Editor

I am satisfied with the manner in which the authors have responded to the comments of the two reviewers. The responses demonstrate that the authors have carefully and seriously considered the comments and suggestions, and provided plausible responses.

I agree with the comment of reviewer 1 that the title of the paper may need to be revised, and I am happy with the reply by the authors.

I therefore invite the authors to submit an improved version of the manuscript, consistent with the responses made to the two reviews. In addition, I would like the authors to consider also the following three minor comments from my side:

Response

We want to thank the Editor for the positive review comments and further improve the quality of this draft.

1. I have one question not raised by the two reviewers, and it relates to what the manuscript states in lines 363-366:
"Note that the information of winter precipitation … was gathered from NOAA ground-based rainfall monitoring gauges where we used the coming year's winter precipitation as a proxy for the snowpack forecast in the causal structure."
This might seem to suggest perfect knowledge on future water conditions, which might seem to be inconsistent with the purpose of the paper, namely to include uncertainty in water management decisions. I invite the authors to explain how this information was included in their modelling framework.

Response

The winter precipitation data from NOAA is perfect knowledge in the current modeling structure. However, the among of snowpack that will be resulted is uncertain. We modify the manuscript and clarify this part. Please check Line 325 to 330. This setting also offer an opportunity if the actual precipitation forecast data become available, we can easily replace the NOAA precipitation with the forecast precipitation.

2. I also invite the authors to address several quite odd typos and grammatical inaccuracies in the manuscript (e.g. in lines 38, 56, 1012, 102, 120, 127, 132, 192, 315, 380, 539, 558, 561).

Response

We correct all these English error in the revised manuscripts. Thank you for the careful review.

3. I also want to point out that SI units are used in HESS. So please also give the SI equivalents (m2 or ha, m, m3 and m3/s) of acre, feet, acre-feet and cfs when used in the text. I did not understand the unit "ac-ft mm" used in the revised Table 1. No clue what it means. Kindly explain. Note that the "manuscript preparation guidelines for authors" explicitly states that "The use of SI units or SI-derived units is mandatory." (https://www.hydrology-and-earth-system-sciences.net/for_authors/manuscript_preparation.html)

Response
SI units have been add to all English units in the manuscript. The conversion we used are: 1 arce-ft = 1234 m^3, 1 acre = 4046 m^2, 1 cfs = 0.0283 cms, 1 ft =0.3048 m,

Success!

Pieter van der Zaag

Reviewer 1

This study aims to demonstrate that a hybrid modeling approach, coupling agent-based, Bayesian, cost-loss, and reservoir management models, yields a more representative simulation of stream flow and changes in irrigated area of the San Juan River Basin. To achieve this, the authors model the interaction between farmer agents and a river routing and reservoir management model. Individual behaviors of farmers are developed using the Theory of Planned Behavior, accomplished by applying Bayesian and cost-loss modeling approaches. In modeling coupled natural-human systems, developing hybrid models to utilize the advantages of each is an interesting approach. However, in its current state, I believe the manuscript needs substantial revision before I can recommend it for publication.

Response

We acknowledge the concern and suggestions from the reviewer. An itemized response of all the comments and the corresponding revisions is described as follow. Line numbers in this document correspond to the clean version (no track changes) of the revised draft.

My greatest objection to the manuscript is that it needs to be better focused. The Introduction wanders in both scope and topic. Additionally, the research objectives are not clearly defined. The study area has clearly defined conflicts for water supply; however, these are not brought up until the Discussion section. Defining the importance of this study earlier in the manuscript is important to justify the research. The Results section contains a significant amount of interpretation that needs to be moved to the Discussion section. Finally, the Conclusion section doesn't address the greater impacts of the study.

Response

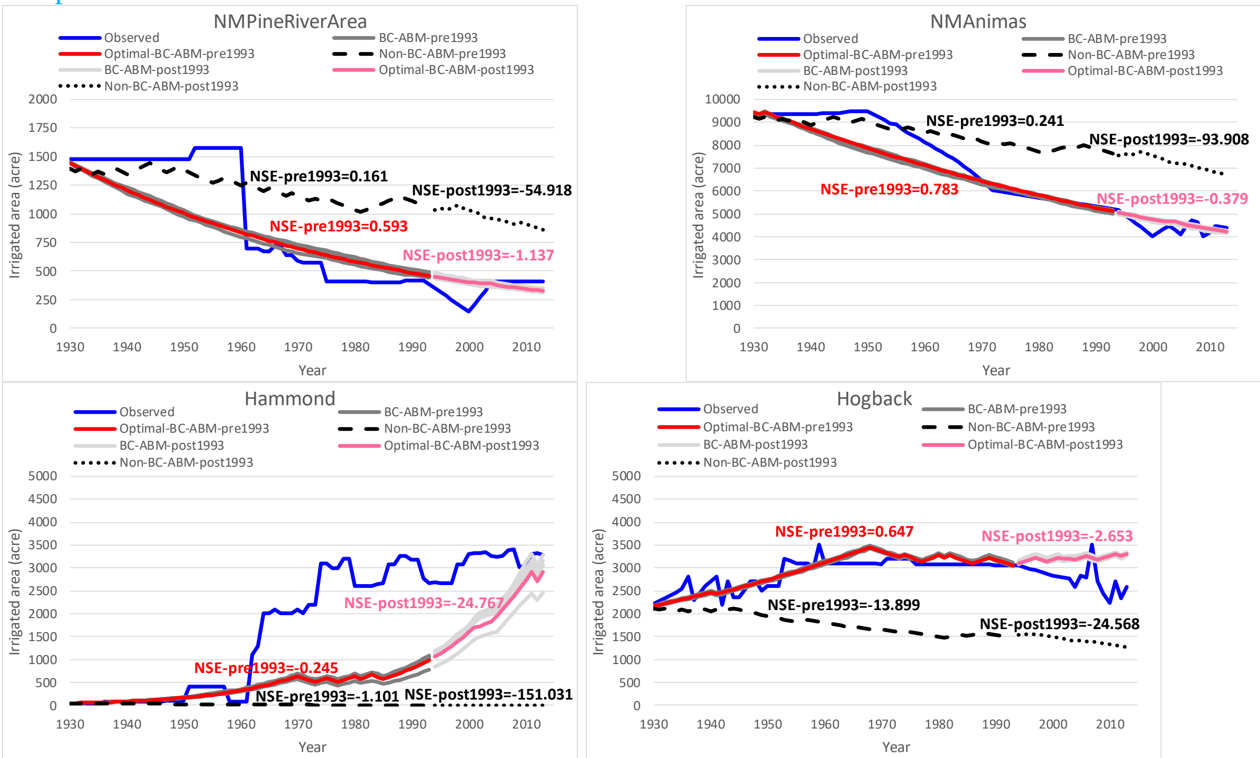
We want to thank the reviewer for these specific suggestions. The introduction has been revised to focus on the challenges of simulating a coupled natural-human system (CNHS), the proposed solutions for water resources management using agent-based model (ABM) and finally using the theory of planned behavior (TPB) for ABM construction. We remove the details of uncertainty sources in the introduction to avoid the disturbance as suggested by Reviewer 2. We only keep some key equations in the Methodology section and move some supporting equations to the Supplemental Materials. The description of water conflict within the San Juan River Basin has been moved from the Discussion to the Case Study section to defining the water supply conflict earlier in the manuscript as suggested by both reviewers. We also add some potential application of the proposed method in the Conclusion.

Another concern is that although the authors have a substantial amount of time-series data, they make no attempt to reserve some of their data in order to validate their model. I would like to see an attempt or justification as to why no validation was conducted.

Response

We thank the comment from the reviewer. There are several reasons why we only show the calibration results. First, the final calibration range of parameters are relative narrow since we are aiming for the trend not the annual fluctuation of the irrigated area, the length of the record (as long as it is "long" enough) will not significantly affect the final outcomes. However, to response reviewer's suggestion, we put some results from example agent in this document. We use the first 65 years (1929-1993) to compute the first NSE and the rest 20 years to compute the second NSE. Since our purpose is to compare the BC-ABM and Non-BC-ABM, we did the same calculation for

Non-BC-ABM as well. One can see that in both pre-1993 and the post-1993 period, BC-ABM still outperform Non-BC-ABM.



Second, the fundamental assumption of calibration and validation is stationarity which might not be hold here especially when human decision is involved. This is also true for any traditional calibration and validation procedure in process-based hydrologic models. If one know a significant land use and land cover change had occurred, the validation results will not (and should not) hold. In our case, the unexpected external driver will significantly affect human behavior and violate the assumption of stationarity. This is also the main reason in the above four examples, the NSE value are lower in the post-1993 period. In the San Juan Basin, the construction of the Navajo Reservoir is the obvious example of external driver change. However, the proposed BC-ABM can potentially allow agents to make adaptive decision by changing their lamda as well as by considering their neighbor's decision which is the suggested method to address the non-stationarity issue.

Third, the current Figure 3 is already a very "busy" figure which means we already have multiple lines, patterns and colors for various purpose and we need to shows that for all 16 agents. Add validation results (which means adding a number of new colors and/or patterns) will make the figure unreadable and might overwhelm our readers. This is the reason why only we show some example here for the reviewer.

More detail on specific sections below:
Introduction: The Introduction section is too long and needs to be condensed. In its current form, the Introduction does not funnel from general to specific information relevant to the study and instead gets bogged down by the history of each modeling approach. Perhaps reframe in the following way: water policy challenges in a CNHS (including uncertainty) -> ABM -> TPB, the quickly explain how BI and CL will address the three components of TPB.

Response

We exactly follow this suggestion and revise the Introduction section. The description of challenges in CNHS model is in Line 33 to 41. We then move to the use of ABM for CNHS modeling in Line 42to 51. Line 52 to 66 describe how we proposed to use TPB to improve ABM that address uncertain risk perception and finally move to some description of using BI and CL to address three components of TPB in Line 67 to 96.

The last paragraph of the Introduction should clearly lay out all of the objectives of the paper. For example: It is the purpose of the study to demonstrate the utility of TPB in modeling human decision-making by 1) evaluating the impacts of uncertain risk perception on agent behavior, 2) comparing model results with conventional agent behavior rules, etc…

Response

As suggested by the reviewer, the following paragraph has been added to the end of the Introduction (Line 97 to 110) to clearly lay out all the objectives of this study:

"*To address these research gaps aforementioned, we developed an ABM based on the BI mapping and CL model, as an implementation of the TPB, and hereafter referred to as the "BC-ABM." The BC-ABM is "two-way" coupled with a river-routing and reservoir management model (RiverWare). Four objectives of this study are: 1) use the BC-ABM to quantify human decision considering uncertain risk perception, 2) demonstrate the improvement of BC-ABM compare to conventional agent behavior rules, 3) use the coupled BC-ABM-RiverWare to explicitly model the feedback loop between human and natural system and 4) test the BC-ABM-Riverware for different scenarios. 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 the impacts of changing risk perception from all agents to the water management 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.*"

We also add a brief description of the study area: the San Juan River Basin in New Mexico in this last paragraph to give our readers an idea where we want to test the proposed method.

Structure the Results section in the same order for ease of comprehension.

Response

Given that we define this manuscript as a methodologic paper, the first three research objectives mentioned above are considered as the improvements of the ABM methodology. Therefore, we present results which are the demonstration of the ABM improvement in the last section of Case Study and follow the suggestion from the reviewer in the order of objective 1 (quantify impacts of uncertain risk perception from agents), objective 2 (compare BC-ABM with conventional ABM) and objective 3 (demonstrate results from both BC-ABM and RiverWare to two-way coupling). Figure 3, 4 and 5 are used to visualize these results (Line 350 to 419).

The research objective 4 is considering as the application or pilot test of the BC-ABM-RiverWare. We present results from several different scenarios including extreme behaviors from agents as well as extreme socioeconomic driver change. Figure 6, 7, 8, and 9 are used to visualize these results (Line 420 to 508).

Methodology: The description of the Bayesian Inference Mapping section suffers from excessive detail in regards to the manipulation of the Bayesian equations. Some of this should be moved into the Supplemental Materials.

Response

The Methodology section has been revised by moving detailed derivations to the Supplemental Materials. We only keep the following equations from the original manuscript. Equation (3), (10), (11), (13), (15) and (16) are in the revised draft for the most critical parts of the BI mapping. We also keep the original Equation (17) for the determination of extremity and Equation (19) and (20) for the Cost-Lost model (Line 151 to 249). We add a section in the Supplemental Materials for the detailed method (Text S1).

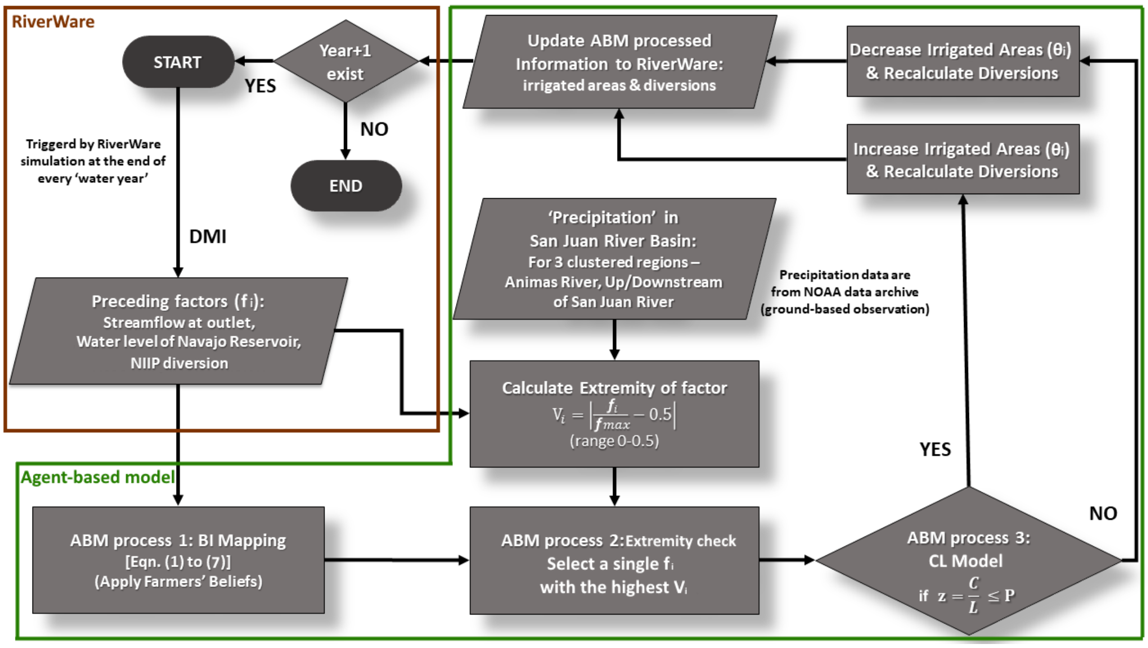
In the agents' decision-making methodology, the authors are calculating the farmer's beliefs for each direct link in the cognitive map, but only choosing one link (resulting from the most extreme variable) to insert into the cost-loss model. Since the authors are not examining the joint probability of making a decision from all preceding factors, it is disingenuous to describe the methodology with the Bayesian network presented. Instead the authors should be explicit in their methodology that they are examining each preceding factor independently. This can be accomplished by describing the model's decision-making process at the beginning of Section 2.2 with the aid of Figure 1.

Response

The following sentence has been added to explicitly mention the associated assumption of using extremity from single instead of multiple factors in the BI mapping:

"*In this study, the extremity of each preceding factor is examined independently assuming each preceding factor is independent to each other (consider one not the joint probability of multiple factors in the BI mapping).*"

Please check Line 210 to 213. Also, following the reviewers' comment, we modify Figure 1 for this topic as well. Please check the new figure below and in the figure file.



The authors should note in their discussion that by only limiting decision-making to one preceding factor, the agents cannot respond to the cumulative effects of their environmental conditions. In the calculation of "extremity" of environmental factors, the authors use the distance of the current value from half of the max value. If the mean of a variable is greater than
that, most the of extremities will be artificial inflated. Using outliers within a variables' natural distribution of values will yield a more accurate characterization of extremities. The authors need to be more explicit in describing the decision model of individual agents. How did the authors determine which factors were important in the agent's decision to increase/decrease irrigation area?

Response

A more detailed explanation with an example has been added to Section 2.2.1 to explicitly describe the use of the extremity in the BI mapping in this study as suggested. Please check Line 213 to 216. The Limitation section is also expanded to include the exclusion of the joint probability of decision-making processes from all preceding factors caused the use of extremity in the BI mapping.

Case Study: This section (3.1) should be moved to the beginning of the methodology. Precipitation, NIIP Diversion, and Flow Violation are the main factors in your decision network; however, you do not describe their characteristics (mean, standard deviation) in your study area.

Response

Since the preceding factors described in Section 3.1 are specific for the case study area, they are not always true for other basins. Therefore, we keep the original paper structure for Section 3.1. However, we follow the reviewer's suggestion in three aspects. First, we add more example preceding factors in the methodology to give our reader a more concrete idea (Line 165 to 168). Second, in the new Table 1, we add the characteristics (mean, standard deviation) of these preceding factors as suggested by the reviewer. Please check Table 1 below and the new table file. Third, we move part of the original Section 5.1 into this new Section 3.1 as suggested by the reviewer in the following comment. This provides a more informative background to our readers about the water conflict situation in the basin. Please check Line 275 to 295.

Group	Number of agents	Factors considered in decision-making processes
1. (upstream of the Navajo Reservoir)	2	• mainstem upstream precipitation[c] (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir[c] (1845 m, 4.07 m), • number of flow violation at the outlet[c] (38.5, 38.8), • cost-loss ratio[s]
2.a (Animas River without shortage sharing)	5	• tributary (Animas) precipitation[c] (79.2 mm, 38.2 mm), • mainstem upstream precipitation[c] (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir[c] (1845 m, 4.07 m), • number of flow violation at the outlet[c] (38.5, 38.8), • cost-loss ratio[s]
2.b (Animas River with shortage sharing)	1	• tributary (Animas) precipitation[c] (79.2 mm, 38.2 mm), • mainstem upstream precipitation[c] (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir[c] (1845 m, 4.07 m), • number of flow violation at the outlet[c] (38.5, 38.8), • shortage sharing[s], • cost-loss ratio[s]
3.a (downstream of the Navajo Reservoir without shortage sharing)	3	• mainstem downstream precipitation[c] (82.9 mm, 96 mm), • mainstem upstream precipitation[c] (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir[c] (1845 m, 4.07 m), • number of flow violation at the outlet[c] (38.5, 38.8), • NIIP annual diversion[s] (0.197 billion m^3, 0.019 billion m^3), • cost-loss ratio[s]
3.b (downstream of the Navajo Reservoir with shortage sharing)	5	• mainstem downstream precipitation[c] (82.9 mm, 96 mm), • mainstem upstream precipitation[c] (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir[c] (1845 m, 4.07 m), • number of flow violation at the outlet[c] (38.5, 38.8), • NIIP annual diversion[s] (0.197 billion m^3, 0.019 billion m^3), • shortage sharing[s], • cost-loss ratio[s]

Section 3.2 and 3.3 should be relabeled to define it as the setup conditions of the coupled model.

Response

Follow the suggestion from the reviewer, we modify the title of Section 3.2 as "The BC-ABM-RiverWare Model Setup." We also move the model diagnose outcomes to the new Section 3.3 and modify the new title as "The BC-**ABM-RiverWare Model** Diagnostics." We present the new Section 3.3 following the order of our research objectives in the last paragraph of Introduction as recommended by the reviewer.

Results: The methodology of the comparative study is introduced in the third paragraph of this section. It should be moved to the methodology section, described sufficiently, and stated as an objective of the paper, or removed entirely.

Response

Following the paper reconstruction suggestion from both reviewers, we move this section into the Case Study part given that we use the historical data from the study area to make the comparative study. However, we do partly follow the reviewer's suggestion and provide a clearer description of the comparative study which is actually not a methodology. The conventional rule-based type, deterministic ABM is the mainstream of the agent-based model and we cite our previous work for this model (Line 385 to 388). The purpose of this comparison is to demonstrate that by introduction BI mapping and CL model, we can better capture the historical pattern and trend of the decision on irrigated area changes.

Also, follow the reviewer's suggestion, we explicitly stated this effort as one of the research objectives. Please check Line 101 to 102.

This section should be strictly limited to presenting the results of the model; however, the authors spend a significant amount of time interpreting the meaning of the results. These interpretations should be moved to the Discussion section.

Response

After the paper restructure process, the current Result section only shows two tested scenarios: the effect of changing agents' risk perception and the effect of changing socioeconomic condition. These scenarios have stronger policy implementation meanings rather than mathematical outcomes. Therefore, explanations are critical for these results to provide a meaning content rather than just describing the figures. We believe most of our readers, who are hydrologists or water resources scientists, not mathematicians, will be more interested in the hydrologic reasoning and can potentially inform water management policy. Please check Line 420 to 508.

Discussion: The authors introduce significant new information in the discussion section, particularly in regards to San Juan Basin water policy, that would be better served in the case study section. The conflict introduced here will help bring a sense of urgency to the research if presented earlier.

Response

We follow the suggestion and move a large part of the original Section 5.1, especially for the water conflict part to the Case Study section (Line 275 to 295). We keep the part that related to our modeling results in the revised Section 5.1 as a deeper discussion on the institutional context and other water policy related issues.

Conclusions: Since the authors used TPB to frame the human decision-making model, the authors should revisit TPB in regards to the successfulness of the approach.

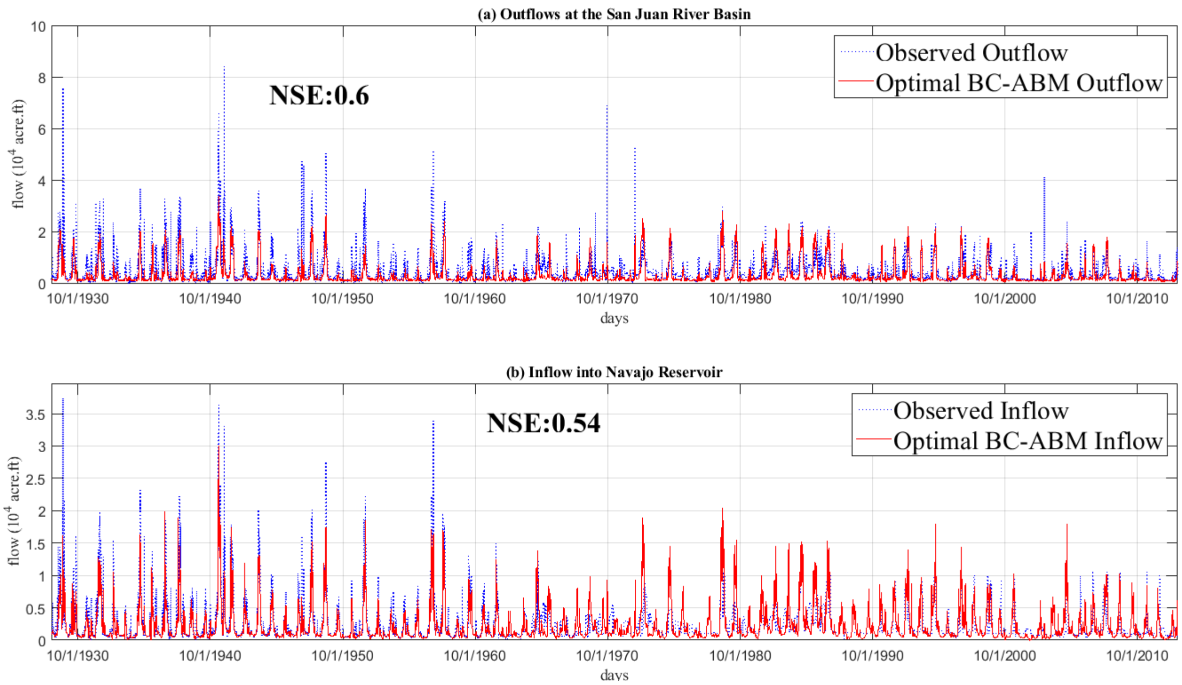
Response

Following the suggestion from both reviewers, we revisit how our proposed BC-ABM can implement TPB in both the Discussion and Conclusion. Please check Line 510 to 526 and also Line 568 to 572.

Figures 5: The authors should explore whether presenting the data as a scatterplot will increase comprehension of model performance.

Response

Since both streamflow and reservoir release are time series, we do feel the line format is a better representation rather than the scatterplot. However, we agree with the reviewer that the original Figure 5 is a bit hard to read. We modify the pattern and the thickness of lines to improve the readability. We keep the color as blue: observation and red: modeling which matches the Figure 4 (calibration results). Please check the new figure below and the new figure file.



Specific Comments: The title is phrased awkwardly and not does give readers enough information on the content of the manuscript.

Response

The title has been changed to "***Using a coupled agent-based modeling approach to quantify risk perception in water management decisions***" to better reflect the modified content.

Table 1: Group 3b should be WITH shortage sharing

Response

The typo has been corrected.

Reviewer 2

General Comments

In this work the authors developed an agent-based model to simulate agents that make decisions related to irrigation management. The agents consider climate and social information to update risk perception and cost of operations, to decide whether to increase or reduce water consumption for irrigation. The agents are located in a river network with a man-made structure that controls water flow. The results show that by considering this environmental and social information along with the perception of risk, agents can replicate water consumption patterns observed in the San Juan river basin. I think this is a very interesting work that provides great methodological tools to develop a coupled hydrological, agent-based model.

The introduction is clear and well supported by the literature. While some points could be made even clearer, the authors did a good job introducing the objectives and the methods proposed.

Response

We want to thank the reviewer for these constructive comments and suggestions which greatly improve the clarity of the entire manuscript. We further condense the Introduction section following the comment from Reviewer 1. Line numbers in this document correspond to the clean version (no track changes) of the revised draft.

I considered the method section to be the most interesting part of this paper. The Bayesian inference (BI) rule provides a great tool that combines robust math and easy applicability to develop the agents' decision-making framework. My main concern with the BI is the assumption or presumption of risk. In the model, when agents ignore incoming information, these agents are labeled as "risk-averse". I do not understand why, by not considering previous information, these agents would be considered risk-averse. My understanding is that risk-averse individuals pay more attention to not have great losses vs. a risk-seeking agent, who would give more importance or weight to potential large gains, thereby discounting loses. I think the authors need to clarify this point.

Response

We agree with the reviewer for the definition of risk-averse. In our reasoning, we define "risk-averse" as "*do not trust the new incoming information because it could be uncertain and rather to stick with her/his own experience*" In other words, an agent is not taking any risk by changing its behavior. The sentence has been modified in the revised draft, please check Line 194 to 196.

Finally, for the methods, a sub-section containing the estimation and calibration methods, and the comparison with real data, is needed. Some aspects of these methods are described when the results were described later in the manuscript, and this created some confusion about the methods that were used.

Response

One sentence has been added to the last paragraph of the Methodology section to remind our readers the model diagnose and the comparison with real data in the case study area (Line 248 to 249).

Both reviewers suggest moving the text for the model diagnose part to the earlier section of the manuscript. Given that the model calibration process requires historical data from the case study area as references, we need to put this section after we describe the case study area. Therefore, we decide to put the original Section 4.1 as the last section of the Case Study in the revised draft. The reasons are two-fold. First, since it is out of the Result section, the confusion that Reviewer 2 described can be avoided. Second, this paper structure rearrangement will follow the suggestion from Reviewer 1 that the order of the outcome presentation is the same as the order of research objectives stated in the last paragraph of Introduction. Please check Line 350 to 419.

The case study is quite interesting and well supported by time-series data. My main comment in this section is about the kind of agents their model is trying to simulate. It is not clear to me who are the ”irrigated” and/or “ditch object” -agents. Are these infrastructure operators, managers, or a group of farmers with influence on the decision made to obtain water? The authors can do better explaining these agents.

Response

Agents are groups of farmers in our study. In the RiverWare model set up, they are quantified as several “water use objects” which we named them as irrigation ditches. These agents (or irrigation ditch) are an aggregation of farmers in that specific area and our assumption is that since USBR aggregate these farmers into several single entities, they will make similar management decision in reality. We add an additional explanation in Section 3.2, please check Line 308 to 311.

Another point that I think needs an explanation is how the social and climate factors that each agent considers as important were elicited. Some agents consider extreme precipitation, while others consider “animas precipitation”. I also suggest that the authors differentiate between climate vs. social factors in Table 1. This would make the different socio-ecological factors that influence each agents’ decisions clearer to the readers.

Response

Precipitation is a preceding factor candidate of all agents. However, depending on the geographical location of agents, they need to consider precipitation at different locations. For example, upstream agents (e.g. the Group 1 in our case) do not need to consider downstream precipitation since that will not affect their water availability. This is an advantage of using ABM which the spatial heterogeneity can be addressed in the model. We add a sentence in the new Section 3.2 to better explain this and also follow the reviewer’s suggestion add a description about how climatic and social factor might affect agents’ decision. Please check Line 316 to 340.

Also following the reviewer’s suggestion, we modify Table 1 with a superscript that distinguishes climatic and social factors. Please check the new Table 1 below and in the new table file.

Group	Number of agents	Factors considered in decision-making processes
1. (upstream of the Navajo Reservoir)	2	• mainstem upstream precipitation^{c} (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir^{c} (1845 m, 4.07 m), • number of flow violation at the outlet^{c} (38.5, 38.8), • cost-loss ratio^{s}
2.a (Animas River without shortage sharing)	5	• tributary (Animas) precipitation^{c} (79.2 mm, 38.2 mm), • mainstem upstream precipitation^{c} (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir^{c} (1845 m, 4.07 m), • number of flow violation at the outlet^{c} (38.5, 38.8),

		• cost-loss ratio^{s}
2.b (Animas River with shortage sharing)	1	• tributary (Animas) precipitation^{c} (79.2 mm, 38.2 mm), • mainstem upstream precipitation^{c} (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir^{c} (1845 m, 4.07 m), • number of flow violation at the outlet^{c} (38.5, 38.8), • shortage sharing^{s}, • cost-loss ratio^{s}
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3.b (downstream of the Navajo Reservoir with shortage sharing)	5	• mainstem downstream precipitation^{c} (82.9 mm, 96 mm), • mainstem upstream precipitation^{c} (180.1 mm, 125.3 mm), • the water level in the Navajo Reservoir^{c} (1845 m, 4.07 m), • number of flow violation at the outlet^{c} (38.5, 38.8), • NIIP annual diversion^{s} (0.197 billion m^3, 0.019 billion m^3), • shortage sharing^{s}, • cost-loss ratio^{s}

I suggest looking at the ODD+D protocol, instead of ODD, to describe the model, because the ODD+D includes the decision-making aspect of the model (Müller et al., 2013). The authors cited this study, but they have not used it.

Response

We modify our ODD document into the ODD+D format, please check the new supplement materials

I consider the discussion to be somewhat weak and not in line with the aim of the study, nor the results. The discussion starts with a reflection about the policies implemented in the study area, but it was only loosely connected to the decisions of the agents, the information these agents considered, and the risk. There is no discussion or reflection about implementing theory-planned behavior, which I think would be a great step to incorporate real theories of human behavior into agent-based models. The authors should highlight this effort. Perhaps the discussion can be constructed around the following question: How do the risk perception, information flow, and costs influence policy outcomes in not only the San Juan river basin, but also in other basins? The discussion should start with a broader statement about the generality of the method and its applicability to other rivers. Then, it should include the implications of the results for policy outcomes, first for the example of the San Juan river, and then for other irrigated areas.

Response

Following the suggestion form both reviewers, we completely restructure the Discussion section. First, most of the original Section 5.1 has been moved to the Case Study which provides a more informative background to our readers about the water conflict situation in the basin. Please check Line 275 to 295. Second, we change the title of the section to "Generalized the modeling framework and policy implementation for other basins" and start this section with a broader statement about the generality of the method and how it addresses the challenges of how the proposed BA-ABM implementing the TPB as a first step to incorporate real theories of human behavior into agent-based models. Please check Line 510 to 526. Third, we use our results in the San Juan River as an example to explain the models' applicability for policy implementation. Please check Line 527 to 539.

Finally, the authors stated in 5.2 that they will discuss future research, yet no specific ideas were provided. In any case, these future directions should be included in the conclusion, rather than the discussion. At a minimum, a real discussion about these ideas, including what would be needed and other considerations, should be included.

Response
We change the title of the revised Section 5.2 as "Model limitations" which we only use this section to discuss the limitations of the current draft such as data availability and model structure in BI mapping as well as extremity. Please check Line 540 to 561.

Following the suggestion from both reviewers, we move the ideas of future research into the Collusion section (Line 586 to 594).

Specific comments
Abstract
I do not consider risk perception and uncertainty to be the same, as the author clearly described in the introduction (Line 107). On line 22, the authors should be more careful when introducing these terms in the abstract.

Response
From revised the abstract following reviewer's suggestion and more specifically talk about risk perception (Line 10 to 28).

Introduction
Line 59: Why do the authors start with the word "therefore" to introduce planned behavior?

Response
The word "therefore" is deleted.

Line 73: Need to introduce the low-cost rule.

Response
We improve the description of the CL model (including the calculation of taking action based on low-cost concept) in Methodology section given that the Introduction is only intended to provide a high-level idea of what is CL model. Please check Line 217 to 239 in the Methodology section.

Line 89-100. In the abstract, the authors suggest that risk perception is included in the BI rule. They then introduce risk perception when discussing the CL rule. This causes some trouble understanding the model.

Response
Line 90 to 96 was previous studies and directly use the CL model for the risk perception. However, as we summarized in Line 94 to 96, this previous study did not provide a detailed methodology

for parameter determination and ignore spatial heterogeneity. Therefore, we want to improve this aspect by the proposed method of using BI mapping to quantify risk perception given that the BI mapping can explicitly consider conditional probability. We highlight this as a gap in the last paragraph of the Introduction section (Line 100 to 104).

Line 128: A line or two is needed stating what "two-way" coupling means. I think they refer to feedback between decisions, perception, and water dynamics. Is this correct?

Response

Since we reorganize the Introduction section, we only briefly mention this term "two-way coupling" in the Introduction section. We provide a detailed description of what we mean by "two-way coupling" in Section 2.1. Please check Line 137 to 143.

Methods

Line 229: A definition of subscripts i and j is needed.

Response

We move this equation to the Supplements Materials as suggested by Reviewer 1. We add the following sentence in the Text S1 to explain "*i*" and "*j*:"

"i is the index for the preceding factor and *j* is the index for the management behavior"

Case Study

Line 313: What does "cfs" stand for? What is this unit?

Response

Add "cubic feet per second." Please check Line 266.

Line 385: What does "matching" the time series mean? Is it based on Least Squares as a Maximum Likelihood? In other words, an explanation is needed on how the comparison between real data and simulated data was carried out.

Response

We reword this as "recreate" the historical trend. Please check Line 348 to 353.

Line 418: An explanation for the Nash-Sutcliffe Efficiency is needed.

Response

The Nash-Sutcliffe Efficiency is widely used in water resource to assess the predictive power of process-based models. We add the original citation into the manuscript (Line 381).

Nash, J. E.; Sutcliffe, J. V. (1970). "River flow forecasting through conceptual models part I — A discussion of principles". Journal of Hydrology. 10 (3): 282–290.

Line 457: The phase including "…multi-objective calibration:.." is not a result. This should be in the methods.

Response
As we mentioned above, we did a complete paper structure reconstruction following the suggestions from both reviewers. This sentence does not fit in the revised draft and has been removed.

Line 585: The statement beginning "The BC-ABM results…" is also not a result. The fact that agents react to climate and socio-economic factors is part of the rules imposed by the model, but it is not a result per se.

Response
Since we restructure the paper, the entire sentence has been removed.

Line 624: I do not understand why the authors introduce multicriteria decision analysis vs. other decision-making tools. It is an important tool, but it is hard to see the connection.

Response
The text about multi-criteria decision analysis in both the Discussion and Conclusion section has been removed completely.

Figure 1: In ABM process 3, what is the question that leads to yes or no? It is related to the opportunity cost, but it needs to be stated in the figure.

Response
We update Figure 1 following suggestions from both reviewers. Please check the new Figure 1 below and in the new figure file.

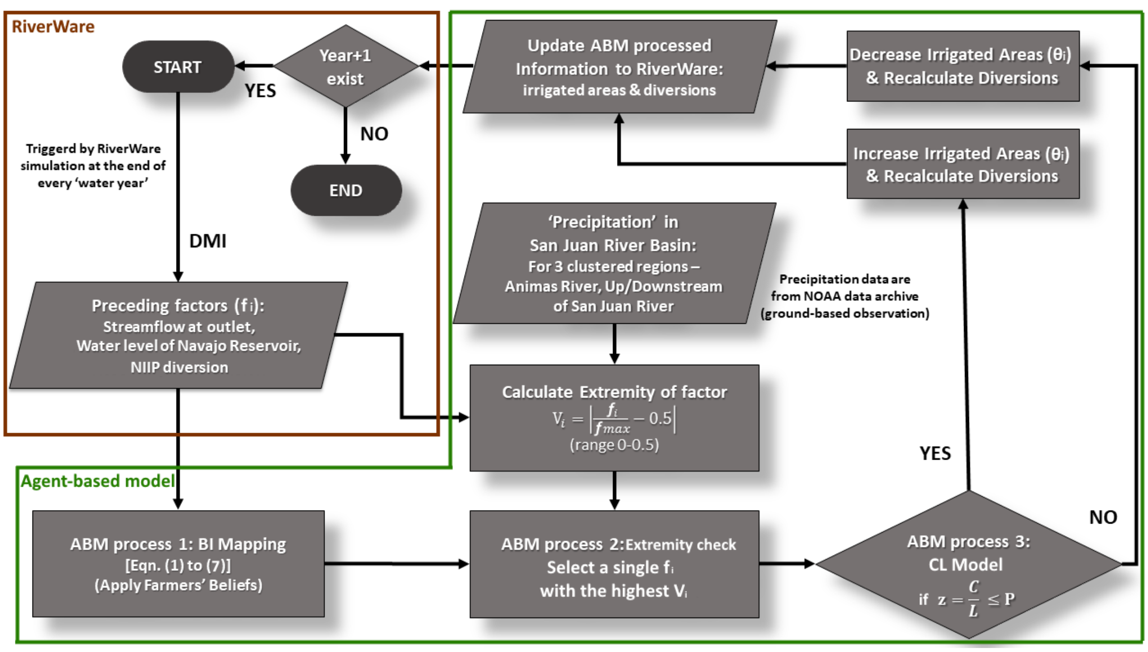
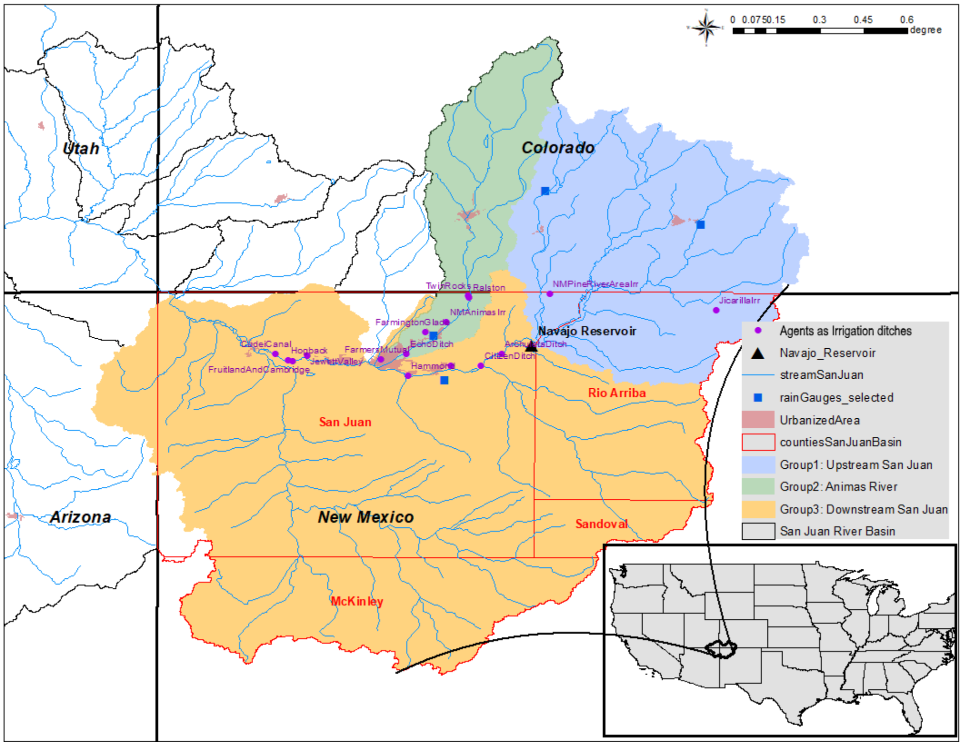


Figure 2: Perhaps a better name for "irrigated agents" is needed.

Response

We update Figure 2 following the suggestion from the reviewer. Please check the new Figure 2 below and in the new figure file.



I hope these comments are useful to the authors.

Response

Again, we want to thank the reviewer for these constructive comments and suggestions which greatly improve the clarity of the entire manuscript.

Using a coupled agent-based modeling approach to quantify risk perception in water management decisions

Commented [EY1]: Reviewer 1, Specific comment: Title.

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Abstract

Managing water resources in a complex adaptive natural-human system is a challenge due to the difficulty of modeling human behavior under uncertain risk perception. The interaction between human-engineered systems and natural processes needs to be modeled explicitly with an approach that can quantify the influence of incomplete/ambiguous information on decision-making processes. In this study, we "two-way" coupled an agent-based model (ABM) with a river-routing and reservoir management model (RiverWare) to address this challenge. 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 psychological thinking process to be specified by a cognitive map between decisions and relevant preceding factors that could affect decision-making. A risk perception parameter is used in the BI mapping to represent 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 risk perception into account. Future studies will focus on modifying the BI mapping to consider direct agents' interactions, up-front cost of agent's decision, and upscaling the watershed ABM to the regional scale.

Commented [EY2]: Reviewer 2, Specific Comment: Abstract.

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

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 uncertainty. 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.

Commented [EY3]: Reviewer 1, Detailed comment: Introduction.

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).

Commented [EY4]: Reviewer 1, Detailed comment: Introduction.

However, one major challenge of applying ABM approach to water management decisions is the difficulty of characterizing human decision-making processes and meet the real-world management intuition. The traditional approach through, for example, survey or interview with local decision makers is extremely limited (e.g., Manson and Evans, 2007) in space and time. 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.

Commented [EY5]: Reviewer 2, Specific comment: Introduction.

Commented [EY6]: Reviewer 1, Detailed comment: Introduction.

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 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).

Commented [EY7]: Reviewer 1, Detailed comment: Introduction.

Commented [EY8]: Reviewer 1, Major comment 1.

To address these research gaps aforementioned, we developed an ABM based on the BI mapping and the CL model as an implementaiton of the TPB (referred to the "BC-ABM" here after). The BC-ABM is "two-way" coupled with a river-routing and reservoir management model: RiverWare" (details in Section 2.1). Four objectives of this study are: 1) use the BC-ABM to quantify human decision considering uncertain risk perception, 2) demonstrate the improvement of BC-ABM compare to conventional agent behavior rules, 3) use the coupled BC-ABM-RiverWare to explicitly model the feedback loop between human and nature system and 4) test the BC-ABM-Riverware for different scenarios. 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 the impacts of changing risk preception from all agents to the water management 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.

Commented [EY9]: Reviewer 1, Detailed comment: research objective about comparative study

Commented [EY10]: Reviewer 1, Detailed comment: Introduction last paragraph.

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/.

There is 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) to coupled models together. 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 ABM that coupled with a physically-based hydrologic model, Soil and Water Assessment Tool. In this paper, we perform a two-way coupling (or sometimes called "tight" coupling) of models which means data/information will be transferred back and forth between the 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).

Commented [EY11]: Reviewer 2, Specific comment: Introduction.

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 is specified by a "risk perception" parameter (Baggett et al., 2006; Pahl-Wostl et al., 2008) representing the 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's belief of changing the irrigation area will be affected by the forecast of snowpack in the coming water year or water availability in an upstream reservoir at the beginning of the growing season. The probability of a preceding factor f (a random variable) exceeding its threshold given a specific management behavior (or making a decision) θ: $P(f|\theta)$ can be expressed using the conditional probability equation shown in Equation (1)

$$P(f|\theta) = \frac{P(f \cap \theta)}{P(\theta)} \tag{1}$$

The probability of θ being made when the preceding factor exceeds the given threshold: $P(\theta|f)$ can be derived using Equation (1) and the equations of marginal probability (see Supplement Materials Text S1 for the derivation details).

$$P(\theta|f) = \frac{P(f|\theta) \times P(\theta)}{P(f|\theta)P(\theta) + P(f|\theta^c)P(\theta^c)} \tag{2}$$

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. Similarly, θ being made when the preceding factor does not exceed the threshold (f^c) may be expressed as

$$P(\theta|f^c) = \frac{P(f^c|\theta) \times P(\theta)}{P(f^c|\theta)P(\theta) + P(f^c|\theta^c)P(\theta^c)} \tag{3}$$

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

$$P(\theta) = P(\theta|f) \times P(f) + P(\theta|f^c) \times P(f^c) \tag{4}$$

A solution of $P(\theta)$ can be obtained by substituting Equations (2) and (3) into (4)

$$P(\theta) = \frac{P(f|\theta) \times P(\theta)}{P(f|\theta)P(\theta) + P(f|\theta^c)P(\theta^c)} \times P(f) + \frac{P(f^c|\theta) \times P(\theta)}{P(f^c|\theta)P(\theta) + P(f^c|\theta^c)P(\theta^c)} \times P(f^c) \tag{5}$$

In this study, we re-name the variables in Equation (5) as follows

Commented [EY12]: Reviewer 1, Detailed comment: case study about proceeding factors.

$$\begin{cases} \Gamma_{pr} = P(\theta) \\ \Gamma_{pd} = P(f) \\ \lambda = P(f|\theta) \end{cases} \tag{6}$$

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 (5) with the expressions in Equation (6), the agent's prior belief of θ, Γ_{pr}^{t} at time t can be expressed as

$$\Gamma_{pr}^{t} = \frac{\lambda\Gamma_{pr}^{t-1}}{\lambda\Gamma_{pr}^{t-1} + (1-\lambda)\left(1-\Gamma_{pr}^{t-1}\right)}\Gamma_{pd}^{t} + \frac{(1-\lambda)\Gamma_{pr}^{t-1}}{(1-\lambda)\Gamma_{pr}^{t-1} + \lambda\left(1-\Gamma_{pr}^{t-1}\right)}\left(1-\Gamma_{pd}^{t}\right) \tag{7}$$

In Equation (7), 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 (7) 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 (7) 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 do not trust the new incoming information because it could be uncertain and rather to stick with her/his own experience. In other words, these agents are not taking any risk by changing their behavior. In this study, the Γ_{pr}^{t} in Equation (7) 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.

Commented [EY13]: Reviewer 2. Major comment: Methodology about risk-averse definition.

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

$$V_i = \left|\frac{f_i}{f_{max}} - 0.5\right| \tag{8}$$

where f_i is the i^{th} preceding factor and f_{max} is the maximal value of f_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 (7). In this study, the extremity of each preceding factor is examined independently assuming each preceding factor is independent to each other (consider one not joint probability of multiple factors in the BI mapping). Taking winter precipitation, a common preceding factor used by farmers as well as in this study to determine the irrigated water demand for the coming year, as an example, f_i represents the winter precipitation of year i, while f_{max} is the maximum historical winter precipitation until the current year in Equation (8).

Commented [EY14]: Reviewer 1, Detailed comment: extremity as a single factor.

Commented [EY15]: Reviewer 1, Detailed comment: extremity example.

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, the probability of taking an action p is related to the expected cost of taking action C and opportunity lost of not taking the action L:

$$p \geq \frac{C}{L} = z \tag{9}$$

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 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 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 7). When Γ_{pr}^{t} is greater than z, this decision will become real world management action since it makes economic senses.

$$\Gamma_{pr}^{t} \geq z = \frac{C}{L} = \frac{\text{the expected cost of taking management action}}{\text{opportunity loss of not taking management action}} \tag{10}$$

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.

Commented [EY16]: Reviewer 1, Detailed comment: move detailed methodology into supplemental materials.

Commented [EY17]: Reviewer 2, Specific comment: CL model

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. We will use the case study to demonstrate the capability of this proposed method and diagnose the model with the historical data.

Commented [EY18]: Reviewer 2, Major comment: Methodology.

3. Case Study

3.1. Background of the 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 cubic feet per second (cfs) or 141.58 cubic meter per second (cms).

Commented [EY19]: Reviewer 2, Specific comments: Case study.

The Navajo Indian Irrigation Project (NIIP) is another major water consumption within the basin beside the 16 major irrigation ditches. The NIIP supplies water to Native American tribes 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 of releases from Navajo Reservoir and maintainance of a daily 500 cfs (14.15 cms) minimum streamflow requirement (Behery, 2017).

To improve water planning and management in the Basin, several state and federal agencies established a steering committee 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 (0.793 billion m^3). consumptive use is substantially greater than the corresponding consumptive use.

The RWP summarizes the related information of water planning such as water rights, future water supply and demand projections, and newly available data. For example, 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 (2041 m), 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). The RWP also projected that the total water demand in the Basin is expected to increase due to the authorized expansion of NIIP irrigation area, while a reduction of future water supply is possible due to climate change by the U.S. Global Change Research Program. 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 the San Juan Basin and become a suitable testbed for our methodology.

Commented [EY20]: Reviewer 1, Detailed comment: Case study and Discussion restructure.

3.2. The BC-ABM-RiverWare Model Setup

Commented [EY21]: Reviewer 1, Detailed comment: Section 3.2 and 3.3 title.

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). In this study, farmers that can make management decisions are quantified as 16 major irrigation ditch objects in RiverWare. They are defined as agents in the study and will decided whether to expand or reduce their irrigated area (e.g. management behavior, θ in Section 2) for the coming year at the end of every water 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.

Commented [EY22]: Reviewer 2, General comment: Case Study about agent definition.

The BI mapping was applied to each group with different causal structures. The climatic preceding factors considered in this study include the mainstem (Navajo) upstream winter precipitation, the tributary (Animas River) winter precipitation, the mainstem downstream winter precipitation, the water level in Navajo Reservoir and the flow violations at the basin outlet (days below 500 cfs or 14.15 cms in a water year). The social preceding factors considered in this study include the cost-loss ratio, the NIIP diversions and the shortage sharing. Table 1 summarizes the number of agents in each group and the proceeding factors they are considering. Given that agents located at different places, the preceding factors that affect agents' decisions will also be different. This is an advantage of using ABM to incorporate spatial heterogeneity in the model.

In this study, 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 precipitation as a proxy for the snowpack forecast in the causal structure. Winter precipitation has a positive effect on snowpack but there is an uncertainty about how much snow will be accumulated. Therefore, when agent expect more winter perception, if they believe it will lead to a lot more snowpack, they will become more aggressive in the irrigated area expansion. Flow violation at the basin outlet and water level of Navajo Reservoir are two system-wide proceeding factors that considered by all the three groups. When flow violation is too frequent or water level is too low, agents tend to be more conservative in the irrigated area expansion. If a shortage were declared, the RiverWare model would reduce the targeted streamflow at the basin outlet to 250 cfs (7.08 cms) and the participating six agents will adjust their water diversion to achieve this newly targeted streamflow. Under the current model 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 Supplement Materials where a standard "Overview, Design concepts, and Details + Decision" (ODD+D) protocol for ABM development is followed (Grimm et al., 2010).

To sumarize, 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. After the completion of ABM simultaion, data transfer from ABM to RiverWare included 1) updated irrigated areas and 2) the corresponding water diversion of each agent. The next section will demonstrate the capability of the proposed model to recreate historical pattern in the San Juan Basin.

3.3. The BC-ABM-RiverWare Model Diagnostics

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

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study, we address this concern by calibrating the coupled BC-ABM-RiverWare model to recreate the historical trend 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 different locations along the San Juan River (at the outlet of the San Juan River Basin and directly downstream of the Navajo Reservoir) for the calibration purpose. The calibrated parameters are the risk perception parameters (λ) and CL ratio (z) of each individual agent. 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 different 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 are manual calibrated ("trial-and-error") with details explained in the Supplement Materials (Text S2). 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.

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The calibration results of irrigated areas 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 Supplement 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, Nash and Sutcliffe, 1970) 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, deterministic ABMs (such as our previous work in Khan et al. 2017), 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 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. Two Non-BC-ABMs were tested and results are also shown in Figure 3. The black solid curve represents the Non-BC-ABM simulation still 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 are given in Figure 5. The results show that the simulated values agree closely with the historical observations evidenced by the NSEs of 0.60 and 0.54, respectively. We do notice that our coupled BC-ABM-RiverWare misses peaks of streamflow possibly due to the lower input streamflow 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.

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4. Scenario Results

The calibration results in Section 3.3 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. Two scenarios are tested in this section: the effect of changing agents’ risk perception and the effect of changing socioeconomic condition.

4.1. The effect of changing agents’ risk perception

Different risk perception scenarios are tested by making stepwise change of all agents’ 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. The gray curves lying between blue and green are the results corresponding to different λ values. The total irrigation area generally increases with an increasing 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 emerging actions will result in larger 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 increasing 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 Supplement Materials). Second, the baseline results (red curves) are closer 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 irrigation ditched since they are the major "players" in the basin. The results clearly show that Jicarilla (Group 1) and NMAnimas (Group 2) are historically risk-averse agents (red curves overlap with blue curves). 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 the Navajo Reservoir and most of them 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 increasing λ for all the four agents.

4.2. The effect of changing 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%) z values for all agents. 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). 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.

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 the 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. We can look at the influence of up-front cost on 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 costs into the current BI mapping as real world stockholders' inputs are needed to re-calibrate all the model parameters.

The time variation of irrigated area for all 16 agents under different up-front cost trends 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 baseline which use calibrated z values. The results show that the influence of changing z on Group 3 agents is relatively significant compare to Group 1 and Group 2. A consistently higher (lower) green (cyan) curve as compared to the baseline is observed. These 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.

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5. Discussion

5.1 Generalized the modeling framework and policy implementation for other basins

The proposed BC-ABM framework in this paper is intended to be a generalizable approach in water resources management and other fields that need to quantify human decisions. This framework directly addresses the *four challenges* summarized by Scalco et al. (2018) about how to apply the TPB in an agent-based setting. The model diagnose process and using the historical irrigated area answer the first challenge: "*Data and Preliminary Model Assessment*." Applying the BI mapping provides a stochastic representation of the decision-making process which eliminates the concern of "*Working with a Static Model*." Combing with the CL model, we can mathematically calculate "*When Does Intention Become Behavior*." Finally, coupling the ABM with the RiverWare is our solution to address the "*Feedback Mechanisms*" challenge in a CNHS. The method can be applied to other basins given that the required input data for BI mapping are publically available such as the precipitation from NOAA and the streamflow from USGS and risk perception (λ) and CL ratio (z) are calibrated parameters. However, the data required for the model diagnose such as long-term historical irrigated area time series might not be available in every basin. In this situation, if one intends to duplicate the proposed method in other basins, some alternative data source, such as land use and land cover changes data from USGS can be used as a proxy of calibration targets.

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The modeling results can be used to inform water management policy. 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 (182.1 to 246.9 km^2) of cropland with 9000 to 12000 ac-ft (11.1 to 14.8 million m^3) 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).

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5.2 Model limitations

Here we discuss two aspects of limitation of current study: data availability and model structure. The lack of historical data to serve as the calibration target is mentioned in the above section already. Another data limitation is for CL ratio calculation and the up-front cost. Currently, CL ratio is treated as a calibrated parameter in BC-ABM framework. The value of CL ratio 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 10), while the farm income and wealth statistics estimated from crop production may be considered as a major part of opportunity loss (L in Equation 10). The third data limitation is the necessary data to create the precise causal structure of BI mapping (Cheng et al., 2002; Premchaiswadi et al., 2010). 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).

Regarding the model structure limitation, the farmer's belief is currently calculated using one single preceding factor in the cognitive map that has the most extremity. The use of extremity from single preceding factor in the decision-making processes assumes that the joint probability of decision-making from multiple preceding factors are not taken into account (the agent may not respond to the cumulative effects of environmental conditions). Finally, the current method does not explicitly consider direct interaction among agents in the BI mapping. 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.

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6. Conclusion

Making water resources management decision in a complex adaptive natural-human system subject to uncertain information is a challenging issue. The interaction between human and natural systems needs to be modeled explicitly with associated uncertainties quantified 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. The proposed ABM framework characterize human decision-making processes by adopting a perspective of the Theory of Planned Behavior implemented 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 feedback between the environment and agents.

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Combining BI mapping and CL model allows 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. Calibration results for this coupled BC-ABM-RiverWare model, as demonstrated in 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 also show that the majority of agents in the basin are risk-averse which confirm the conclusion of Tena and Gómez (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.

Future work can target further methodology development to include direct agent interaction into the BI mapping. For example, agents' decisions can be affected by observing its neighbor's actions, and this information will always be treated with $\lambda = 1$. This means agents will always believe their own observations (i.e. "to see is to believe"). In addition, we only defined groups of farmers as agents in this study. Future work can seek to add power plant, city/municipality, and reservoir as different type of agents. The direct and indirect interaction among these different types of agent (such as farmers and power plants might or might not have to compete with water from the reservoir) will provide a more comprehensive picture in the entire food-energy-water-environment nexus.

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