



Research papers

Impact of climate change on adaptive management decisions in the face of water scarcity

Y.C. Ethan Yang^{a,*}, Kyongho Son^{a,1}, Fengwei Hung^a, Vincent Tidwell^b^a Department of Civil and Environmental Engineering, Lehigh University, United States^b Sandia National Laboratories, United States

ARTICLE INFO

This manuscript was handled by G. Syme, Editor-in-Chief, with the assistance of Ashok Mishra, Associate Editor

Keywords:

Upper Colorado River Basin
Adaptive capacity
Agent-based model
Drought contingency plans
Tribal water rights

ABSTRACT

Reoccurring drought through the early 2000s has caused a serious water scarcity issue in the Colorado River Basin. Previous modeling studies have focused on the impact of climate change without considering the adaptive behaviors of farmers and under-utilized Indian water rights. In this paper, we use a coupled agent-based water resource model (ABM) to investigate how the adaptive decisions of farmers can affect water resource management under both climate change impacts and fully utilized Indian water right conditions. We used five General Circulation Model projections with RCP8.5 scenarios for the study. The results of farm-level decision-making showed different responses in irrigated areas that were changing due to climate change impact. While winter precipitation changes might partially explain the behavior changes, no specific pattern could be concluded based on their location. Also, farmers' responses about annual water diversion showed more significant inter-year variation compared to irrigated areas. Basin-level metrics showed that climate change impacts will generally worsen water scarcity issues as measured in Navajo Reservoir storage, flow to Lake Powell, and in-stream flow requirement. But these basin-level water scarcity metrics cannot reflect individual farm-level impacts under climate change, which is why modeling the bottom-up management actions is necessary. When the under-utilized Indian water rights are fully used, it is more likely to trigger the shortage sharing agreement due to the higher tribal water depletion. Evaluation of model uncertainty and a more realistic setup for adaptive actions under drought contingency plans are suggested for future research.

1. Introduction

Clean and sufficient water supply is one of the Sustainable Development Goals prompted by the United Nations (UN, 2015). However, water scarcity, along with poor water quality and inadequate sanitation, still plagues food security and livelihood choices for poor families across the world. Among many river basins suffering water scarcity around the world, the Colorado River Basin (CRB) in the United States (US) is one of the most important based on its quantity and supply coverage. The entire CRB is under water stress due to a long-lasting drought dating back to the early 2000s. Udall and Overpeck (2017) concluded that between 2000 and 2014, annual flow reductions averaged 19.3%; this was below the 1906–1999 period, which is the worst 15-year drought on record. This long-lasting drought raised the prospect of water delivery curtailments and decreased hydropower production, among other effects (Steele et al., 2018; Stern and Sheikh, 2019). However, despite previous efforts to alleviate future shortages,

the basin's hydrological outlook has generally worsened in recent years (Rhee et al., 2019).

Numerous studies have concluded that ongoing climate change has worsened water scarcity in the CRB due to streamflow decline (for example, Cook et al., 2019; Dawadi and Ahmad, 2012; Ficklin et al., 2013; Milly and Dunne, 2016; Parsons et al., 2018; Xiao et al. 2018). This decline has been statistically confirmed to be associated with the increasing temperature, since the precipitation pattern in the region has not significantly changed for the past 50 years (McCab et al., 2017; Udall and Overpeck, 2017; Vano and Lettenmaier, 2014; Woodhouse and Pederson, 2018; Wi et al., 2012). These previous studies focused on climate change impacts by discussing the risk of water scarcity on hydropower generation and irrigation, but they did not have a quantitative analysis of adaptive water management actions such as water delivery curtailments, water shortage sharing plans, and adaptation of water conservation technology. Therefore, without considering the demand response side of water management, the suggested risk of

* Corresponding author.

E-mail address: yey217@lehigh.edu (Y.C.E. Yang).¹ Currently at Pacific Northwest National Laboratory.

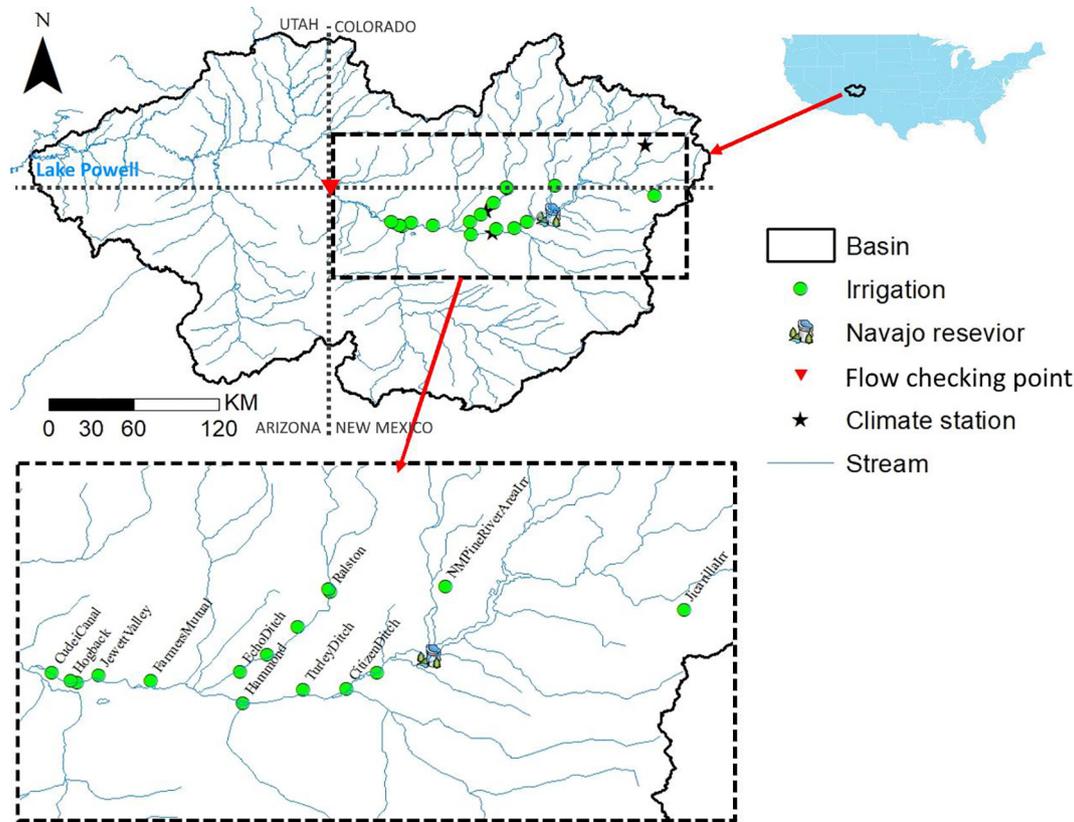


Fig. 1. San Juan River Basin, NIIP, 16 irrigation districts, environmental flow checking point, and Navajo Reservoir. 2.

water scarcity caused by climate change impacts might be over- or underestimated.

We define adaptive water management in this paper as the societal response to mitigate water scarcity impacts. In general, these responses can be classified into top-down planning, such as the 2019 Colorado River Drought Contingency Plans (DCPs) Authorization Act approved by Congress (*P.L. 116-14*), and bottom-up behavioral reaction from local residents. The DCP approach considered the entire basin establishing (additional) rules, regulations, and curtailment requirements across the riparian states. For example, under the 2019 Upper CRB DCP, the Upper Basin states (Wyoming, Colorado, Utah, and New Mexico) agree to manage upstream reservoirs to keep the surface of Lake Powell 35 feet above the minimum elevation needed to run the dam's hydroelectric plant. Also, the demand management program in the 2019 DCP includes seller and buyer agreements allowing for temporary paid reductions in water use (Stern and Sheikh, 2019). However, this top-down planning might be difficult to implement in reality, as highlighted by Sullivan et al. (2019): differences in rules and social norms are not addressed, and they could cause problems when norms underlying rules are interpreted differently. Therefore, they suggested a qualitative study that considers the power dynamics among stakeholders. Meanwhile, the heterogeneous water conservation decision-making process of different users need to be considered, as suggested by Taylor et al. (2019), to help advance the DCP process. These types of bottom-up approaches have become popular in recent years. Studies have used the decentralized management concept (Garrick, 2018; Yang et al., 2009) or ABM (Hyun et al., 2019; Khan et al., 2017; Yang et al., 2019) to quantify the behavior change of local residents as a bottom-up adaptive management plan.

Another challenge of future water management in the CRB (especially the Upper CRB) is the under-utilized Indian water rights. These water rights are often the most senior in a basin, and their highest priority holds even if other users may have already developed a water infrastructure of their own (Jankowski, 2018). The full utilization of

Indian water rights will affect other established users. Even if existing water users can lease water from tribes, the additional cost and technological and legal barriers will be a challenge (Bushnell, 2012). There are 22 recognized tribes in the entire CRB and they are collectively entitled to 2.9 million acre-feet (MAF = 3.6 billion cubic meters, BCM) per year of Colorado River water. In the Upper CRB, the current tribal water diversion is about 0.67 MAF (0.83 BCM) per year, but the reserved plus unresolved water rights might push the total water diversion toward 1.82 MAF (2.24 BCM) per year, a 300% increase (USBR, 2018). Therefore, it is necessary to consider fully-utilized Indian water rights in the CRB for any water management studies and quantify their effect in the DCP or adaptive management plan.

To address these research gaps, the objective of this paper is to quantify bottom-up adaptive water management from farmers under climate change impacts and fully used Indian water rights. We apply a coupled agent-based water resources model (Hyun et al., 2019) to simulate different climate change scenarios while considering farmers' adaptive behaviors (i.e., their decisions on water withdrawal can change year-by-year based on previous experiences and future water availability). We also test the influence of under-utilized Indian water rights, following Bennett et al. (2019), to identify the timing and magnitude of farmers' behavioral changes. The San Juan River Basin located in the Upper CRB was selected as the case study area. The rest of the paper is structured as follows. We introduce the water use situation in the study area in Section 2. The model that we applied and the scenarios we tested are presented in Section 3. We show different scenario results from the model at the system and farmer level in Section 4. The model uncertainty issue and limitations are discussed in Section 5, followed by the conclusions.

2. Water uses in the San Juan River basin

The San Juan River (SJR) Basin (Fig. 1) is a representative of the diversity present across the CRB with a drainage area of 64,570 km².

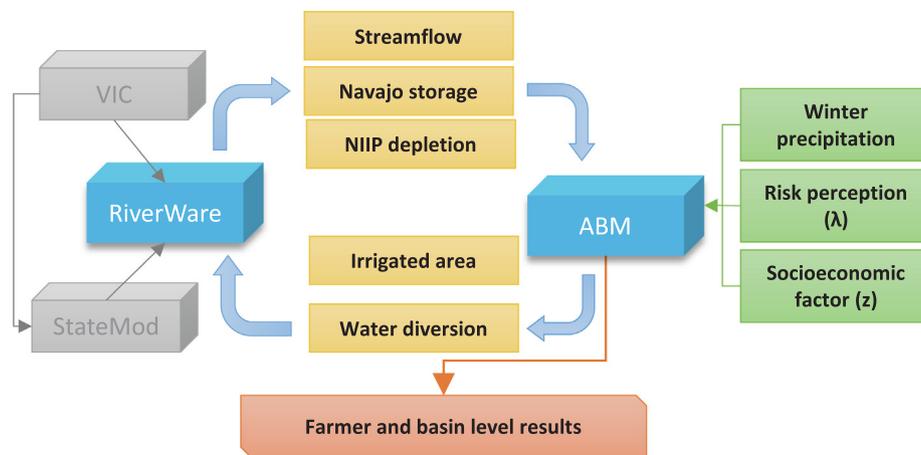


Fig. 2. Schematic of modeling platform modified from Hyun et al. (2019). VIC and StateMod models provide necessary inputs (climatic and hydrologic) to RiverWare Model, which is two-way coupled with agent-based decision-making model. 3.

The upper SJR originates in the San Juan Mountains (part of the Rocky Mountains) of Colorado that imparts a snowmelt-driven character to the runoff. The lower SJR, located in New Mexico and Arizona, traverses high-desert, with intermittent streams that drain into the main tributary of the San Juan during the summer, when they are charged by summer monsoonal rains (Bennett et al., 2019). All of these physical characteristics are very similar to the entire CRB and make it a suitable candidate for the demonstration.

The Navajo Nation is the largest water user in the SJR and its current water diversion is utilized mostly for agriculture by the Navajo Indian Irrigation Project (NIIP). This is a result of years of negotiation among the Navajo Nation, the US government and the State of New Mexico, and it finally became federal law in 2009 (Bennett et al. 2019). Currently, NIIP only diverts 50% of its water rights, which is about 200,000 acre-feet (247 million cubic meters). However, according to the 2009 settlement, water uses by the Navajo Nation will increase with the expansion of the NIIP. There are 16 other major irrigation ditches; four cities and two power plants located in New Mexico also use water from the SJR. Irrigation is the largest portion of non-tribal water use, followed by the cooling water uses for the two power plants. The main planting season runs from May to October, with hay, corn, and vegetables as the principal crops in the region. Navajo Reservoir is the main water infrastructure in the basin, which is used for flood control, irrigation, domestic/industrial water supply, and environmental flows. The active storage of the reservoir is 1.3 MAF (1.6 BCM). The maximum release rate is limited to 5000 cubic feet per second (cfs) or 141.58 cubic meters per second (cms).

The updated regional water plan (2016) summarizes the corresponding action that water users in the SJR need to take under drought conditions. The ten 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 2019 Upper CRB DCP requires the Navajo Reservoir’s operation (along with others such as Blue Mesa Reservoir and Flaming Gorge Reservoir not in the SJR basin) to maintain the water level in Lake Powell potentially through a drawdown of their own storage. However, no detailed information is available on how Navajo Reservoir might change its operation at the time this paper is written (February 2020).

3. Method and scenario setup

3.1. Modeling approaches for water resources in the SJR

The SJR has been the target of several previous modeling studies. Ewers (2005) used a system dynamics model to evaluate the tradeoff between competing water uses in irrigation and power generation. However, this model was not process-based and used a stochastic flow generator to simulate inflow (water supply). The setup for Navajo Reservoir and NIIP water use was overly simplified and did not fully represent the complexity of water infrastructure operation in the basin. Ficklin et al. (2013) developed a Soil and Water Assessment Tool model for the entire Upper CRB. They used the naturalized flow for calibration targets and did not consider the water withdrawal and reservoir operation. Bennett et al. (2018) used the Variable Infiltration Capacity (VIC) model to evaluate the impact of forest distribution on streamflow under climate change. Similar to Ficklin et al. (2013), this study only considered the naturalized flow. Bennett et al. (2019) conducted a follow-up study and used a VIC-Riverware modeling framework to address the water infrastructure complexity in the SJR. They tested the climate change and NIIP water use impact on five key basin-wide metrics. We followed Bennett et al. (2019) and added the adaptive behavior of farmers into the modeling framework via ABM to further evaluate the influence of bottom-up adaptive management in this basin.

Hyun et al. (2019) developed an Agent-Based-Riverware modeling (ABM-Riverware) framework that quantified the decisions of major irrigation districts on water withdrawal and irrigated areas in the New Mexico portion of the SJR. This ABM-Riverware model requires climatic (from VIC) and hydrologic inputs (from Colorado Surface Water Availability, StateMod) for the reservoir and river routing simulation, as well as factors that affect farmer behavior for the simulation of agent decisions. A schematic of the modeling platform is given in Fig. 2. The 16 major irrigation districts in New Mexico are grouped by location as upstream of Navajo Reservoir (Group 1), the Animas River (Group 2), and downstream of Navajo Reservoir (Group 3). This ABM-Riverware framework uses Bayesian inference (BI) mapping to quantify the psychological thought process of farmers with a cognitive map between decisions and relevant preceding factors that could affect decision-making. A risk perception parameter (the “ λ ” value in Hyun et al. 2019) is used in the BI mapping to represent farmer beliefs in the preceding factors and treated as parameters to be calibrated. The range of the λ values is from “0.5” (risk-averse, which means farmers will make decisions fully dependent on their previous experience) to “1” (risk-seeking, which means farmers will make decisions fully dependent on new information). The preceding factors we used in this study are (1) next year’s winter precipitation as a proxy of the snowpack, (2) last

year's flow violation at the basin outlet, (3) Navajo Reservoir storage at the end of the water year (September) and (4) last year's NIIP annual water diversion. These preceding factors have been confirmed as the main factors for farmers making irrigation decisions in the region and some example cognitive maps that visually link farmers' irrigation decisions with those factors can be found in [Hyun et al., 2019](#). The framework also used the cost-loss model to address farmer behavior caused by changing socioeconomic conditions ("z" value in [Hyun et al. 2019](#)). The z value, which was calculated as the ratio between the "expected cost of taking management action that will potentially increase the gross economic profit" and "the expected opportunity loss of not taking such management action," is an abstract representation of an agent's profitability, with 1 being extremely profitable and 0 being absolutely unprofitable. Their results showed that historical adaptive behaviors could be captured by this ABM-Riverware framework, and they provided an improved representation of human decision-making processes compared to conventional rule-based ABMs, which do not take risk perception into account. Technical details of this ABM-Riverware framework can be found in [Hyun et al. \(2019\)](#). We utilized this framework in this paper to understand how these adaptive behaviors might evolve under climate change.

We recalibrated the ABM-Riverware framework using irrigated area data after the 1960s. The main reason was that farmer beliefs in the preceding factors showed a significant change after the Navajo Reservoir was built, especially for downstream farmers like Hammond and Fruitland-Cambridge. Because of the missing precipitation data issue in the NOAA database, PRISM monthly winter precipitation products ([PRISM, 2019](#)) were applied in this study. The recalibration results using Nash–Sutcliffe Efficiency (NSE, [Nash and Sutcliffe, 1970](#)) and Kling-Gupta Efficiency (KGE, [Gupta et al., 2009](#)) are shown in [Figs. S1 and S2](#), respectively, and the calibrated ABM parameters for each agent ("λ" and "z" values) are listed in [Table S1 in the supplementary materials](#).

3.2. Scenarios and water scarcity metrics

Several previous studies quantified the climate change impact on streamflow at the SJR. For example, [Wilby et al. \(1999\)](#) and [Miller et al. \(2011\)](#) used raw and statistically downscaled General Circulation Model (GCM) outputs to simulate the streamflow in the SJR and its tributary. Both of their results showed a decreasing trend in streamflow under climate change. [Bennett et al. \(2018\)](#) and [Bennett et al. \(2019\)](#) used five GCMs: IPSL-CM5A-LR, CanESM2, IPSL-CM5B-LR, HadGEM2-ES, and MIROC-ESM, and they used the latest representative concentration pathway (RCP) 8.5 projection in CMIP5 ([Talyor et al., 2012](#)) for a similar purpose. In this paper, we used the same five GCMs and RCP 8.5 projection as our climate change scenarios with a simpler naming system: IPSL5AR (IPSL-CM5A-LR), CANESM (CanESM2), IPSL5B (IPSL-CM5B-LR), HadGEM2 (HadGEM2-ES), and MIROC (MIROC-ESM). [Fig. S3 in the supplemental materials](#) shows the mid-term and long-term climate projections of the five GCMs. All five GCMs predict a warmer climate with an increase of temperature 2.4–3.6 °C, and only IPSL5AR and HadGEM2 predict a drier climate. The winter precipitation (a key preceding factor that affects agent decisions) change inside the San Juan Basin from these five GCMs was also compared with the historical range (PRISM data) in [Fig. S3 of the supplemental materials](#).

Following [Bennett et al. \(2019\)](#), we used five different basin-wide metrics to compare water scarcity across different scenarios ([Table 1](#)). Mean annual storage in Navajo Reservoir provided a general measure of water available to the basin for use. San Juan-Chama diversions (transboundary water supply via the San Juan-Chama project to the Rio Grande Basin) provided a general measure of impact beyond the SJR. The total annual shortage was summarized within the SJR basin water shortage from all irrigation districts. Mean average streamflow at Bluff, UT represented the water contribution from the SJR to the entire Upper

CRB (Lake Powell). Impacts on environmental or instream flows were measured at the Four Corners gage (located near the border of New Mexico and Arizona). Current operations have a minimum target of 21 days above 5000 cubic feet per second (cfs) (14.15 cubic meter per second) between March 1 and July 31 to maintain the critical habitat.

[Fig. 3](#) summarizes all scenarios tested in this paper. The ABM-Riverware model is used to quantify farmer decisions about irrigation area and annual water diversion and their resulting impact on five basin-level evaluation metrics under 1) historical climate, 2) future climate, and 3) the combination of climate scenarios with changing NIIP water diversions. We used three different settings for future farmer behaviors to test the impact of bottom-up management: 1) "Business-as-usual" used 2013 irrigated areas of each agent throughout the entire simulation period, 2) historical minimum irrigated areas of each agent (as a boundary condition test) were used, and 3) dynamically changing irrigated areas with ABM were used as the adaptive management. The results in the next section follow this logic.

4. Results

4.1. Climate change impacts on farmer decisions

[Fig. 4](#) shows the historical irrigated areas from 1929 to 2013 as black dash lines for each of the 16 irrigation districts and the future irrigated area under five GCMs, plus full NIIP water diversion with different colored lines. The x-axis is the year and the y-axis is the irrigated area in acres (1 acre = 0.40 ha). Note that we assume the farmers risk perceptions (λ) toward preceding factors and external socioeconomic conditions (z) are constant. But since the preceding factors themselves (especially winter precipitation) are changing, the actual decision of farmers will change accordingly. Overall, most irrigation districts showed a decreasing pattern of irrigated areas under most of the future climate conditions and, to a large extent, the curves seemed to follow the historical trend. Among future climate scenarios, IPSL5AR tended to have the lowest irrigated area, as they were the driest GCM basin-wide. CANESM and MIROC predicted relatively wetter future climate conditions, but not every district showed an increasing trend of irrigated areas. Some interesting pattern of irrigated area tipping points was observed and can potentially be explained by winter precipitation patterns. For example, IPSL5AR showed a medium winter precipitation value in the upstream of the Navajo Reservoir region (Group 1, [Fig. 4a](#)), which was the reason the irrigated area under IPSL5AR was not the lowest. Also, the average winter precipitation had a clear shift around 2050 from 147 mm to 126 mm, which could possibly cause the trend to change from increasing to decreasing in the irrigated area of NMPineRiverAreaIrr. A similar reason also caused a tipping point (from increasing to decreasing irrigation area) in EchoDitch around 2080 under HadGEM2. Under IPSL5B, some districts (Jicarilla, TwinRock, FarmingtonGlade, and EchoDitch) in Group 1 ([Fig. 4a](#)) and Group 2 (Animas River, [Fig. 4b](#)) had a tipping point around 2045 can be explained by the winter precipitation trend. The tipping points indicated that available water for agriculture uses reached its potential, and the drier climate condition could subdue the agriculture production. Before 2045, there was a slightly increasing trend of winter precipitation until 2050. The winter precipitation of Group 1 and Group 2 under these GCMs are given in the supplemental materials ([Fig. S4](#)). Different agents' risk perception and their relative upstream–downstream location might also affect their decision. For example, risk perception parameters showed that Jicarilla is a risk-averse agent (with lower λ values), while NMPineRiverAreaIrr is a risk-seeking agent (with higher λ values). Under the IPSL5AR scenario, the winter precipitation showed a decreasing trend, so Jicarilla gradually adjusts its irrigation area to adapt the future climate. NMPineRiverAreaIrr was optimistic about the future water availability until it realized that winter precipitation decreased, and then it was forced to make a significant change in the irrigation area. However, under wetter GCM like CANESM, the increasing

Table 1
Calculated five metrics for evaluating the water supply impacts under historical and future climate scenarios.

Metrics	Location	Description
Mean annual storage	Navajo Reservoir	Purpose: Representing the general water availability; Calculation: Average the annual storage of Navajo Reservoir
Mean annual diversion	San Juan-Chama project	Purpose: Representing the impact on water exporting to the Rio Grande Basin; Calculation: Average the annual water diversion by the San Juan-Chama Project
Total annual shortage	SJR basin	Purpose: Representing the local water shortage; Calculation: Sum of the water shortage from all irrigation districts
Mean annual flow	SJR basin outlet at Bluff, UT (ISF_Bluff)	Purpose: Representing the water contribution from the SJR to the entire Upper CRB (Lake Powell); Calculation: Average the annual streamflow at ISF_Bluff
Instream flow requirement	Four Corners	Purpose: Maintaining critical habitats along the mainstem of SJR; Calculation: Numbers of days between March and July with daily streamflow higher than 5000 cfs at SanJuanAtFourCorners

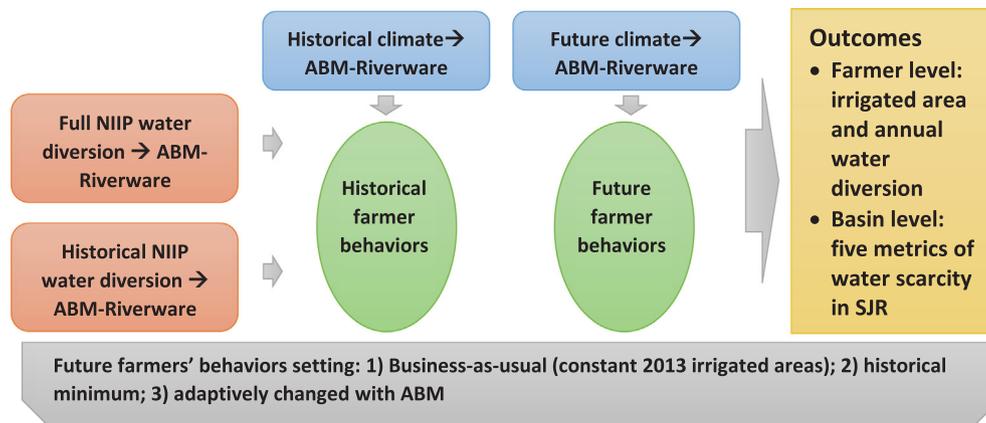


Fig. 3. Model testing scenarios. ABM-Riverware model was used to quantify farmer decisions on irrigation area, annual water diversion, and five basin level evaluation metrics under 1) historical climate, 2) future climate, and 3) changing NIIP water diversion. 4.

irrigated area in Jicarilla might partially result in NMPineRiverAreaR decreasing the irrigated area.

Among the 16 irrigation ditches, six of them, CitizenDitch (Fig. 4c), Hammond (Fig. 4c), FarmersMutal (Fig. 4b), FruitlandAndCambridge (Fig. 4c), JewettValley (Fig. 4c), and Hogback (Fig. 4c), participated in the shortage sharing agreement. And in our ABM setting, we hypothesized that these districts responded to the agreement and curtailed their irrigated area by half of the previous year. After multiple years of irrigated area curtailment, this setting allowed us to mimic a real-world migration effect, if local framers decided to move out of the basin. The modeling results showed that toward 2100, under the driest future climate condition (IPSL5AR), irrigated areas of these six irrigation ditches will become (close to) zero, which indicated that these farmers may move out of the SJR basin. A similar pattern of farmers was observed in previous ABM studies (Hailegiorgis et al., 2018). This hypothesis needs additional tests in future studies with experts from the population dynamic. We further address this topic in the discussion section.

Fig. 5 shows the annual water diversion for irrigation of these 16 agents under different climate change, plus full NIIP water diversion impacts from 2014 toward the end of this century. In general, the trend (either increasing or decreasing) was very similar to the irrigated area in Fig. 4. However, the annual water diversion showed a larger inter-year variation than the irrigated area. The main reason for this variation was because the annual irrigation requirement was calculated inside Riverware by evapotranspiration. Since precipitation and temperature changed every year, the irrigation requirement also changed accordingly for the irrigated areas. Also, this inter-year variation was largest for agents located in the Animas River. This was because the total water availability in the tributary (i.e., the Animas River) was limited compared to the mainstem SJR.

4.2. Climate change impacts on five basin-level metrics

The impact of future climate change, plus full NIIP water diversion, on five basin-level metrics are shown in Fig. 6. Fig. 6a shows the mean annual storage of the Navajo Reservoir that represents basin water availability. In general, water storage in Navajo Reservoir under climate change will be at a similar level as historical climate conditions, except for the driest GCM: IPSL5AR. This result was comparable with Bennett et al. (2019) and confirmed that the Navajo Reservoir has the capacity to smooth the intensifying inter-annual flow variability driven by climate change. Fig. 6b shows that, in terms of water export from SJR to the Rio Grande Basin, MIROC will result in a similar level of water export. But other GCMs showed a decreasing pattern in San Juan-Chama project diversion, while HadGEM2 and IPSL5AR result in the largest shortages among the five GCMs. Bennett et al. (2019) also showed that these two GCMs will cause the largest out-of-the-basin water delivery shortage. Fig. 6c shows the sum of the local water shortage among irrigation districts. The driest GCM, IPSL5AR, showed a severe local water shortage as expected. Fig. 6d shows the average streamflow to Lake Powell that tries to fulfill the Upper Colorado Water Compact. Again, it is not surprising that the two drier GCMs, IPSL5AR and HadGEM2, showed the lowest flow, and MIROC, a relatively wetter GCM, showed an increase of streamflow to Lake Powell. Bennett et al. (2019) also showed MIROC and CANESM had higher than historical water delivery to Lake Powell. Finally, Fig. 6e shows the numbers of days between March and July that has daily streamflow at Four Corners larger than 5000 cfs. The black dash line represents the minimal 21 day target. The wetter GCM, MIROC, shows more years that this target will be met (66 out of 85 simulation years) and the drier GCM, IPSL5AR, shows the least years (24 out of 85 simulation years). A similar conclusion was made by Bennett et al. (2019) that meeting minimum flow

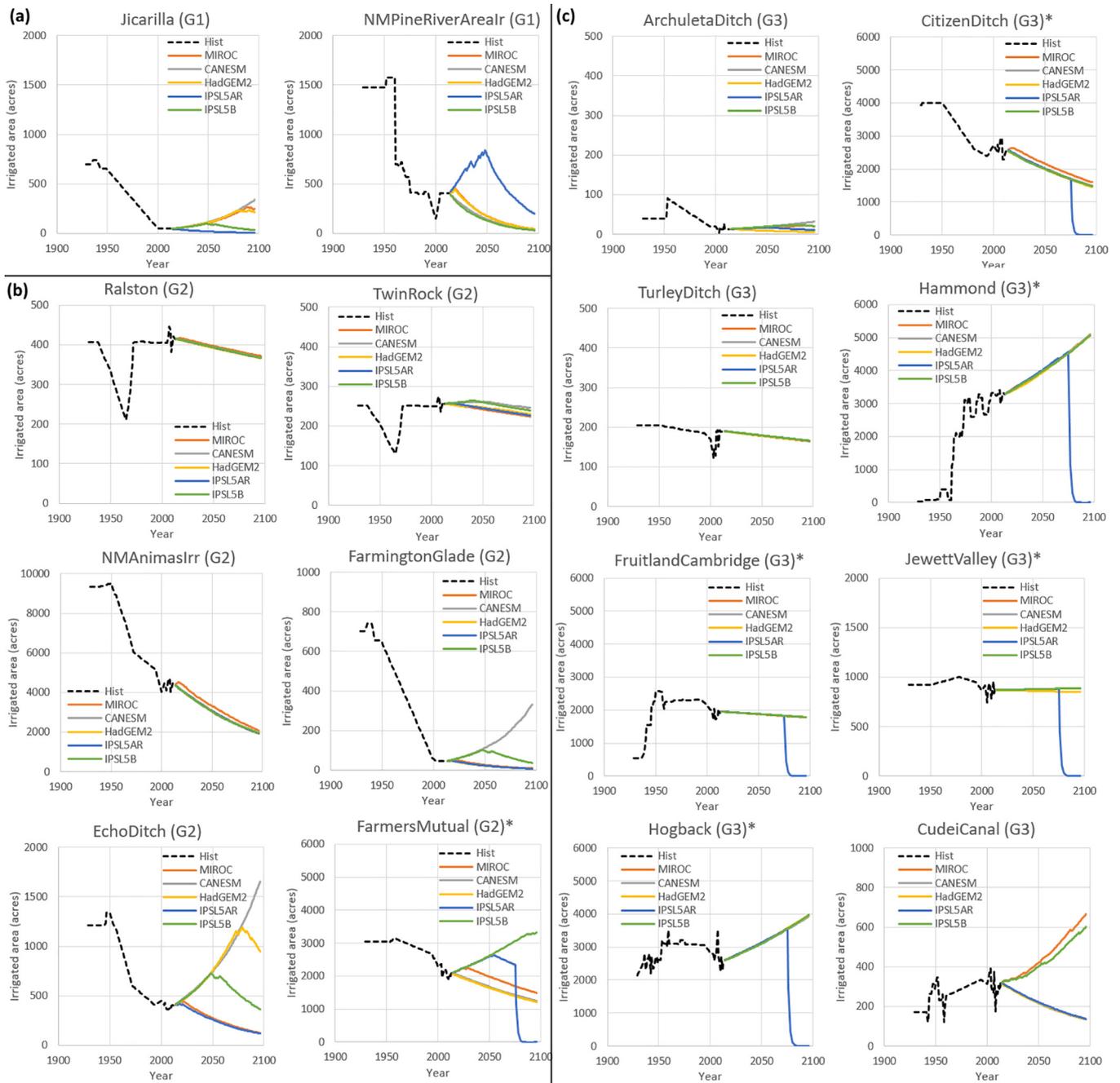


Fig. 4. Historical (black dash lines) and future (colored lines) irrigated areas under different climate change and full NIIP water diversion impacts on 16 irrigation districts (agents). Agents are grouped: (a) G1 (upstream of Navajo), (b) G2 (Animas River), and (c) G3 (downstream of Navajo), based on their locations. Star next to the agent names means agent is participating in shortage sharing agreement. 5.

requirements was likely to be a major challenge in the SJR under climate change impacts.

We used the wetter GCM, MIROC, and the drier GCM, IPSL5AR, to test how bottom-up management might help mitigate the negative impact at a basin-wide scale. Fig. 7 showed the results when we changed the irrigated area setting from dynamic adaptive behavior driven by ABM into the 1) constant 2013 area for all districts (the Year 2013 is the latest year we have the historical value) or 2) the historical minimal irrigated area value for all districts. The results indicated that at the basin level, these three different settings of future farmer behavior did not result in any differences under MIRCO. Under the IPSL5AR, some small improvements were observed in Navajo storage, local water shortage, streamflow to Lake Powell, and instream flow requirement

under the minimum irrigated area setting.

When we compare Figs. 4, 5 and 7, we can highlight the differences of climate change impact on individual irrigation districts and basin-wide metrics. While climate change impact might significantly affect some irrigation districts' irrigated areas (Fig. 4) and water diversions (Fig. 5), these behavioral changes are not observed in any of the basin-wide water scarcity metrics (Fig. 7). This comparison shows water allocation in this basin is close to a "zero-sum" game while someone use more water, others must use less water to satisfy the basin-wide constraints. Therefore, basin-wide water scarcity metrics might not be able to reflect the changing local water diversion and irrigated area conditions. When policymakers try to implement any DCP in this basin, they should consider this situation and incorporate heterogeneous bottom-

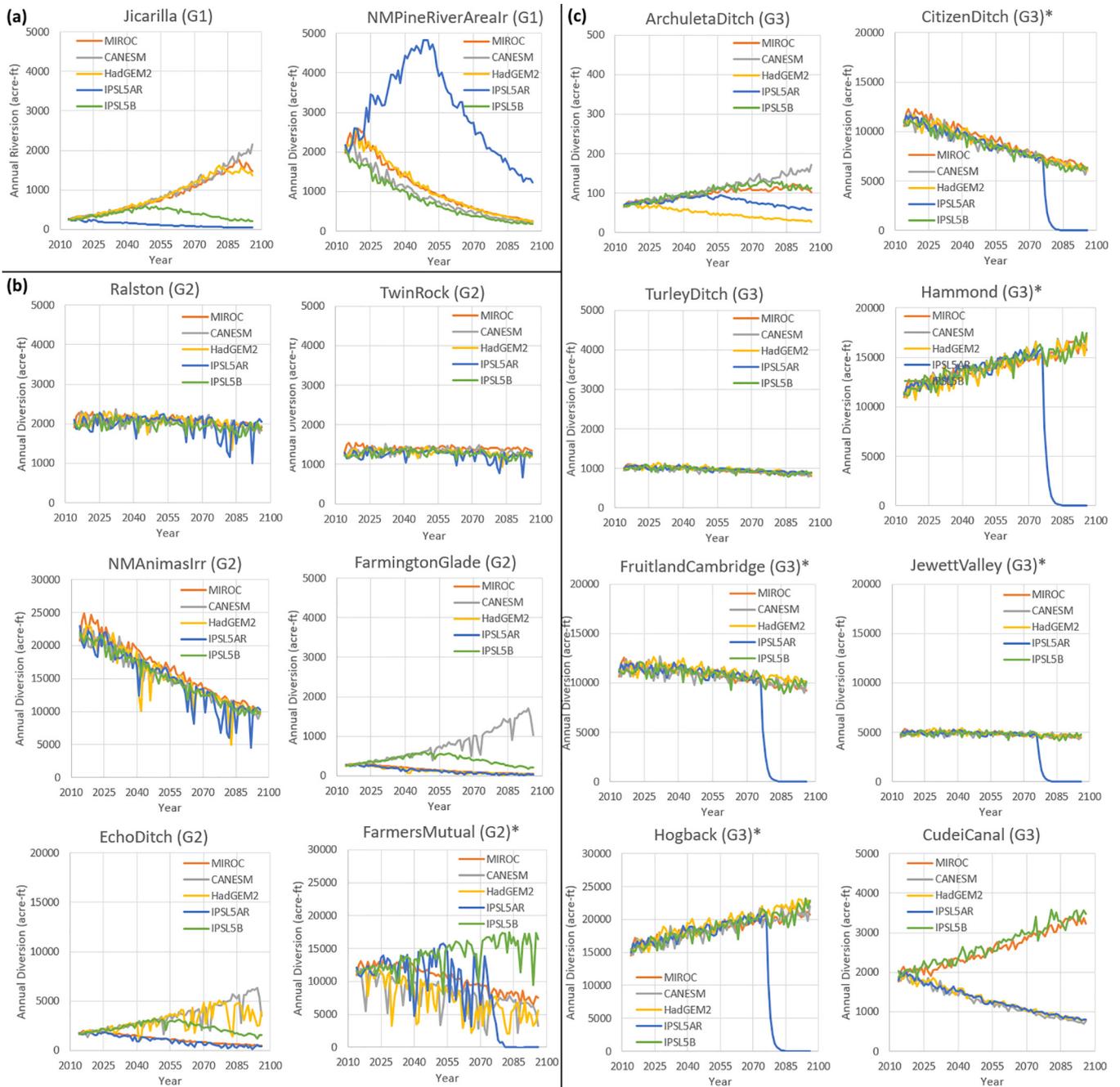


Fig. 5. Future annual water diversion under different climate change and full NIIP water diversion impacts on 16 irrigation districts (agents). Agents are grouped: (a) G1 (upstream of Navajo), (b) G2 (Animas River), and (c) G3 (downstream of Navajo), based on their locations. Star next to the agent names means this agent is participating in shortage sharing agreement. 6.

up decision-making process from farmers’ behavioral change in the DCP.

4.3. Sensitivity of the unutilized NIIP water rights

Section 4.1 and Section 4.2 demonstrated the impact of full utilization of Indian water rights on both farmer- and basin-level water scarcity. In this section, we went a step further and showed the impact of Indian water rights on individual irrigation districts in the SJR basin. We changed the annual NIIP depletion target inside Riverware from full water use to current water use. The annual depletion for all tested runs is given in the supplemental materials (Fig. S5). In the ABM setting, the NIIP depletion will directly affect agents in Group 3 (downstream of

Navajo Reservoir), because NIIP directly takes water from the Navajo Reservoir. The NIIP depletion also indirectly affects other agents because Navajo storage affects all agents, especially agents who participated in the shortage sharing agreement. Fig. 8 shows six agents (including all three groups) as a demonstration of current and full utilization of Indian water rights under the wetter GCM (CANESM) and drier GCM (IPSL5AR) conditions.

The modeling results showed that under wetter future climate conditions, most agents would slightly reduce their irrigated areas and associated water diversions to allow larger water storage in the Navajo Reservoir and fulfill the full use of NIIP diversion (solid gray lines are lower than dotted gray lines). This difference was more noticeable in Group 3 agents, because they were located downstream of the Navajo

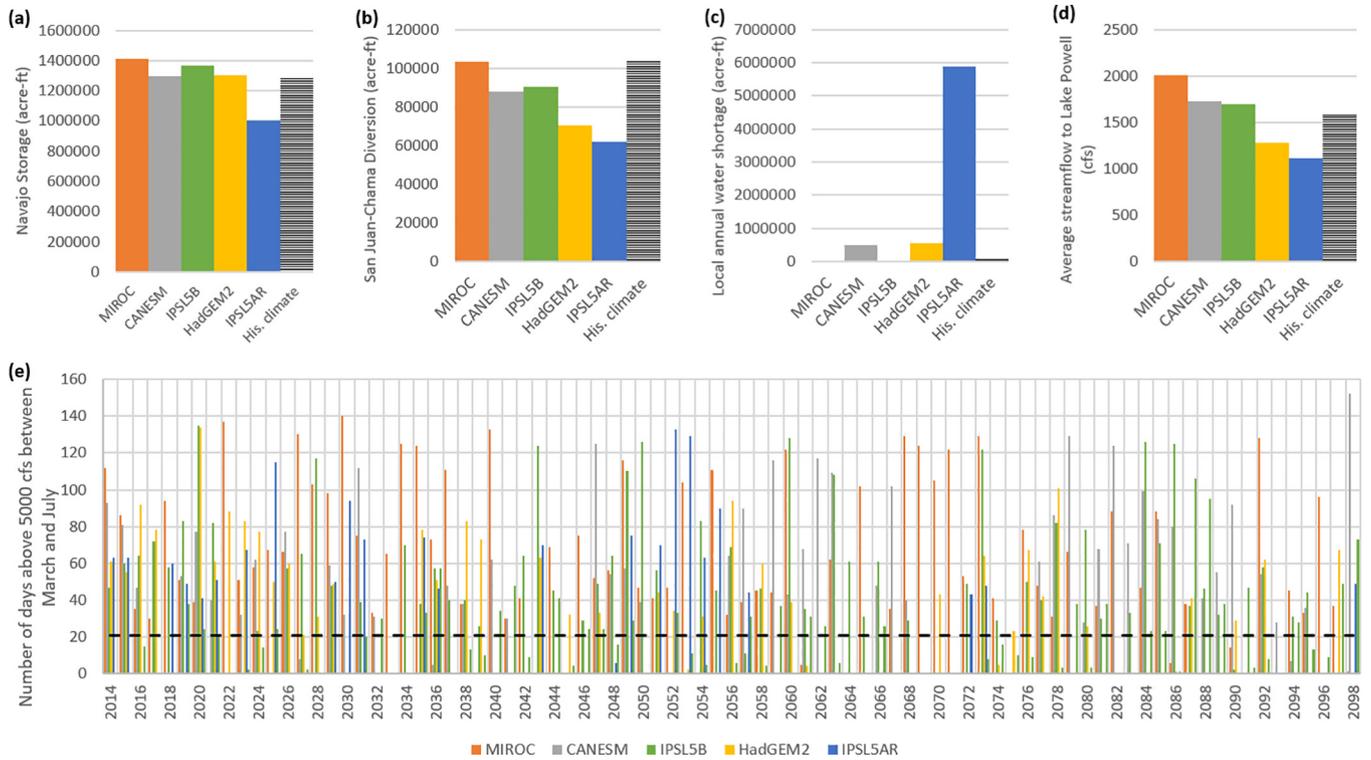


Fig. 6. Five basin level metrics for water scarcity under different climate change impacts and full NIIP water diversion. (a) Mean annual storage of Navajo Reservoir; (b) mean annual diversion of San Juan-Chama project; (c) total water shortage in the SJR Basin; (d) mean annual streamflow to Lake Powell; and (e) number of days about 5000 cfs between March and July at Four Corners. 7.

Reservoir. A similar pattern was observed under the dry future climate condition, solid blue lines lower than dotted blue lines meant that all agents were reducing their own irrigated areas and water diversions.

However, one significant difference was the triggering of the shortage sharing agreement. The current NIIP water diversion under the drier future climate condition would not trigger the shortage sharing

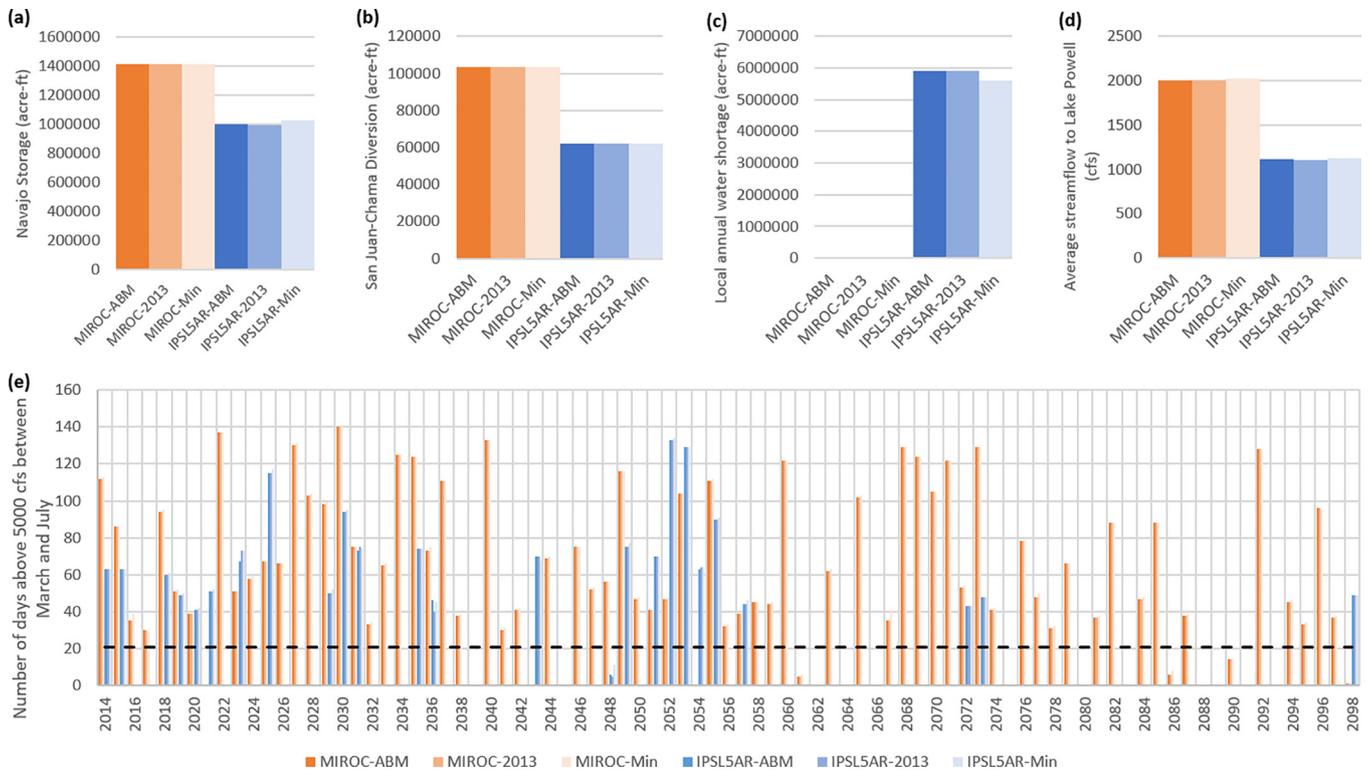


Fig. 7. Five basin level metrics for water scarcity under IPSL5AR (drier) and MIRCOC (wetter) future climate condition plus full NIIP water diversion with different farmer behavior settings: (a) mean annual storage of Navajo Reservoir; (b) mean annual diversion of San Juan-Chama project; (c) total water shortage in the SJR Basin; (d) mean annual streamflow to Lake Powell; and (e) number of days about 5000 cfs between March and July at Four Corners. 8.

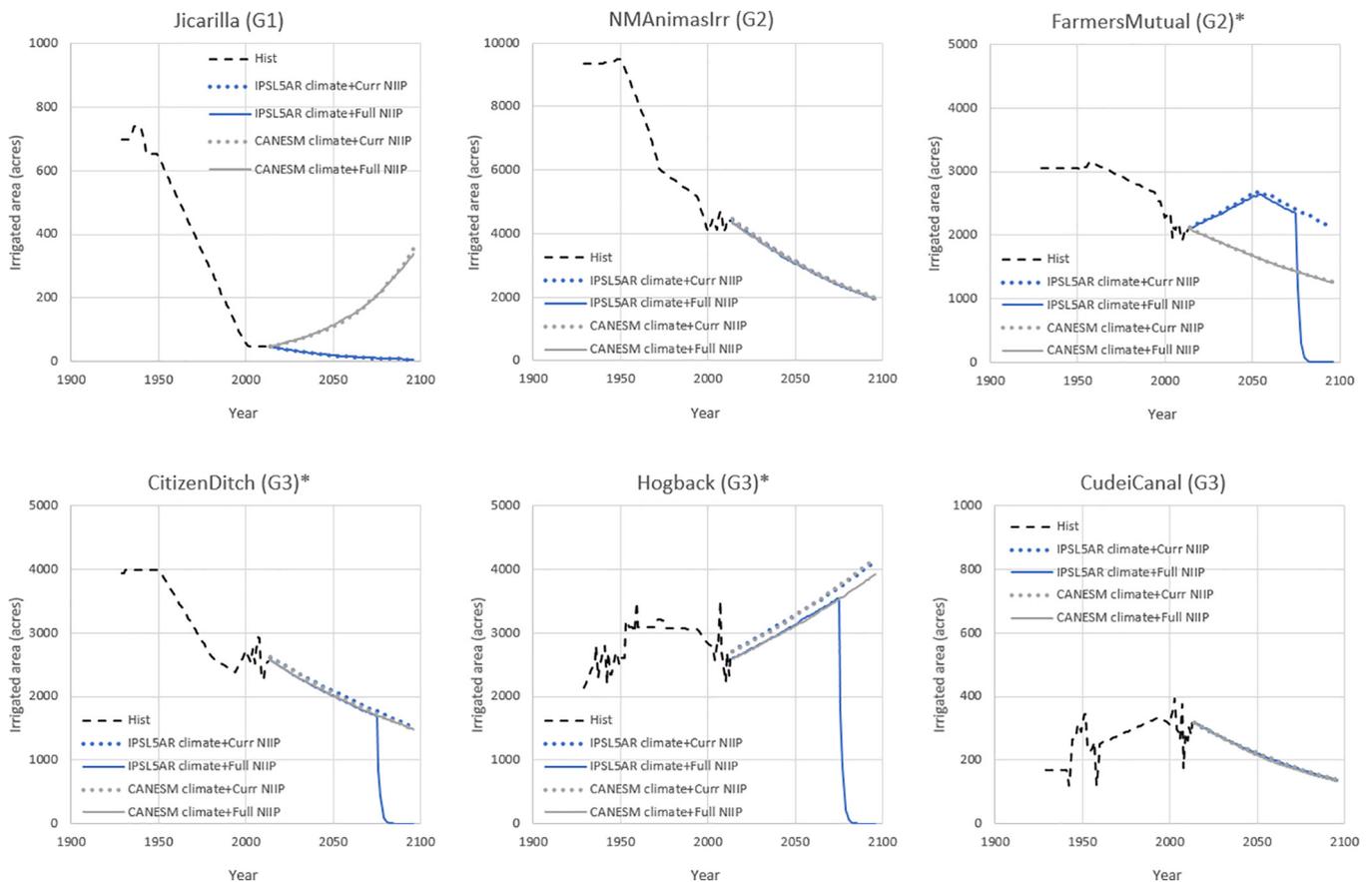


Fig. 8. Effect of increasing NIIP water diversion on irrigation areas under IPSLSAR (drier) and CANESM (wetter) climate scenarios. Star next to the agent names means this agent is participating in shortage sharing agreement. 9.

agreement. Therefore, even with some water scarcity issues, most farmers will remain in the region if NIIP will maintain the current water use. This result implied that the expansion of the most senior water rights in the basin might potentially drive junior water right users out.

5. Discussion

5.1. Informing DCP implementation with modeling results

The coupled ABM-Riverware model was applied in this paper to evaluate the impact of climate change, plus full NIIP water diversion, on both farmer decisions concerning irrigated areas and the resulting impacts of agent decisions on five basin-level water scarcity metrics. In the first discussion section, we tried to explain how our modeling results provide information for basin-wide DCP implementation. In our simulation, SJR delivered an average of 1.14 MAF per year to Lake Powell under historical climate conditions. MIROC, CANESM, and IPSL5B showed increasing streamflow (1.450, 1.246, and 1.224 MAF, respectively), and HadGEM2 and IPSL5A showed decreasing streamflow (0.927 and 0.807 MAF). If we use historical climate conditions as a basis, under MIROC, CANESM, and IPSL5B, SJR basin had the potential to contribute an additional 0.309, 0.105, and 0.083 MAF per year to Lake Powell, respectively. Alternatively, the average Navajo Reservoir storage is about 1.283 MAF under historical climate conditions. Again, if we used this value as a basis, our results showed that under MIROC, CANESM, and IPSL5B, the Navajo Reservoir can release additional 0.129, 0.013, and 0.085 MAF downstream. If we combine these two water sources, there will be an additional 0.438, 0.118, and 0.168 MAF of water delivered to Lake Powell and the Lower Basin under MIROC, CANESM, and IPSL5B, respectively. Although these amounts are not a significant amount of water, it can help with water curtailment in the

Lower Basin and Mexico. For example, the additional 0.438 MAF under MIRCO can cover 100% of the water curtailment in the Lower Basin and Mexico if Lake Mead’s water level drops to 1075–1090 ft (Stern and Sheikh, 2019). Even if the water level dropped to 1050–1075 ft, this amount of water could cover 70% of the curtailment (Stern and Sheikh, 2019). These results indicated that if the Upper Basin DCP can be implemented properly, the water scarcity condition in the entire CRB can be mitigated.

5.2. Effect of parameter uncertainty on modeling results

In the results section, we demonstrated the effect of different GCMs by using five GCM outcomes and the effects of under-utilized Indian water rights via different model settings. To further improve this coupled modeling framework, we tested the uncertainty associated with the model itself. In general, three types of uncertainty are commonly discussed in the scientific community (Yang and Wi, 2018): model input uncertainty (i.e., data uncertainty), model structure uncertainty (i.e., equation uncertainty), and model parameter uncertainty. Previous studies have discussed the data uncertainty (Vano et al., 2014) and model structure uncertainty (Miller et al., 2012) in the CRB, and we want to further explore the effect of model parameter uncertainty and test the equifinality issue (Beven, 2006) on our results.

In the model calibration process, we applied the Monte Carlo approach to test 200 parameter sets. The best 20 sets with the highest NSE value compared to historical irrigated areas were selected. The calibration results of these sets are shown in Fig. S6 of the supplemental materials. We then ran the ABM-Riverware model under the driest GCM, IPSLSAR, using these best 20 sets and showed the results in Fig. 9. In Fig. 9, the results of the best set are highlighted by blue lines, which are the parameters we used in Section 4. The results of the other 19 sets

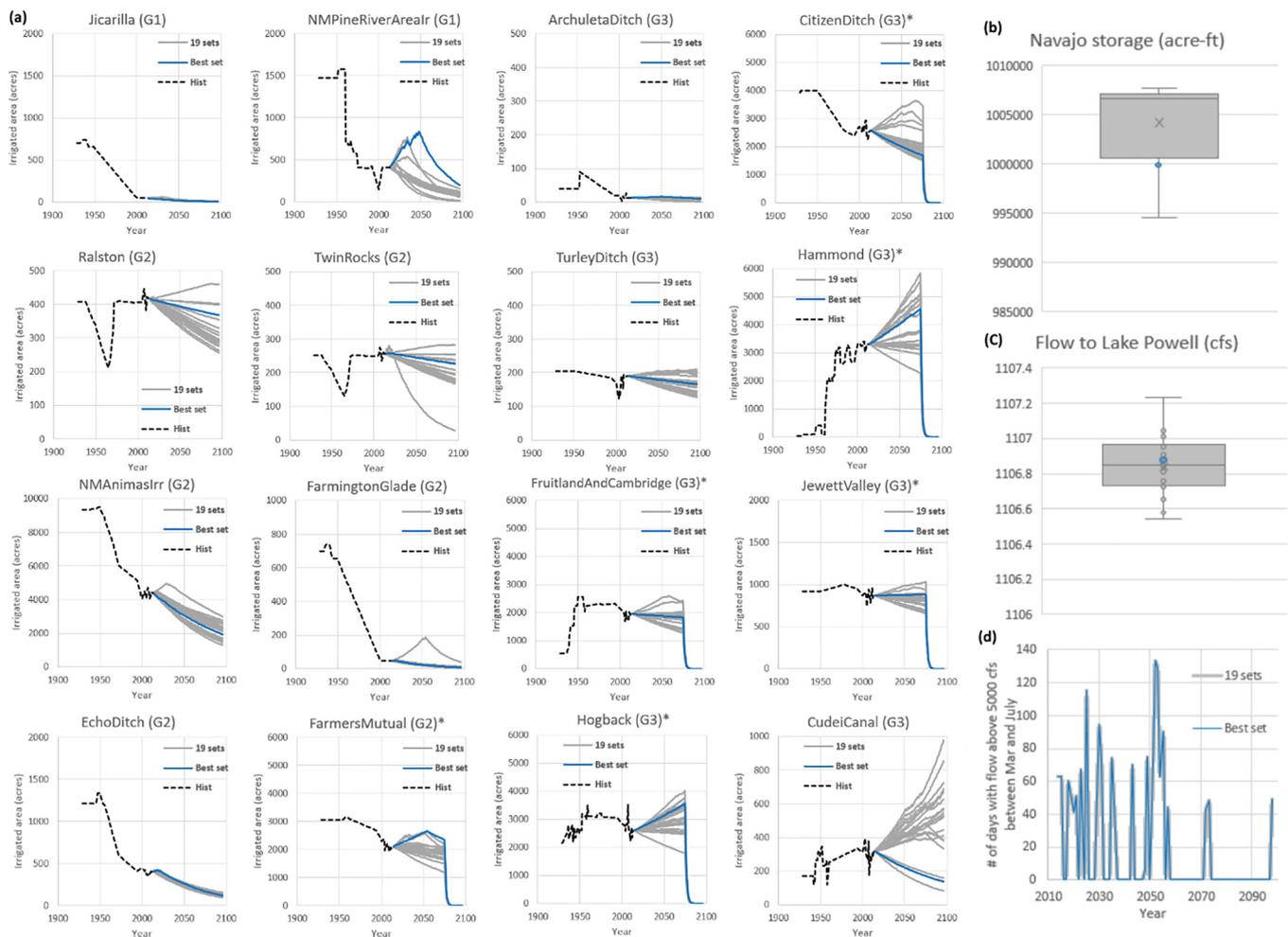


Fig. 9. Effect of model parameter uncertainty on (a) irrigation areas of 16 districts; (b) Navajo storage; (c) streamflow to Lake Powell; and (d) numbers of days between March and July above 5000 cfs at Four Corners under IPSL5AR climate scenarios and full NIIP water diversion.

are shown as gray lines. Fig. 9a shows the farmer’s irrigated area, and Fig. 9b, c and d show three basin-level water scarcity metrics: the Navajo storage, streamflow to Lake Powell, and the number of days between March and July above 5000 cfs at Four Corners, respectively. The effect of model parameter uncertainty was more significant at the farmer level than the basin level. Among agents, those located downstream of the Navajo Reservoir (Group 3) showed the largest variation in the irrigated area compared to Groups 1 and 2. This was because the Navajo Reservoir provides a more stable water supply to the downstream irrigation districts. Therefore, different sets of risk perception parameters (λ) and socioeconomic condition parameters (z) might be able to achieve a similar value of NSE (i.e., equifinality issue). The actual annual diversion of each agent is in the supplemental materials (Fig. S7). Fig. 9b, c, and d barely showed any differences to indicate that basin-level metrics will not be able to demonstrate the equifinality issue. This could be a concern of those modeling studies that only focus on basin-level results and want to explore the effect of DCP at the local level. A comprehensive evaluation of model uncertainty might be needed in the future to further explore this aspect.

5.3. Model limitation

There are other limitations and assumptions in our model worth further discussion. First, the hypothesis of the action of future farmers on the shortage sharing agreement will need further examination. The current ABM assumes 50% curtailment of irrigated areas change, which is an arbitrary number, and the migration results cannot be confirmed

with any historical data. The curtailment of irrigated areas can be updated by standalone Riverware simulation to reflect actual shortages of water. Furthermore, a survey study or local farmer engagement workshops will be needed to quantify the likelihood of local intentions for migration under drought conditions. Second, as we mentioned in Section 2, no detailed information is available about how the Navajo Reservoir will change its operation under Upper Colorado DCP. When such information becomes available, the same model can incorporate the new operation rule and test the effect on both basin-level water scarcity metrics and farmer-level decisions. We can also use such information to verify our discussion in Section 5.1 about whether SJR can help with the water curtailment in the Lower Basin. Finally, even though we have metrics to look at climate change impact beyond the SJR basin (streamflow Lake Powell and water export to the Rio Grande), a regional scale model, such as the Colorado River Simulation System, can better show how these changes might affect the entire CRB.

6. Conclusion

The continuous drought through the early 2000s has caused a serious water scarcity issue in the CRB. While different modeling approaches have been used to quantify the impact of climate change, only a few consider the adaptive behaviors of farmers and the combined effect of climate change and under-utilized Indian water rights. This paper used a coupled ABM-Riverware model to quantify the bottom-up adaptive water management under climate change as well as the influence of under-utilized Indian water rights to identify the potential

tipping point of farmer behavioral changes, that is, the timing of farmer decisions to switch from increasing to decreasing irrigation area.

The case study results of the SJR basin show that:

- 1) Farmers have different responses to expand or reduce irrigated areas to climate change impact. While changes in winter precipitation might partially explain the behavioral tipping point, no specific pattern can be concluded based on their location.
- 2) Farmer responses to annual water diversion showed larger inter-year variation compared to irrigated area, and farmers located along the Animas River showed the highest variation because the water supply in the tributary is relatively limited.
- 3) Climate change will, in general, worsen water scarcity issues in different basin-level metrics, such as Navajo Reservoir storage, flow to Lake Powell, and instream flow requirements, which echo several previous studies.
- 4) Basin-level water scarcity metrics cannot reflect farm-level impacts under climate change, which emphasizes the importance of modeling bottom-up management actions.
- 5) Full utilization of Indian water rights will likely trigger the shortage sharing agreement under the drier future climate compare to current tribal water use.

Future studies can focus on several different directions to improve the results of this work. A comprehensive evaluation of modeling uncertainty, including input data, model structure (i.e., equations), and model parameters, can benefit the scientific community and advance our understanding of the coupled human-natural system model. The irrigated area curtailment under drought condition, the effect of reservoir reoperation under drought contingency plan, and the regional impact beyond the SJR basin all need further evaluation. Also, interviews with farmers or surveys about farmer decision behaviors can improve our understanding of the decision process the ABM modeling, which is another future research direction.

CRedit authorship contribution statement

Y.C. Ethan Yang: Conceptualization, Methodology, Visualization, Supervision. **Kyongho Son:** Data curation, Software. **Fengwei Hung:** Software, Writing - original draft. **Vincent Tidwell:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the Office of Science of the US Department of Energy as part of research in the Multi-Sector Dynamics, Earth and Environmental System Modeling Program. We want to thank the editors and two anonymous reviewers, who helped us improve the quality of this paper. The modeling data of this paper can be downloaded at: <https://doi.org/10.25584/data.2020-04.1193/1616451>.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhydrol.2020.125015>.

References

Bennett, K.E., Bohn, T.J., Solander, K., McDowell, N.G., Xu, C., Vivoni, E., Middleton, R.S., 2018. Climate-driven disturbances in the San Juan River sub-basin of the

- Colorado River. *Hydrol. Earth Syst. Sci.* 22, 709–725.
- Bennett, K.E., Tidwell, V.C., Llewellyn, D., Behery, S., Barrett, L., Stansbury, M., Middleton, R.S., 2019. Threats to a Colorado river provisioning basin under coupled future climate and societal scenarios. *Environ. Res. Commun.* 1, 095001.
- Beven, K., 2006. A manifesto for the equifinality thesis. *J. Hydrol.* 320 (1–2), 18–36.
- Bushnell, D. S. 2012. *American Indian Water Rights Settlements*. University of New Mexico, School of Law, http://utoncenter.unm.edu/pdfs/American_Indian_Water_Right_Settlements.pdf. Accessed on 12/15/2019.
- Cook, B.I., Seager, R., Williams, A.P., Puma, M.J., McDermaid, S., Kelley, M., Nazarenko, L., 2019. Climate change amplification of natural drought variability: the historic mid-twentieth-century North American drought in a warmer world. *J. Clim.* 32, 5417–5436.
- Dawadi, S., Ahmad, S., 2012. Changing climatic conditions in the Colorado River Basin: Implications for water resources management. *J. Hydrol.* 430–431, 127–141.
- Ewers, M., 2005. Combining hydrology and economics in a system dynamics approach: modeling water resources for the San Juan Basin. *Proc. 23rd International Conference of the System Dynamics Society*, July 17–21, Boston.
- Ficklin, D.L., Stewart, I.T., Maurer, E.P., 2013. Climate change impacts on streamflow and subbasin-scale hydrology in the Upper Colorado River Basin. *PLoS ONE* 8 (8), e71297.
- Garrick, D.E., 2018. Decentralisation and drought adaptation: applying the subsidiarity principle in transboundary river basins. *Int. J. Commons* 12 (1), 301–331.
- Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *J. Hydrol.* 377, 80–91.
- Hailegiorgis, A., Crooks, A., Cioffi-Revilla, C., 2018. An agent-based model of rural households' adaptation to climate change. *J. Artif. Soc. Soc. Simul.* 21 (4), 4.
- Hyun, J.Y., Huang, S.Y., Yang, Y.C.E., Tidwell, V., Macknick, J., 2019. Using a coupled agent-based modeling approach to analyze the role of risk perception in water management decisions. *Hydrol. Earth Syst. Sci.* 23, 2261–2278.
- Jankowski, J., 2018 *Native American Tribal Water Rights in the Colorado River Basin*. The University of California, Davis, https://watershed.ucdavis.edu/education/classes/files/content/page/Ecogeomorphology.PaperFinal.JesseJankowski_0.pdf. Accessed on 12/15/2019.
- Khan, H.F., Yang, Y.C.E., Xie, H., Ringer, C., 2017. A coupled modeling framework for sustainable watershed management in transboundary river basins. *Hydrol. Earth Syst. Sci.* 21, 6275–6288.
- McCab, G., Wolock, D.M., Pederson, G.T., Woodhouse, C.A., McAfee, S., 2017. Evidence that recent warming is reducing upper Colorado river flows. *Earth Interact.* 21 (10), 1–14.
- Miller, W.P., Piechota, T.C., Gangopadhyay, S., Pruitt, T., 2011. Development of streamflow projections under changing climate conditions over Colorado River basin headwaters. *Hydrol. Earth Syst. Sci.* 15, 2145–2164.
- Miller, W.P., Butler, R.A., Piechota, T., Prairie, J., Grantz, K., DeRosa, G., 2012. Water management decisions using multiple hydrologic models within the San Juan river basin under changing climate conditions. *J. Water Resour. Plann. Manage.* 138 (5), 412–420.
- Milly, P.C.D., Dunne, K.A., 2016. Potential evapotranspiration and continental drying. *Nat. Clim. Change* 6 (10), 946–949.
- Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models: Part 1. A discussion of principles. *J. Hydrol.* 10, 282–290.
- Parsons, L.A., Coats, S., Overpeck, J.T., 2018. The continuum of drought in Southwestern North America. *J. Climate* 31, 8627–8643.
- PRISM Climate Group, Oregon State University, 2019. <http://prism.oregonstate.edu>, created 4 Feb 2004. Accessed at 12/17/2019.
- Rhee, G., Salazar, J., Grigg, C., 2019. How long does a 15-year drought last? On the correlation of rare events. *J. Clim.* 32, 1345–1359.
- Steele, C., Reyes, J., Elias, E., Aney, S., Rango, A., 2018. Cascading impacts of climate change on southwestern US cropland agriculture. *Clim. Change* 148, 437–450.
- Stern, C. V., Sheikh, P. A. 2019. *Management of the Colorado River: Water Allocation, Drought, and the Federal Role*, Congressional Research Service, R45546.
- Sullivan, A., White, D.D., Hanemann, M., 2019. Designing collaborative governance: insights from the drought contingency planning process for the lower Colorado River basin. *Environ. Sci. Policy* 91, 39–49.
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93, 485–498.
- Taylor, P.L., MacLroy, K., Waskom, R., Cabot, P.E., Smith, M., Schempp, A., Udall, B., 2019. Every ditch is different: barriers and opportunities for collaboration for agricultural water conservation and security in the Colorado River Basin. *J. Soil Water Conserv.* 74 (3), 281–295.
- United Nations (UN). 2015. *Transforming our World: The 2030 Agenda for Sustainable Development*, <https://www.refworld.org/docid/57b6e3e44.html>, accessed on 12/14/2019.
- U.S. Bureau of Reclamation (USBR) 2018. *Colorado River Ten Tribes Partnership, Colorado River Basin Ten Tribes Partnership Tribal Water Study, Study Report*, <https://www.usbr.gov/lc/region/programs/crbstudy/tws/finalreport.html>. Accessed on 11/05/2019.
- Vano, J.A., Lettenmaier, D.P., 2014. A sensitivity-based approach to evaluating future changes in Colorado River discharge. *Clim. Change* 122 (4), 621–634.
- Vano, J.A., Udall, B., Cayan, D.R., Overpeck, J.T., Brekke, L.D., Das, T., Hartman, H.C., Hidalgo, H.G., Hoerling, M., McCabe, G.J., Morino, K., Webb, R.S., Werner, K., Lettenmaier, D.P., 2014. Understanding uncertainties in future Colorado River streamflow. *Bull. Am. Meteorol. Soc.* 95, 59–78.
- Wi, S., Dominguez, F., Durcik, M., Valdes, J., Diaz, H.F., Castro, C.L., 2012. Climate change projection of snowfall in the Colorado River Basin using dynamical downscaling. *Water Resour. Res.* 48, W05504. <https://doi.org/10.1029/2011WR010674>.

- Wilby, R.L., Hay, L.E., Leavesley, G.H., 1999. A Comparison Downscaled and Raw GCM A comparison of downscaled and raw GCM output implications for climate change scenarios in the San Juan River. *J. Hydrol.* 225, 67–91.
- Woodhouse, C.A., Pederson, G.T., 2018. Investigating runoff efficiency in upper Colorado River streamflow over past centuries. *Water Resour. Res.* 54, 286–300.
- Xiao, M., Udall, B., Lettenmaier, D.P., 2018. On the causes of declining Colorado River streamflows. *Water Resour. Res.* 54, 6739–6756.
- Yang, J., Yang, Y.C.E., Chang, J., Zhang, J., Yao, J., 2019. Impact of dam development and climate change on hydroecological conditions and natural hazard risk in the Mekong River Basin. *J. Hydrol.* 579, 124–177.
- Yang, Y.C.E., Cai, X., Stipanović, D.M., 2009. A decentralized optimization algorithm for multi-agent system based watershed management. *Water Resour. Res.* 45, W08430. <https://doi.org/10.1029/2008WR007634>.
- Yang, Y.C.E., Wi, S., 2018. Informing regional water-energy-food nexus with system analysis and visualizations – A case study in the Great Ruaha River of Tanzania. *Agric. Water Manage.* 196, 75–86.