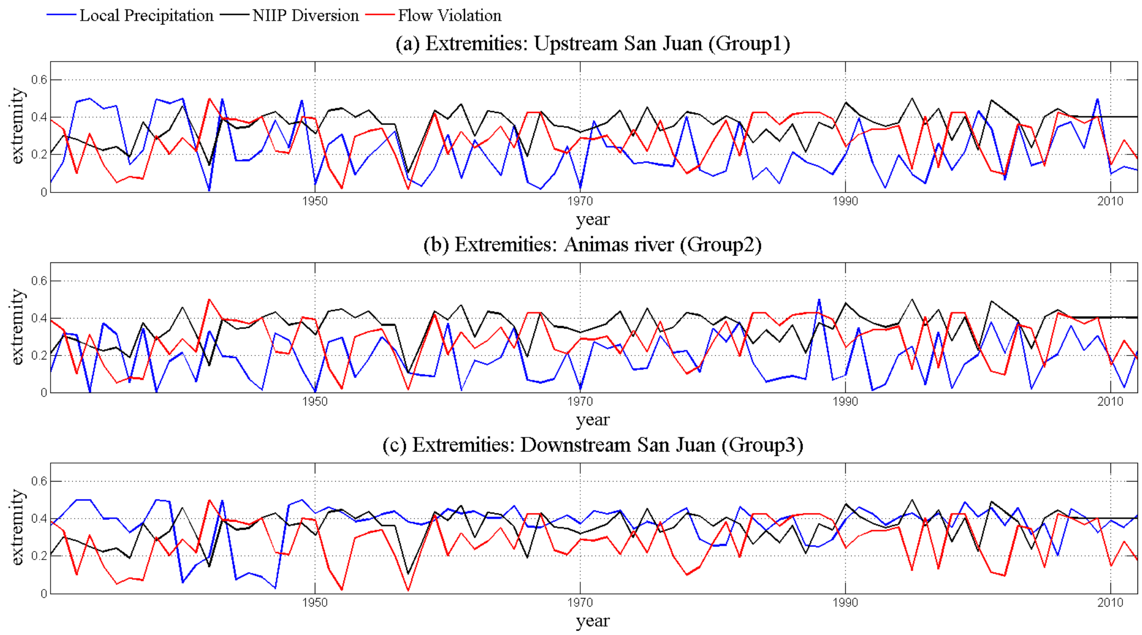


Figure S2. Extremities of preceding factor considered by (a) Upstream San Juan River, (b) Animas River, and (c) Downstream San Juan agents.

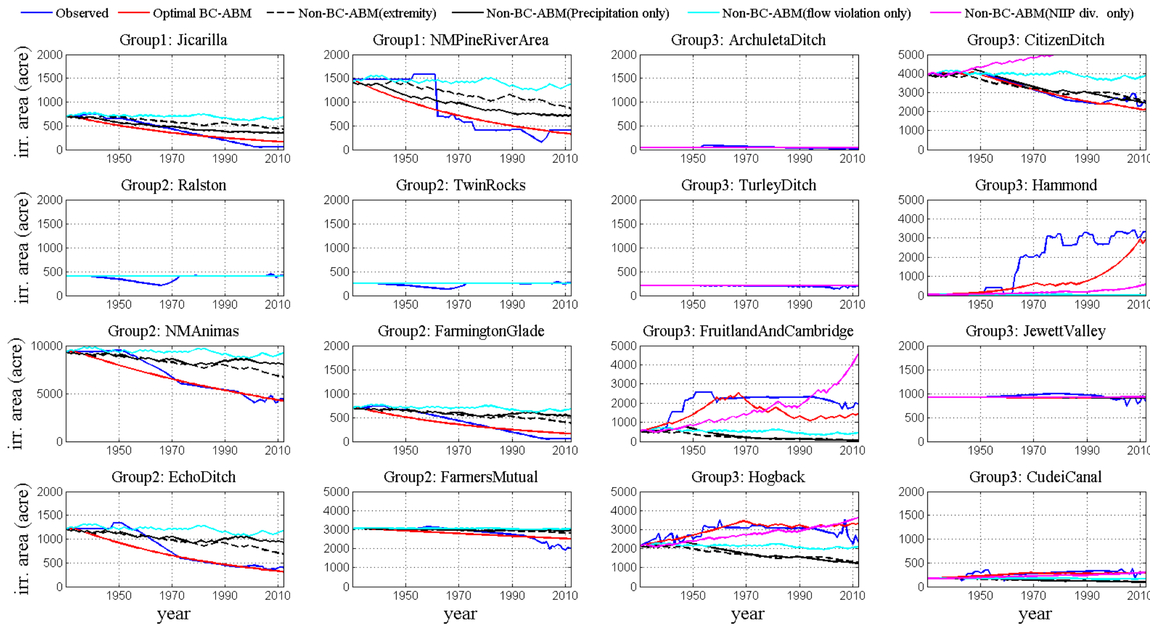


Figure S3. The simulated irrigation area changes during 1928 to 2013 from BC-ABM (solid red), Non-BC-ABM with extremity (dashed black), and Non-BC-ABM based on single preceding factor such as precipitation (solid black), flow violation (solid cyan), and NIIP diversion (solid magenta) versus historical irrigation areas (solid blue).

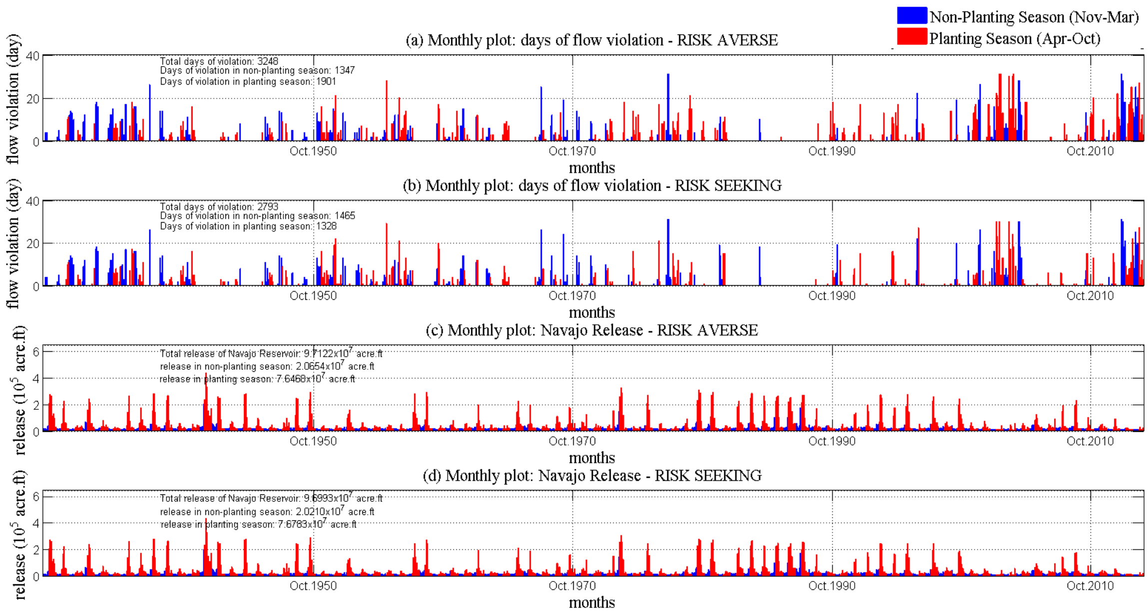


Figure S4. (a) Monthly view of days of flow violation with the case of the “Risk Averse”; (b) Monthly view of days of flow violation with the case of the “Risk Seeking”; (c) Monthly view of Navajo Reservoir Release with the case the “Risk Averse”; (d) Monthly view of Navajo Reservoir Release with the case of the “Risk Seeking”

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