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Spatial planning for water sustainability projects under climate uncertainty: balancing human and environmental water needs

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Abstract

Societies worldwide make large investments in the sustainability of integrated human-freshwater systems, but uncertainty about water supplies under climate change poses a major challenge. Investments in infrastructure, water regulation, or payments for ecosystem services may boost water availability, but may also yield poor returns on investment if directed to locations where water supply unexpectedly fluctuates due to shifting climate. How should investments in water sustainability be allocated across space and among different types of projects? Given the high costs of investments in water sustainability, decision-makers are typically risk-intolerant, and considerable uncertainty about future climate conditions can lead to decision paralysis. Here, we use mathematical optimization models to find Pareto-optimal satisfaction of human and environmental water needs across a large drought-prone river basin for a range of downscaled climate projections. We show how water scarcity and future uncertainty vary independently by location, and that joint consideration of both factors can provide guidance on how to allocate water sustainability investments. Locations with high water scarcity and low uncertainty are good candidates for high-cost, high-reward investments; locations with high scarcity but also high uncertainty may benefit most from low regret investments that minimize the potential for stranded assets if water supply increases. Given uncertainty in climate projections in many regions worldwide, our analysis illustrates how explicit consideration of uncertainty may help to identify the most effective strategies for investments in the long-term sustainability of integrated human-freshwater systems.

1. Introduction

Climate change will transform the availability of freshwater globally, ultimately impacting both human water security and ecosystem services related to water quantity (Milly *et al* 2005, IPCC 2014). Nearly 80% of the global population faces some water security threat (Vörösmarty *et al* 2000), and over one-fifth of the world population is likely to experience chronic water scarcity in the next century (Arnell 2004, Schewe *et al* 2014). In resource limited areas, the maintenance of river flows, critical for the preservation of freshwater ecosystem services, will become increasingly difficult (Barnett *et al* 2005).

Planning for both human and environmental water sustainability under climate change is challenging due to the combination of uncertain future water availability, high costs of new infrastructure or policy interventions, and the potentially dire consequences of under-allocating water for societal or environmental needs. Globally, up to $1 trillion USD may be needed to provide safe and efficient water supplies (Hutton and Varughese 2016, Larsen *et al* 2016), but costs may rise substantially if investments in water sustainability are misaligned with changes in water availability. Thus, a key challenge for decision-makers is anticipating how water availability might change under possible future climates.

Global climate models (GCMs) have long been used as tools to understand our climate system but have recently been repurposed to aid climate adaptation decision-making (Weart 2010). To capture local-scale projected changes, downscaling techniques are applied to produce estimates of temperature and precipitation which may be used to help identify when and where water scarcity may arise. Ideally, these projections allow for sustainability strategies to be established in advance; however, regional-to-local scale climate projections can vary widely depending on various aspects, such as GCM and downscaling methods implemented (Hawkins and Sutton 2009, 2011, Wootten *et al* 2017), leaving decision-makers to contend with substantial uncertainty in projections of future water availability.

Decision-makers in other domains often deal with uncertainty by employing highly adaptable strategies, in which investments are reversible (Groves and Game 2016). Unfortunately, these strategies are difficult to implement in water resource planning because investments in infrastructure are not easily re-allocated. Likewise, water sustainability practices that depend on campaigns for individual behavioral change can have long ramp-up periods and require large investments in human capital. Because of the associated expense and inflexibility, both investment types encourage a risk intolerant attitude. Low risk tolerance often leads to decision making based on historical trends rather than future projections (Adger *et al* 2009) or a delay of action while waiting for models to converge. Both approaches are reactionary and lose valuable time to get in front of potentially catastrophic changes (Adger *et al* 2009). If climate projections are incorporated into decision-making, low risk attitudes may focus actions only on regions where models are robust (in high agreement), or actions that attempt to avoid 'worst-case scenarios'. Nonetheless, explicit consideration of spatiotemporal patterns of uncertainty in climate projections may help to inform water sustainability planning (Fletcher *et al* 2019, Wineland *et al* 2020a). Indeed, the most effective climate adaptation strategies may vary with levels of uncertainty (Dessai and van der Sluijs 2007, Farzaneh *et al* 2020).

While there is a rich literature on water resource planning under climate uncertainty (Hallegate *et al* 2012), we identify two research gaps. First, spatial planning questions (i.e. how to allocate investments in water sustainability across space and among different types of projects) are poorly studied. Previous climate-related work has focused on minimizing climate risk to hydropower (Brekke *et al* 2009, International Hydropower Association (IHA) 2019) and water infrastructure investments (Alavian *et al* 2009), and how to maintain public water supplies under climate uncertainty (Arnell and Delaney 2006), largely neglecting spatial planning. Moreover, decisions to initiate water sustainability projects are typically based on a rich set of incommensurable sociopolitical factors (Mendoza *et al* 2018). To boost water availability, water managers often rely on a combination of small and large infrastructure projects (e.g. wastewater reuse facilities and new reservoirs), behavioral incentives (e.g. education or economic programs to change water demand), environmental restoration (e.g. removal of water-intensive invasive species), and changes to reservoir operations (Konrad *et al* 2012), among other actions (Oklahoma Water Resources Board (OWRB) 2012). Because these portfolios of projects involve a broad range of stakeholders with different priorities and risk tolerance (Jacobs and Buijs 2011, Wineland *et al* 2020b), prescriptive plans may be less useful than conceptual frameworks that allow decision-makers to weigh projected water scarcity and climate uncertainty alongside sociopolitical factors.

A second research gap concerns strategies for meeting both human and environmental water needs while accounting for climate uncertainty. While many papers identify strategies for balancing human and environmental needs (see Horne *et al* 2016 for a review), work in this area has not yet addressed decision-making under future uncertainty. Similarly, while recent papers on planning for societal water needs have included sophisticated consideration of climate uncertainty (see Herman *et al* 2020 for a review), including the use of multi-objective optimization under climate uncertainty (Guiliani *et al* 2016, Quinn *et al* 2018), work in this area has not included strategies for meeting both human and environmental needs. Thus, John *et al* (2020) identify a key research gap at the intersection of these two groups of papers: how to balance human and environmental water needs while remaining resilient to future climate variability.

In this paper, we investigate strategies for allocating different types of water sustainability investments across a drought-prone river basin to meet both human and environmental water needs. Our approach centers on quantifying how future water scarcity and climate-driven uncertainty vary across time and space under different future climate conditions. To quantify scarcity, we use high-resolution climate and hydrological projections for the Red River basin (RRB) (Zamani Sabzi *et al* 2019a) to drive a basin-scale mathematical optimization model for water resources planning (Zamani Sabzi *et al* 2019b). Our optimization model seeks to balance societal and environmental flow targets across the entire RRB by manipulating storage and release decisions across its network of reservoirs. Conceptually, the model identifies the extent to which it might be possible to alleviate water scarcity across the basin simply through alternative water management decisions (e.g. changes to reservoir operations; Konrad *et al* 2012); however, any water scarcity that remains under these optimal water allocations can only be resolved

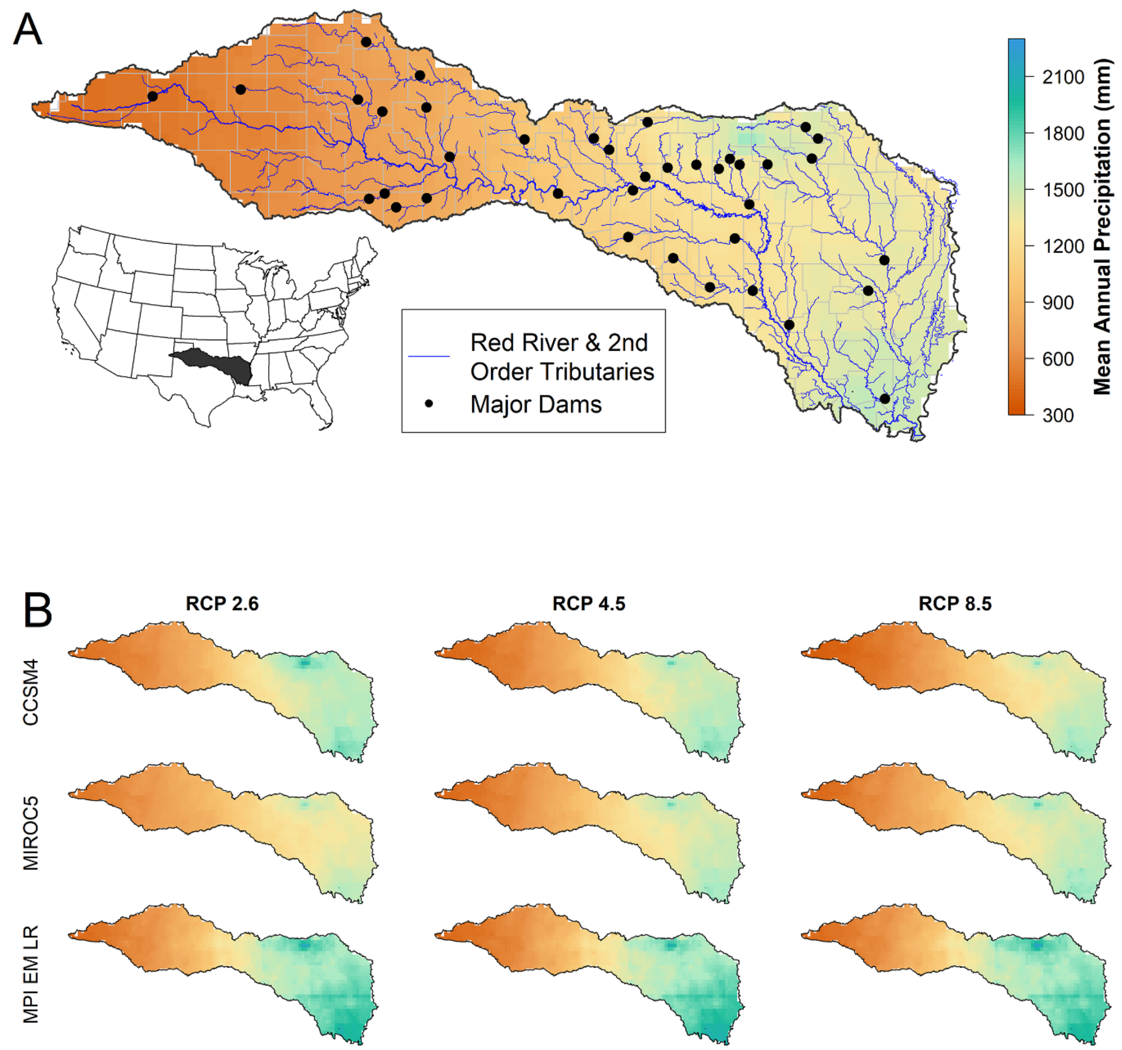

Figure 1. Mean annual precipitation (mm) across the Red River basin (RRB) based on (A) historical observations (1961–2011) (Livneh *et al* 2013) and (B) downscaled climate projections for a near-future period (2031–2050) from all combinations of three global climate models and three future representative concentration pathways (Bertrand and Mcpherson 2019).

through infrastructure, technology, or reduced consumption. To quantify climate-driven uncertainty, we report the agreement (or robustness) across future climate projections of water scarcity at each individual reservoir (i.e. inability to meet local societal and environmental water needs). We then demonstrate how joint consideration of both projected water scarcity and its uncertainty might reveal regions with secure sustainability investment opportunities and alternatively where 'low regret' investments are necessary and the value of reducing climate projection uncertainty is high. Our ultimate aim is not to prescribe specific projects at specific locations, but to illustrate how our conceptual framework might allow decision-makers to have an improved understanding of how water scarcity and climate uncertainty vary across the basin.

2. Methods

2.1. Study region

We focus on the Red River, a major river basin in the south-central USA where water availability follows a strong spatial gradient from west to east. Historical precipitation follows this gradient from the RRB's headwaters in the arid Texas panhandle (less than 600 mm yr^{-1}) to wet Mississippi river lowlands (greater than 1500 mm yr^{-1}) (figure 1(A)). More than 3 million people currently live within the RRB (US Census Bureau n.d.) with a high economic dependence on water. Just outside the basin boundaries, growing metropolitan areas like Oklahoma City, OK and Dallas, TX rely on RRB water and have approved construction projects to expand withdrawals (114th Congress 2016). Water quantity also plays a key role in regulating ecosystem services related to water quantity and quality (e.g. salinity, algal blooms, and pathogens), which strongly impact residents (Green *et al* 2015). Water availability is also critical for endangered species of fish and mussels (e.g. Ouachita rock-pocketbook *Arkansas wheeleri*) (Vaughn and Pyron 1995). Reservoirs have been constructed throughout the basin for flood control mechanisms and water storage. While most reservoirs play a key role in ensuring societal water supplies, a subset dry during drought conditions or are anticipated to dry with future groundwater mining and climate change (Brikowski 2008). These engineering interventions each create a decision point at which humans can choose how much water to store for future uses and how much water to release downstream to maintain instream flows (Guo et al 2019).

2.2. Climate model selection and downscaling

Three GCMs from the Coupled Model Intercomparison Project Phase 5 (Taylor et al 2012) were selected based on their historical performance over the region and climate sensitivity as described in Bertrand and Mcpherson (2019). These GCMs (i.e. Max Planck Institute for Meteorology Earth System Model-Low Resolution (MPI-ESM-LR) (Giorgetta et al 2013), Community Climate System Model, version 4 (CCSM4) (Kluzek 2010), and Model for Interdisciplinary Research on Climate, version 5 (MIROC5) (Watanabe et al 2011)) were found to capture a representative range of temperature and precipitation biases and climate sensitivities across the larger GCM ensemble. Including only three GCMs was necessitated by the computational demand of the subsequent downscaling and hydrologic modeling. Downscaled versions of these GCMs under multiple representative concentration pathways (RCP 2.6, 4.5, 8.5) (van Vuuren et al 2011) illustrate diverging projections for annual precipitation and thus water availability. CCSM4 generally predicts the drier conditions, MIROC5 is more moderate in its precipitation shifts, and MPI-ESM-LR predicts increased precipitation across large parts of the basin (figure 1(B)).

Downscaled future climate projections over the RRB were produced for each GCM/RCP combination for a future period (2011–2099) using the Cumulative Density Function transform (Vrac and Michelangeli 2009) to create a new spatial scale of 1/8 degree for all models (Bertrand and Mcpherson 2019). Transfer functions used to predict future regional parameters were calibrated using daily temperature and precipitation observations sourced from Livneh et al (2013) over the historical period (1961–2005). Daily precipitation values from these projections were used to estimate monthly precipitation contributions to each reservoir in our network model (section 2.3).

2.3. Hydrologic model

Estimates of runoff and streamflow under historical (1961–2011) and future (2011–2099) climate scenarios were derived from a variable infiltration capacity (VIC) model parameterized with land cover and future climate data (Xue et al 2016). Details of the VIC calibration process are given by Xue et al (2016). Briefly, Livneh data were used as observations to benchmark VIC outputs (version 4.1.2.h.), and all data were re-gridded to 1/8°. A digital elevation model (DEM) was derived from the 30 arcsec DEM (HydroSHEDS) and flow direction fields were obtained from the river-routing network data set produced by Wu et al (2011). Calibration was via multisite cascading calibration over an abbreviated time period (1983–1990). Model validation used Livneh data (1991–2011), and assessment scores included the Nash-Sutcliffe model efficiency coefficient (calibration: 0.62, validation: 0.59), correlation coefficient (c: 0.8, v: 0.79) and percent bias (c: 7%, v: 11%).

The parameterized VIC model computed unit-area based runoff across the RRB under all climate projections described above for historical and predictive time periods. These model results informed reservoir inflow and evaporation estimates for the optimization model described in the next section. Inflow was derived from naturalized streamflow estimates of the reservoir's basin. Daily evaporation rates were converted to monthly evaporation volumes per reservoir by summing across days and multiplying by the typical surface area of the reservoir. For more details on the hydrologic modeling process, see Xue et al (2016) and Zamani Sabzi et al (2019a).

2.4. Network model and optimization

We used a mathematical model to optimize water allocation in a network of reservoirs to meet both societal and ecosystem water needs. Using a water balance approach, we model the inflows and outflows of each reservoir in the RRB network at monthly timesteps, and a total time horizon $T = \{t = 1, 2, \ldots, |T|\}$. In the RRB, a monthly timestep is the shortest frequency at which instream flow and reservoir release decisions might realistically be made; indeed, the current version of the Oklahoma Comprehensive Water Plan advocates seasonal, not monthly, flow targets (Oklahoma Water Resources Board 2012). Reservoir (d) receives a given inflow (I_t^d) from ground and surface water sources as well as a total estimated precipitation amount (Pr_t^d). These sources are combined with water stored in the reservoir from the previous time step (S_{t-1}^d) before the model subtracts losses: evapotranspiration (E_t^d), releases for agriculture and municipal use (A_t^d), and water released downstream (F_t^d). The downstream releases from reservoirs directly upstream are also added into the inflow for each reservoir $\left(\sum_{d \in D^{(d)}} F_t^d\right)$. Equation (1) gives the full water balance equation.

$$S_{t-1}^d + \left(\sum_{d \in D^{(d)}} F_t^d\right) + I_t^d + \mathrm{Pr}_t^d - E_t^d - A_t^d - F_t^d = S_t^d \quad (\forall t \in T \text{ and } \forall d \in D) \tag{1}$$

At each time step, the key management decision is to determine the total quantity of water to withdraw from each reservoir for societal uses (A_t) and the quantity to release downstream to support ecology and ecosystem services (F_t). Water withdrawn from the reservoir or released downstream should be as close as possible to target values for societal water needs, TA_t, and environmental water needs, TF_t, respectively. When water supply is limited, simultaneously satisfying both targets will be infeasible. In these circumstances, we quantify water deficiencies as DA_t and DF_t with the following constraints:

$$A_t^d + DA_t^d \geq TA_t^d \qquad (\forall t \in T \text{ and } \forall d \in D) \tag{2}$$

$$F_t^d + DF_t^d \geq TF_t^d \qquad (\forall t \in T \text{ and } \forall d \in D) \tag{3}$$

The 'satisfaction' for meeting consumptive use and instream flow targets for reservoir d ($\forall d \in D$) at time step t ($\forall t \in T$) is defined as $Z_t^{A,d} = \left(1 - \frac{DA_t^d}{TA_t^d}\right)$ and $Z_t^{F,d} = \left(1 - \frac{DF_t^d}{TF_t^d}\right)$ respectively. By averaging these satisfaction levels across all time steps and all reservoirs we can define the two objective functions:

$$\text{Max } Z^A = \frac{\sum_{\forall d \in D}\left(\sum_{\forall t \in T}\left(1 - \frac{DA_t^d}{TA_t^d}\right)\right)}{|T|\,.\,|D|} \tag{4}$$

$$\text{Max } Z^F = \frac{\sum_{\forall d \in D}\left(\sum_{\forall t \in T}\left(1 - \frac{DF_t^d}{TF_t^d}\right)\right)}{|T|\,.\,|D|} \tag{5}$$

Subject to:

$$S_{t-1}^d + \left(\sum_{d \in D^{(d)}} F_t^d\right) + I_t^d + \Pr_t^d - E_t^d - A_t^d - F_t^d = S_t^d \tag{6}$$

$$S_t^d \leq C_d^F \tag{7}$$

$$A_t^d + DA_t^d \geq TA_t^d \tag{8}$$

$$F_t^d + DF_t^d \geq TF_t^d \tag{9}$$

$$A_t^d, F_t^d, DA_t^d, DF_t^d, \text{ and } S_t^d \geq 0. \tag{10}$$

$$(\forall t \in 1, 2, \ldots, |T| \text{ and } \forall d \in 1, 2, \ldots, |D|)$$

Constraint (6) reinforces the water balance equation (equation (1)) at each time step. Constraint (7) ensures that the water quantity per reservoir does not exceed capacity (C_d^F). Constraints (8)–(10) estimate water deficiencies and keep all values of water quantities positive.

To parameterize this model, we calculated the set of upstream reservoirs ($D^{(d)}$) and identified a maximum capacity (C_d^F) for each reservoir node in the network from the National Hydrography Data set (U.S. Geological Survey 2017). Parameter estimates representing climatic conditions (I_t^d, $\Pr_t^d$, and E_t^d) are drawn from downscaled climate projections and VIC modeling described in previous sections (Xue et al 2016, Bertrand and Mcpherson 2019). Water withdrawal target values $\left(TA_t^d\right)$ are derived from water rights data using data from Texas Commission on Environmental Quality, the OWRB, and the US Geological Survey (for Arkansas and Louisiana) and are summarized in the Bertrand and Mcpherson (2019) RiverWare model for the basin. Initialization conditions for the reservoirs were also drawn from this RiverWare model. Target volumes for downstream releases $\left(TF_t^d\right)$ were calculated as 60% of the average annual flow in each reach based on instream flow recommendations from Tennant (1976). Alternate target-setting methods could be implemented within the same modeling framework. The optimization ran over 240 timesteps (20 years) with all years' subject to the same parameterized conditions. In this way, we could assess any burn-in period due to initial conditions or incongruous behavior at the terminal end of the time period, sometimes observed in dynamic optimizations. The first and last 12 timesteps were disregarded from analysis for this reason. Our optimization model is a linear programming model coded and solved using LINGO software. More details on the optimization method and model can be found in Zamani Sabzi et al (2019b).

2.5. Analysis

We performed several analyses using optimal water allocation solutions from the RRB network model to explore tradeoffs in water management objectives as well as spatiotemporal water scarcity trends under climate change.

First, we delineated tradeoff curves using Pareto-optimal solutions that balance consumptive societal withdrawals and downstream environmental flows targets. Figure 2 displays the average satisfaction of societal water targets (Z^A) across all time steps and all reservoirs (horizontal axis) against the average satisfaction of environmental water targets (Z^F) across all time steps and reservoirs (vertical axis). Each climate projection curve (i.e. the set of points that belongs to a particular combination of climate projection and future time period) was created by systematically varying the relative importance (i.e. weight) of meeting societal vs. environmental water targets. To create figure 2, the relative weights of the two objectives Z^A and Z^F were varied inversely from 0 to 1. Eighteen curves are illustrated, representing all combinations of nine climate scenarios and two time periods: near present (2010–2030) and future (2031–2050).

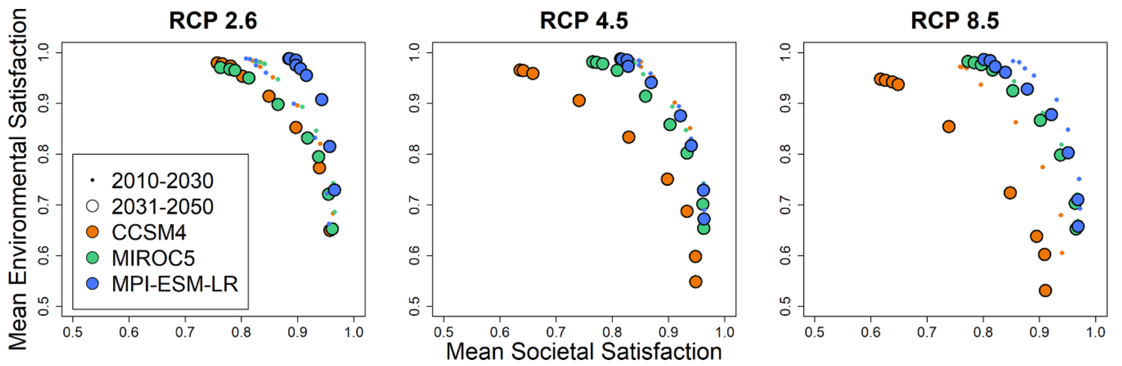

Figure 2. Optimal trade-off curves balancing RRB-wide satisfaction of societal and environmental water targets. Trade-off curves are calculated for the nine climate projections resulting from all combinations of three RCPs (panels) and three GCMs (colors within panels) for two time periods—early century (2010–2030; small circles) and near future (2031–2050; large circles).

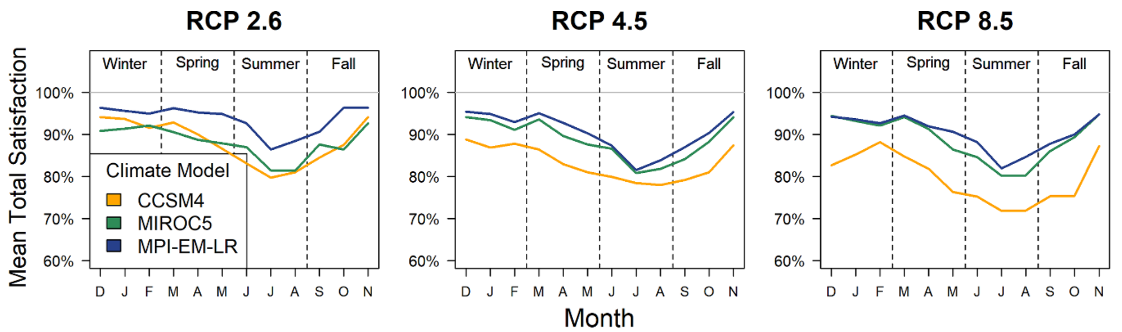

Figure 3. Seasonal and monthly RRB-wide total satisfaction of combined societal and environmental water targets, calculated as the mean satisfaction across all reservoirs in the network. Satisfaction levels are optimized for the nine climate projections resulting from all combinations of three RCPs (panels) and three GCMs (colors within panels) for the near future time period (2031–2050).

For the remaining analyses (figures 3 and 4), we assigned equal weight to meeting societal and environmental water goals (0.5 weight for Z^A and Z^F). We then calculated total satisfaction for a particular reservoir in a particular month as the average of the societal satisfaction ($0 < Z^A < 1$) and environmental satisfaction ($0 < Z^F < 1$). To compare basin-wide total satisfaction across months, we calculated mean total satisfaction in each month (i.e. the vertical axis in figure 3) by averaging total satisfaction across all reservoirs in the network. To further aggregate to seasonal satisfaction, we averaged satisfaction values within a three-month period following standard meteorological definitions of seasons (*Winter* = December, January, February; *Spring* = March, April, May; *Summer* = June, July, August; *Fall* = September, October, November). To spatially compare average annual satisfaction across all reservoirs, the total satisfaction solution to each reservoir was averaged across all monthly solutions (figure 4).

3. Results

Our basin-scale optimization model reveals that conflicts between societal and ecosystem water needs will likely increase in the future, and the severity of the tradeoff in each climate scenario reflects net water availability (figure 2). Pareto optimal near-future trade off curves for the driest GCM (CCSM4) lie parallel or interior to those of the intermediate (MIROC5) and wettest (MPI-ESM-LR) GCMs, illustrating how net water availability in each climate projection influences the potential for water scarcity given competing uses. These differences tend to be amplified with increasing RCP.

Across all GCMs and RCP, we find that the seasonality of water scarcity in the RRB remains constant under optimal water allocation (figure 3). *Summer* consistently exhibits the lowest average satisfaction (i.e. highest water scarcity), ranging from 73% in CCSM4/RCP 8.5 (the driest climate projection) to 89% in MPI-ESM-LR/RCP 2.6 (a wetter climate projection). *Fall* is the next scarcest season (satisfaction: 79%–94%), followed by *Spring* (81%–95%) and *Winter* (85%–96%). Given that the rank order of scarcity among seasons remains the same across all climate projections, critical periods for short-term water conservation actions (e.g. seasonal payments or incentives to reduce water usage) are likely to exhibit consistent seasonal timing.

We also find that spatial patterns of water scarcity and climate-driven uncertainty vary independently

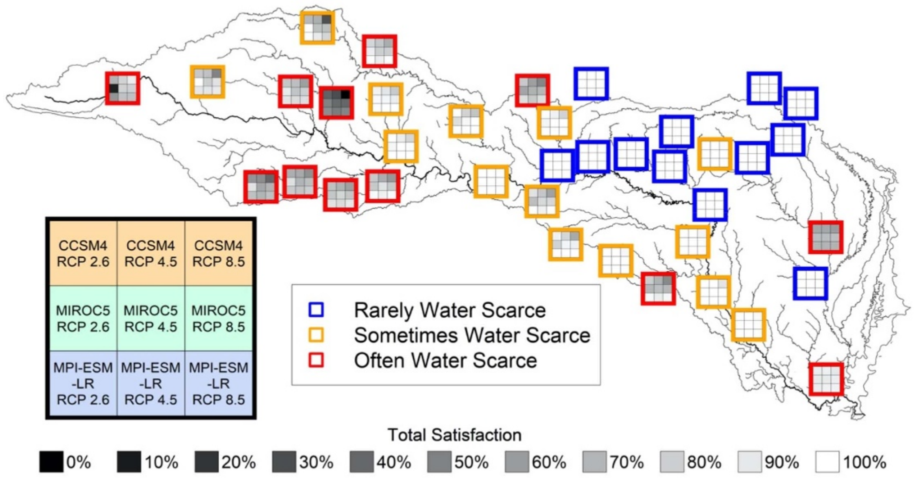

Figure 4. Spatial patterns of water scarcity across the RRB under nine climate projections in the near future period, 2031–2050. The 3×3 grid at each reservoir location displays local water scarcity at that location across nine climate projections; each grid cell gives the total satisfaction of combined societal and environmental water use targets (see grayscale legend) for a particular climate projection (see 3×3 grid legend). Many western reservoirs experience some water scarcity in all nine projections (red locations), while many eastern reservoirs do not experience scarcity in any of the nine projections (blue). Locations outlined in yellow experience water scarcity under some, but not all, climate projections.

across the basin (i.e. agreement among projections is not related to the central tendency of scarcity from reservoir to reservoir) (figure 4). Many eastern reservoirs never show water scarcity in any climate projection, rendering them 'rarely water scarce'. Conversely, many western reservoirs are often water scarce and experience water deficiencies under all GCM/RCP combinations. Yet for roughly 1/3 of the reservoirs in the RRB, water scarcity occurs under some climate projections but not in others ('sometimes water scarce' in figure 4), indicating that capacity to meet future water needs in these areas is uncertain.

4. Discussion

Given uncertainty in climate projections worldwide, our analysis illustrates how joint consideration of climate uncertainty and impacts, such as hydrologic responses, may be used to evaluate climate adaptation strategies at a regional scale. Our work builds on (a) efforts to identify strategies for balancing human and environmental water needs, which have yet to account for future climate uncertainty (Horne *et al* 2016) and (b) efforts to plan for societal water needs, which account for climate uncertainty but not environmental water needs (Herman *et al* 2020). Our work is at the intersection of these two research lines and informs sustainability strategies for meeting human and environmental water needs under climate uncertainty.

4.1. Recommendations for water sustainability under climate uncertainty

Water resource managers in the RRB invest in a wide range of projects to enhance water sustainability, including voluntary incentives to water users to reduce consumption; retrofitting of existing infrastructure; wastewater reuse and recycling; invasive species removal (e.g. salt cedar); artificial recharge of aquifers; and the potential construction of new reservoirs (Oklahoma Water Resources Board 2012). Our identification of three classes of reservoirs (sometimes, often, and rarely water scarce) illustrates how joint consideration of spatiotemporal patterns of both water scarcity and future climate uncertainty might guide decision-makers' efforts to distribute investments among these various project types and across the RRB (figure 5). For reservoirs and regions classified as 'often water scarce' water resource planners can be confident that investments in water sustainability will boost water availability under all projections. Therefore, planners in this region may make 'secure investments' in high cost, high reward infrastructure projects (e.g. reservoirs, pipelines or desalination structures (Mashburn and Sughru 2003)) because there is relatively low risk that they will become stranded assets. Nevertheless, infrastructure projects at some 'often water scarce' locations may not be cost-effective; further return-on-investment analysis may be needed to site infrastructure projects among these locations (Rodriguez *et al* 2012, Neeson *et al* 2015) or prioritize locations for economic incentives to reduce demand (Qureshi *et al* 2010).

Similarly, persistent water availability in regions deemed 'rarely water scarce' allows for a 'secure resource' strategy (figure 5). Assuming that societal water needs do not increase dramatically, and that water is efficiently allocated across the RRB, there should be enough surface water in these regions to satisfy future societal and ecological needs.

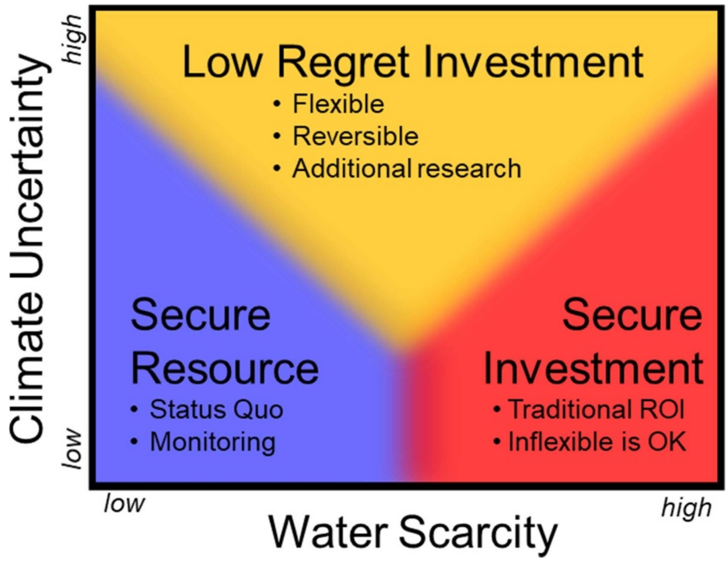

Figure 5. Effective strategies for allocating investments in water sustainability depend on joint consideration of future water scarcity (horizontal axis) and climate projection uncertainty (vertical axis) that helps to determine water availability. In locations where projected water scarcity is high and climate uncertainty is low, a 'secure investment' strategy of selecting projects based on return-on-investment may be appropriate because there is low uncertainty in future returns (i.e. expected gains in water sustainability from a project). In locations with high uncertainty (yellow), the most appropriate investment strategies entail low-regret investments that minimize the potential for stranded assets; value of information from additional research in these locations is also high. In low scarcity areas, water resource availability is 'secure' and priorities include monitoring and evaluation of proposals for expanded societal use.

Therefore, 'status quo' management may be appropriate, including careful monitoring of current consumption and evaluation of proposals for expanded societal use.

Regions classified as 'sometimes water scarce' require careful planning: under-investment in water sustainability may have dire consequences if future water availability declines, but investments have the potential to become stranded assets in a wetter future. Thus, decision-makers may prefer 'low regret' (flexible, low-cost or temporally targeted) investments (figure 5). Here, flexibility is a priority. For example, short-term grants or renewable incentives for water-use reduction would allow investments to shift among regions as climate patterns change. Indeed, economic incentives have been shown to be effective tools for reducing water demand (Qureshi *et al* 2010, Nikouei *et al* 2012) and the costs of reallocating them are minimal compared to those of infrastructure projects. Similarly, lease programs for high-efficiency irrigation infrastructure would enable equipment to be moved to locations with greatest benefit (Robertson *et al* 1982). For smaller dams, flexible designs would enable dam height to be raised to increase storage without incurring the up-front costs of a single large reservoir (Fletcher *et al* 2019). In the residential sector, investments in water sustainability programs (e.g. incentivizing efficient appliances and low-flow toilets) (Oklahoma Water for 2060 Advisory Council 2015) involve relatively little financial outlay, but the aggregate water savings could be substantial if widely adopted.

Our approach employs top-down modeling (i.e. the use of downscaled hydrologic projections to map uncertainty) to enable bottom-up, location-specific decision-making (Dessai and van der Sluijs 2007) to address IPCC recommendations to consider climate uncertainty in planning efforts (IPCC 2014). For example, the application of our conceptual framework (figure 5) to the RRB (figure 4) provides a basis for a diverse set of stakeholders to evaluate a range of water resource projects with different levels of risk. With large investments in water sustainability expected over the coming decades (Hartman and Kober 2020), our framework may be most useful for choosing among candidate projects at a regional level. For example, the OWRB and the Texas Water Development Board have both identified the reuse of wastewater as an important strategy for boosting water availability (Oklahoma Water Resources Board 2012). Given that wastewater reuse infrastructure is both expensive and inflexible, our climate uncertainty map could be used to identify locations where water reuse infrastructure has low potential of becoming a stranded asset over the coming decades. While this study used relatively few GCMs, this climate uncertainty map approach could be implemented with additional GCMs and downscaling techniques (if feasible for interested stakeholders) to capture a broader range of the climate uncertainties. For locations with greater climate uncertainty, more flexible investments, such as education or economic incentives to change water users' behavior, may be more appropriate.

4.2. Priorities for future modeling and analysis

Our analysis highlights locations where the value of information from additional data and modeling may be high. Notably, regions with the highest uncertainty in future water scarcity may highlight research investment opportunities where there is value for reducing uncertainty in climate projections. For example, the northernmost reservoir, Foss, has <20% water satisfaction under the CCSM4, RCP 8.5 projection; in this possible future, serious water conflicts will occur unless investments in water sustainability are made. Yet Foss exhibits 100% water satisfaction under two other climate projections, in which case investments would become stranded assets. Thus, information from additional climate and water modeling would be highly valuable if it enables decision-makers to better compare risks and consequences of water shortages (under dry projections and little investment) vs. stranded assets (under wet projections and large investment). Specifically, there is a need for improved understanding of groundwater-surface water interactions across the basin. Many Great Plains rivers have diminished hydrological connectivity with aquifers due to groundwater pumping (Perkin *et al* 2017), but groundwater-surface water interactions are poorly understood in key sub-basins (Oklahoma Water Resources Board 2012).

We identified strategies for allocating sustainability investments among different types of projects and across space by coupling climate projections with a basin-scale water planning model. We focused on the nine projections most representative of future climate over the RRB; nevertheless, estimates of future uncertainty in water scarcity may shift with consideration of additional climate projections. Further, we examined outcomes for the near future (up to 30 years), but consideration of longer time horizons may be important for certain management strategies or infrastructure types. Our analysis also allowed the planning model to have perfect foresight over future climate conditions; repeating our analysis with non-perfect foresight would increase future uncertainty but our conceptual framework (figure 5) would still apply.

We also assumed that societal water demand remained constant in all future projections; future work could integrate uncertain water demand projections (Oklahoma Water Resources Board 2012) into our conceptual framework (figure 5) by replacing the vertical axis with a more comprehensive estimate of water uncertainty stemming from all sources. We also assumed that environmental flow targets were equally important in all reaches; future analyses could place greater weight on meeting flow targets in reaches where species are projected to be highly impacted by climate change (Gill *et al* 2020) or where ecosystem services are highly valued (Castro *et al* 2016, Burch *et al* 2020). Alternatively, by considering our results in combination with studies about human actors in the basin, such as the stakeholder perceptions of water management decisions (Kharel *et al* 2018) and the influence of irrigation on low flow events (Krueger *et al* 2017) future research could focus on further refinement of feasible water management strategies and model feedback loops of such strategies on water availability.

5. Conclusion

We used a basin-wide model to show that in many instances, priority times and locations for water sustainability investments remain constant across climate projections. Identification of these low-uncertainty locations may allow planners to make secure investments in water sustainability that would normally be inhibited by low risk tolerance. Alternatively, adaptation strategies in high-uncertainty locations may include low regret projects or investments in research. Overall, our analysis illustrates how improved understanding of spatiotemporal patterns of climate uncertainty may reveal best strategies for ensuring the long-term sustainability of integrated human-freshwater systems.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Author contribution statement

R F and T M N designed research. D H R, A M W, H Z S, and H A M developed data sets. H Z S, S R, R F, and T M N developed the optimization model, and S R ran optimization analyses. R F and T M N led data analysis and interpretation with input from all co-authors. R F and T M N drafted the paper, and all co-authors contributed to revisions.

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