Science of the Total Environment 871 (2023) 161964

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Assessment of vulnerability to water shortage in semi-arid river basins: The value of demand reduction and storage capacity

Ahmed A. Gharib [a,c,*], Joey Blumberg [b], Dale T. Manning [b], Christopher Goemans [b], Mazdak Arabi [a]

[a] Civil and Environmental Engineering Department, Colorado State University, Fort Collins, CO, United States
[b] Agricultural and Resource Economics Department, Colorado State University, Fort Collins, CO, United States
[c] Drainage Research Institute, National Water Research Center, Delta Barrage (El-Kanater), Cairo, Egypt

HIGHLIGHTS

- Vulnerability to shortage varies across regions and sectors within a river basin.
- Water shortage would increase significantly in the future without adaptation.
- Reservoirs can mitigate the consequences of earlier water supplies and later demands.
- Water demand management strategies are effective in mitigating the vulnerability.
- Additional storage capacity is only beneficial under certain conditions.

ARTICLE INFO

Editor: Ashantha Goonetilleke

Keywords:
Climate change
Storage capacity
Reservoirs
Water shortage
Weap model
Water resources management

ABSTRACT

Interest in securing reliable water supplies has increased due to climate change and rapid population growth. This challenge is significant in growing areas with limited water supplies. To meet water demands, water managers are considering new storage infrastructure to increase the reliability of water supplies while also identifying opportunities to reduce water use per person. Although these strategies change water consumption patterns, their success at reducing shortages across space and time for different climate change scenarios remains unclear. In this paper, population- and climate-dependent future water supply and demand models are developed and integrated into a water allocation model calibrated for the South Platte River Basin of Colorado. Eight future climate scenarios are simulated using four statistically downscaled models from the Coupled Model Inter-Comparison Project Phase 5 (CMIP5) with two Representative Concentration Pathways (RCP). Lastly, findings from the water allocation model simulations are generalized beyond the study area using a novel approach by introducing dimensionless indices to characterize water shortage and basin conditions. Results reveal a threshold ratio of total storage capacity to mean water supply with a value of 0.64 above which additional storage has no effect on total water shortages. This threshold communicates the limitation of building storage infrastructure as a strategy to adapt to decreasing average water supplies for basins considering increasing storage capacity. However, basins with low current capacity are likely to fall below the threshold and could invest in reservoirs to mitigate future shortages.

1. Introduction

Over half of the global population face water shortages for at least one month every year (Mekonnen and Hoekstra, 2016; Muratoglu et al., 2022). Climate change and population growth continue to place pressure on scarce water resources (Cook et al., 2014; Dai, 2013; Flörke et al., 2018; Martinsen et al., 2019; Richter et al., 2013), increasing the complexity of water resources management (Momblanch et al., 2019). In the United States, water supplies are expected to face more extreme hydrologic events (Brown et al., 2019; Foti et al., 2014a; Leng et al., 2016; Naz et al., 2016) which can lead to more severe and protracted droughts (Wehner et al., 2017). Adaptation to increasing water scarcity can be achieved through a variety of demand- or supply-side strategies.

Demand-side strategies involve reducing total water use, which may include employing water-efficient appliances and irrigation systems, applying deficit irrigation, reducing irrigated landscapes, and improving industrial water-use efficiency (Chinnasamy et al., 2021; Dieter et al., 2017; Hering et al., 2013; Ma et al., 2015; Nouri et al., 2019; Paterson et al., 2015; Sharvelle et al., 2017). Despite demand reduction efforts, Brown et al. (2019) project that continued population growth coupled with changing water supplies will cause water shortages to increase across the US.

* Corresponding author at: Civil and Environmental Engineering Department, Colorado State University, Fort Collins, CO, United States.
E-mail address: ahmed.gharib@colostate.edu (A.A. Gharib).

http://dx.doi.org/10.1016/j.scitotenv.2023.161964
Received 14 September 2022; Received in revised form 28 January 2023; Accepted 29 January 2023
Available online 1 February 2023

Regarding supply management, Brown et al. (2019) find that additional storage infrastructure has limited impacts on reducing water scarcity. However, increasing water availability through storage infrastructure investment continues to receive attention (Foti et al., 2012; Kim et al., 2019), in part because of the significant interest in maintaining agricultural production (Qin et al., 2020; Rosegrant and Ringler, 2000; P. Thornton et al., 2018). For example, the recently passed "Infrastructure Investment and Jobs Act" (HR 3684) in the US contains more than $1 billion for the construction of water storage and conveyance projects (Gleick et al., 2021). To ensure the efficacy of projects financed with scarce public funds, it is important to identify the conditions in which additional water storage can decrease the prevalence of water shortages.

Some recent studies have modeled climate effects on water supplies and demands across the US without explicitly testing adaptation strategies (Blanc et al., 2014; Foti et al., 2012, 2014b, 2014a; Roy et al., 2012; Strzepek et al., 2010). Brown et al. (2019) simulate the effectiveness of four alternative adaptation strategies in reducing expected water shortages across the US at the HUC-4 level, however return flows were not considered. Among adaptation strategies for water supply management, reservoirs are often found to bolster climate change resiliency by increasing water availability (Hallegatte, 2009; Iglesias and Garrote, 2015) and, in turn, economic activity (Biemans et al., 2011). Water availability is the location- and time-specific water available to be diverted from a stream. In that context, reservoirs increase the water availability, not the water supply. Contrasting these findings, Brown et al. (2019) conclude that additional reservoirs have minimal effect on decreasing future water shortages. However, reservoirs may be more effective at reducing shortages at finer spatial and temporal resolutions (Brown et al., 2019). In general, reservoirs have no effect if water is the limiting factor (Brown et al., 2019; Foti et al., 2012; Kim et al., 2019).

In this paper, a model of water supply and demand in the South Platte River Basin (SPRB) of Colorado is developed to examine if additional storage infrastructure reduces the vulnerability to water shortage -the probability of water demands exceeding water supplies- through the end of the 21st century. The model contains detailed information on water supplies, demands, and allocation rules at a half-monthly timestep. The Variable Infiltration Capacity (VIC) model is used to measure and project water supply, the Integrated Urban Water Model (IUWM) model to simulate urban water demand, and the DayCent model to estimate agricultural water requirements, all of which depend on downscaled models of climate change projections. Water supplies are aggregated at the HUC-8 level, and 75 users represent both agricultural and urban water demands at different points along the stream system. A water allocation model is built and calibrated using the Water Evaluation and Planning (WEAP) system (Yates et al., 2005) for the historical period 1985–2014, and an uncertainty analysis is conducted to estimate the results' errors. Required water diversions, consumptive use, and water shortages are then simulated for four future climate models with two Representative Concentration Pathways (RCP) through the end of the 21st century, and the effects of storage capacity and demand reduction on water shortage are examined through 150 model-scenario combinations. Two dimensionless indices are identified that characterize the system: the ratios of storage capacity and average water demand to average water supply. The indices reflect the conditions the drive the most effective policy decisions for a given basin. The indices convey whether policymakers should prioritize demand reduction strategies or additional storage based on the current state of their basin.

The present paper contributes to the relevant literature in several aspects. First, the model captures the climate's role in influencing water supply and demand at a fine spatial (HUC-8) and temporal (half-monthly) scale. The finer scale allows for the examination of shortages from both prolonged drought and short periods of high demand and low supply. Second, information is also disaggregated to the sector-level[1] to examine how water scarcity impacts agricultural and municipal users located at different points along the South Platte River. Third, return flows are explicitly incorporated into the model. This innovation is particularly important in the SPRB because total water diversions are 200 % of the average water supply (CWCB, 2015), implying that return flows are critical for meeting current and future water demands. Lastly, the presented generalized basins classification from their supply, storage, and demand conditions is an innovation in this study through the identified threshold.

[1] The sectors include municipal and agricultural water users, which have high and low priority levels in our water allocation model. Therefore, impacts are also examined by water right priority.

2. Methods

2.1. Study area and model overview

Colorado provides a relevant case study for many western US states due to its quickly increasing population and climate-change-driven changes to water supplies and demands. Colorado was one of the fastest-growing states during the last decade, with a 14.8 % increase totaling 5.7 million people (United States Census Bureau, 2020). This population growth is estimated to continue in the future with an estimated total population of 10 million by 2050 (CWCB, 2019b). Climate models predict changes in annual streamflow by 2050 of between −5 % and 8 % (Lukas et al., 2014) and temperatures have increased since the beginning of the 20th century (Lukas et al., 2014; NOAA, 2021). Since 1980, the statewide average temperature has increased by 1.1 °C (Lukas et al., 2014), a trend that is expected to accelerate with increases of 1.4 to 3.6 °C by 2050.

The SPRB, within Colorado, is a snow-dependent basin located in a semi-arid region with highly variable hydrology and The SPRB is one of the fastest-growing areas in the US, with dense agriculture and urban communities. The long-term mean annual water supply from native and transferred sources is 2.34 billion cubic meters (BCM) (CWCB, 2015). Surface water diversions totaled 4.93 BCM/y, with 2.59 BCM/y coming from return flows. The State Water Plan (CWCB, 2015) expects the gap between water demand and supply to range from 0.44 to 0.58 BCM/y by 2050 (CWCB, 2015), and it is estimated that the SPRB will face an 8.5 % decrease in stream discharge for every 1 °C increase in temperature in the worst-case climate scenario (Aliyari et al., 2021). Overall, examining strategies that decrease water shortages can produce significant benefits for the study area in this research as well as provide general insights into vulnerable basins throughout the western US.

Irrigated agricultural land is primarily located downstream of urban areas, and return flows from cities are often used to meet agricultural water demands (Fig. 1a). Following Dozier et al. (2017), the SPRB in our simulation, is divided into five regions: North, North Central, Central, South Metro, and East, which creates a spatially heterogeneous distribution of water demands (Fig. 1a). Each region represents one or more counties and has 15 stylized users. Twelve agricultural (Ag) users represent six staple crops using flood or sprinkler irrigation systems, and three urban users represent demands for (1) residential indoor, (2) commercial, industrial, and institutional indoor (CII), and (3) total (residential plus CII) outdoor water use. Fourteen nodes represent the model's water supply at the subbasins' (HUC 8 level) headwaters (Fig. 1a). Additionally, six main hydraulic structures are connected to the subbasins, representing the water transferred to the SPRB from other watersheds. In each subbasin, existing reservoirs are aggregated into one representative reservoir.

The modeling framework contains three main components (Fig. 2). First, land use and population data are summarized at the annual level, and climate data are summarized at the daily level. These data are then used as inputs for the second component of the framework, the water supply and demand models, which provide output at the half-monthly timestep for the model regions and subbasins described above. Lastly, water is allocated to users at each timestep using the WEAP model (Yates et al., 2005), hereinafter referred to as WEAP-SP. WEAP uses linear programming to solve the optimization function of maximizing water demand satisfaction subject to mass balances, allocation priority, water availability, and other constraints. The model runs at each timestep sequentially without foresight.

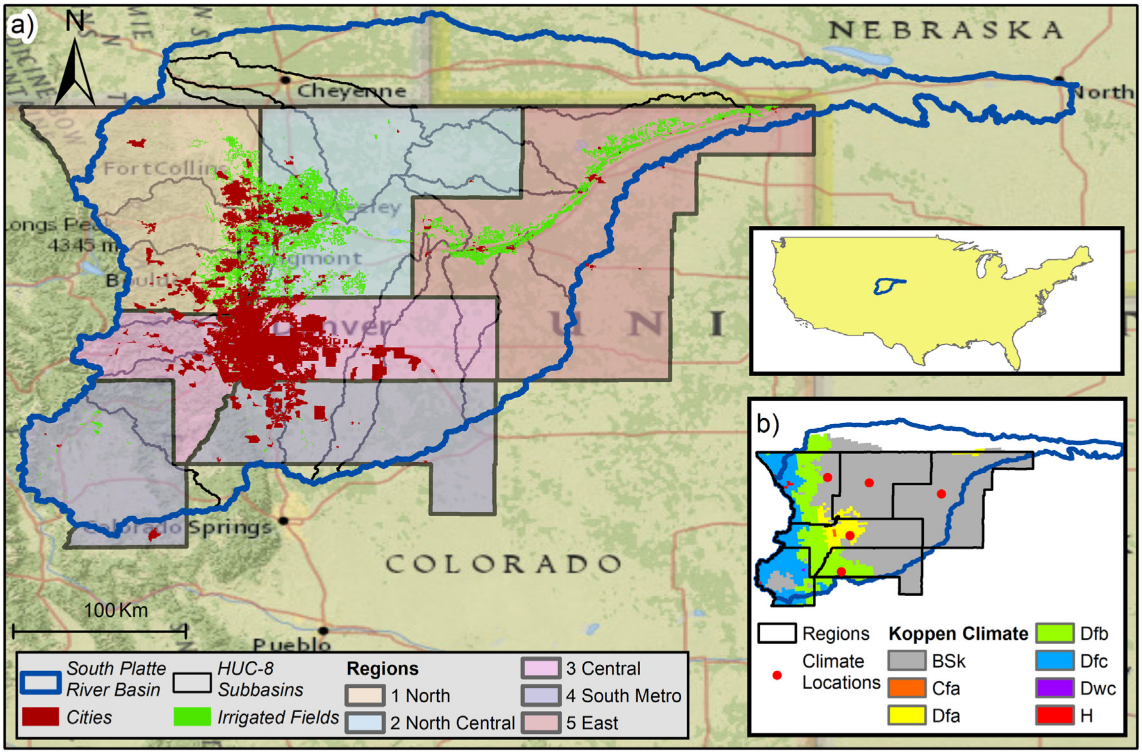

Fig. 1. a) South Platte River Basin (SPRB) extent, cities and irrigated fields in SPRB, the five modeled regions, and the HUC-8 subbasins. b) The study boundary with Koppen climate classification and the selected climate location in each region.

In total, WEAP-SP has 20 supply nodes, 60 Ag demand nodes, 15 urban demand nodes, ten reservoir nodes, one outflow requirement node, natural river links, diversion links from rivers to demand nodes, and return flow links from demands nodes to streams (Fig. S1). WEAP-SP runs from 1981 to 2099, with the first four years to initiate the model, followed by 30 years for calibration from 1985 to 2014, defined as the historical period. Future water allocations from 2015 to 2099 are then simulated using eight climate scenarios. Two 30-year periods—the near-future period from 2025 to 2054 and the far-future period from 2070 to 2099—are compared with the historical results. Lastly, the relative effectiveness of several adaptation strategies, described in Section 4, at reducing expected shortage is examined. The following sections provide additional detail on each of the model components and the uncertainty analysis for results.

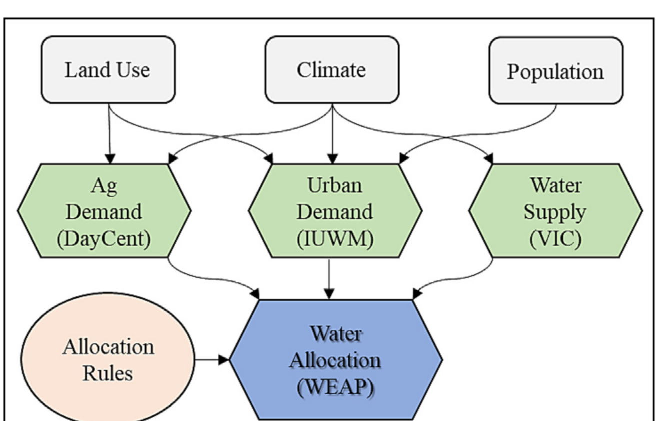

Fig. 2. The integrated modeling framework.

2.2. Climate data

Climate data is essential for this study and used in all three of the water supply and demand models (Fig. 2). According to Koppen Climate Classification (Chen and Chen, 2013), the SPRB is primarily a cold semi-arid climate (BSK), humid continental climate (Dfa & Dfb), or Subarctic climate (Dfc) (Fig. 1b), depending on seasonal temperature, precipitation patterns, and vegetation types (Chen and Chen, 2013). To capture the heterogeneity in climate classifications, one location near the centroid of each region is selected to represent the climate in the water demand models' simulations (Fig. 1b).

Historical climate data from 1980 to 2015 is obtained from Naz et al. (2016), which is calculated using a combination of three datasets: the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Daly et al., 2008), Daymet dataset (P. E. Thornton et al., 1997), and the North American Regional Reanalysis (NARR) dataset (Mesinger et al., 2006). Daily precipitation and minimum and maximum temperature estimates from Daymet are biased corrected at a monthly time scale using PRISM, and wind speed is obtained from NARR.

Several global climate models (GCM) predict the future climate at different scales. However, GCM estimates are inappropriate for high-resolution studies as they generally have a coarse grid resolution (roughly 150 to 200 km grids) (Heidari et al., 2020; Naz et al., 2016). Hence, climate projected data from Abatzoglou and Brown (2012), that use Multivariate Adaptive Constructed Analogs (MACA) to downscale GCMs from coarse to high spatial resolution were used in this study. The MACA daily dataset has 20 climate models downscaled for the entire conterminous United States (CONUS) from 1950 to 2099 at approximately a 4 km grid under 4.5 and 8.5 Representative Concentration Pathways (RCP) scenarios from the Coupled Model Inter-Comparison Project Phase 5 (CMIP5). Joyce and Coulson (2020) selected five of the available climate models to represent five ranges of predicted future climate in CONUS: hottest (HadGEM2-ES365), driest (IPSL-CM5A-MR), wettest (CNRM-CM5), warmest (MRI-

CGCM3), and a model representing the middle predictions. For this study, the four extreme models -HOT, DRY, WET, and WARM- under RCPs 4.5 and 8.5 are used for future projections, resulting in a total of eight climate scenarios from 2015 to 2099 (Refer to supplementary materials section 3 for more details).

2.3. Water supply

In the SPRB, total water supply is the water yield produced within the basin plus the water transferred from adjacent basins via hydraulic structures. The within-basin water yield, comprised of surface runoff and baseflow, was simulated by Heidari et al. (2020) using the Variable Infiltration Capacity (VIC) model (Liang et al., 1994). VIC is a semi-distributed macroscale scale model used to solve full water and energy balances and simulate land-atmosphere fluxes and flow routing (Heidari et al., 2020; Warziniack et al., 2022). Building on work by Oubeidillah et al. (2014) and Naz et al. (2016) to set, calibrate, and evaluate the VIC model at a grid size of 4 km for CONUS, Heidari et al. (2020) ran the model using the five selected climate models by Joyce and Coulson (2020) and summarized the results at the subbasin level, as described in the previous section.

Although several studies have been published using Heidari et al. (2020) results (Heidari et al., 2021a; Heidari et al., 2021b; Warziniack et al., 2022), none of them checked the bias between the water yield simulations using historical and modeled climate data. To address this, Kolmogorov-Smirnov (KS) test was performed to compare the statistical performance of the water yield in SPRB generated from the eight climate scenarios and the historical climate during 1985 to 2014. In seven of the eight scenarios, excluding the DRY-8.5 scenario, KS results suggest that their simulated annual water yield follows the same distribution of the water yield generated using the historical climate data. This finding supports the use of water yield generated from these seven scenarios without bias correction; additional analyses are available in section 14 of the supplementary materials. In this paper, the DRY-8.5 scenario is nevertheless included to represent an extreme drought scenario. This simulated water yield is referred to as the native water supply.

The transferred water from nearby basins, referred to as out-of-basin water supply, represents approximately 20 % of the mean annual total water supply in the SPRB. The HydroBase database, maintained by the Colorado Division of Water Resources (CWCB, 2019a), provides daily streamflow from out-of-basin water sources downstream of the hydraulic structures. Six major structures are identified to represent the out-of-basin supply, which account for almost 98 % of the historical transferred water. Future out-of-basin supplies at each hydraulic structure are forecasted using the ‘forecast’ package in R (Hyndman and Khandakar, 2008), which performs an Auto-Regressive Integrated Moving Average (ARIMA) model with automatic parameter estimation and an external regressor. The ARIMA model predicts the future half-monthly out-of-basin supply extending from the historical out-of-basin supply time series. The native water supply from VIC is used as the external regressor.

2.4. Water demand

2.4.1. Land use, population, and urban water demand

Climate, land use, population, and housing are the main components for estimating urban water demand. Land use data is acquired from the Multi-Resolution Land Characteristics (MRLC) consortium National Land Cover Database (NLCD) raster images and then processed for years 2001, 2006, 2011, and 2016 using ArcGIS to calculate the urban area in each region. In the NLCD, urban areas are represented by open space areas and low-, medium-, and high-intensity developed areas. MRLC also provides the 1992 NLCD, but with a different format, so the desired four urban categories for 1992 are estimated using the conversion factors suggested by Fry et al. (2009). Annual land uses are then linearly interpolated between observed years for each region.

In the SPRB, urban land use and population are projected to increase. The Integrated Climate and Land Use Scenarios (ICLUS) tool developed by the Environmental Protection Agency (EPA) provides land use changes and population projections on a decadal basis from 2020 to 2100 for different scenarios (EPA, 2017). The “SSP5 RCP85 HadGEM2-ES” scenario is selected from the ICLUS V2.1.1 (EPA, 2020) database, because its 2050 projected population lies in the range of possible population projections of the Colorado Water Plan (CWCB, 2019b). Also, land use in this scenario represents the highest developed urban area. The ICLUS land use data is reclassified to the NLCD land use categories through estimating conversion parameters by matching the 2010 ICLUS with the 2011 NLCD datasets.

Historical annual population is obtained from the Colorado Department of Local Affairs (DOLA, 2020) and future population from ICLUS (EPA, 2020). ICLUS provides the decadal population projections at the county or multi-county level, so model regions 3 and 4 in this study are combined in the ICLUS dataset. To rectify this, a linear regression model is used to estimate the population in region 3 as a function of the population in region 4 using their annual historical records, achieving a fit of 0.96 R-squared. The same linear model is then used to split the future population of the two regions. The Colorado Department of Local Affairs also provides the number of households, which is required in the water demand model, so another linear regression model is used to estimate the number of households as a function of population (0.99 R-squared). It is then used to predict the future number of households from the projected population (Eq. 1), refer to supplementary section 2 for details about all the regression models used in this study.

$$\textit{Number of Households} = 0.4026 * \textit{Population} \tag{1}$$

Using the variety of data described above, the Integrated Urban Water Model (IUWM), a municipal water use forecasting tool, is used to simulate urban water demand in each region (Sharvelle et al., 2017). IUWM uses a daily mass balance approach to estimate the water demand in three categories: residential indoor, CII, and outdoor residential (Sharvelle et al., 2017). IUWM inputs include daily precipitation, daily temperature, urban land use in the NLCD format, population, the number of households, and other model parameters.[2] IUWM also can simulate the use of alternative water sources (i.e., wastewater, greywater, and stormwater) and water conservation for indoor and outdoor demands.

Five IUWM models are built to simulate the urban water demand in each of the five regions using the relevant climate data. IUWM requires many calibration parameters. Neale et al. (2020) and Sharvelle et al. (2017) calibrated models for the cities of Denver and Fort Collins, both located in the SPRB, and their reported calibration parameters are applied to the relevant regions in the present study. Historical and future annual urban water demands are presented in Fig. 3, where climate is the only input that varies across the future scenarios.

2.4.2. Agricultural consumptive use (net water irrigation requirement)

This study simulates water demands for irrigated lands with access to surface water. Two trends are observed in the agricultural sector in the SPRB: declining total irrigated lands and the steady transition from flood to sprinkler irrigation. Six irrigated crops account for 99 % of irrigated land in the SPRB: corn, alfalfa, grass pasture, wheat & small grains, sugar beets, and dry beans (CWCB, 2019a). In 1976, irrigated lands were 3400 km^2 with 5 % as sprinkler irrigation (CWCB, 2019a). In 2015, irrigated lands decreased to 2589 km^2 with 43 % as sprinkler irrigation (CWCB, 2019a). For this analysis, the irrigated crop area, crop mix, and irrigation technologies for future simulations are fixed at 2015 levels. Hence, only climate drives the variability in Ag water demands over time.

Net irrigation requirements for each crop in each region are estimated using the DayCent model (Parton et al., 1998). DayCent is a daily timestep version of the CENTURY model, which is used widely in agroecosystem studies to simulate terrestrial croplands, grasslands, forest lands, and savannas (Del Grosso et al., 2000). Inputs for DayCent include daily temperature,

[2] Net irrigation requirement met, plant factor, the minimum threshold temperature for which irrigation is applied, irrigation efficiency, and indoor demand power function parameters.

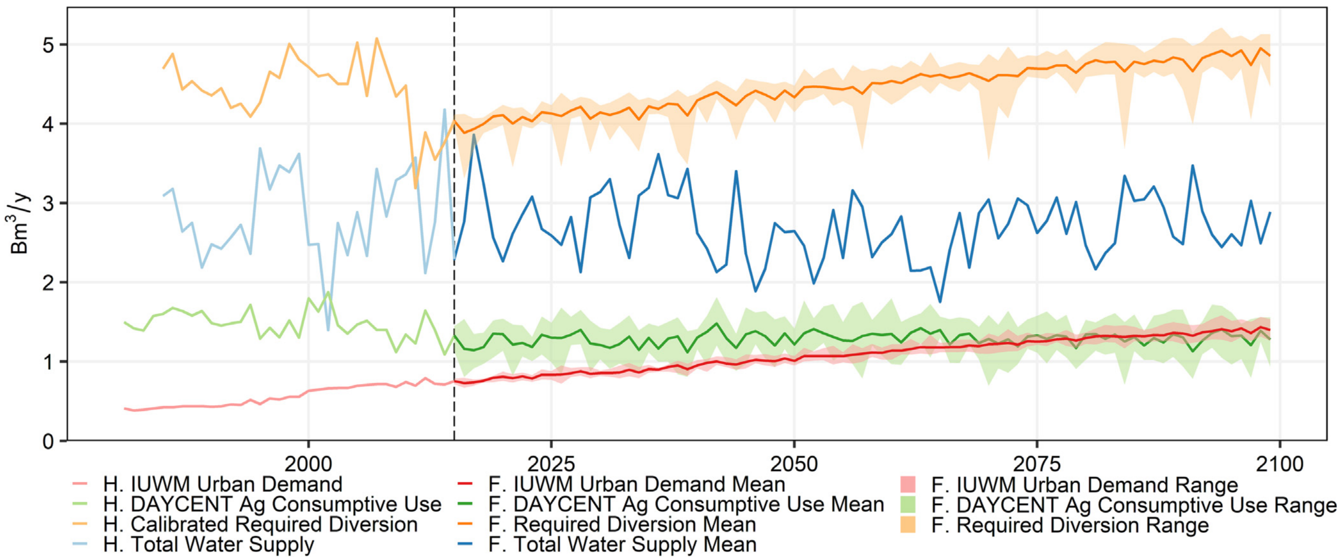

Fig. 3. Annual estimated required water diversion, simulated ag consumptive uses, simulated urban water demands, and simulated total water supply. The lighter lines are the historical values, and the darker lines are the means of the future baseline scenarios. The areas around the means present the maximum and minimum values of the future baseline scenarios; this range is not shown for the water supply (blue curve) because it covers the entire plot area. Refer to Fig. S10 for the inflow range.

daily precipitation, soil classification, land use, cultivation schedules, planting, and nutrient amendments. The model simulates several of ecosystem parameters including soil carbon, water balance, plant productivity, methane emissions, nitrous oxide, and nitrogen dynamics (Del Grosso et al., 2006; Dozier et al., 2017; Ogle et al., 2010; Robertson et al., 2018; Stehfest et al., 2007; Zhang et al., 2020). The output used in this study is the irrigation depth, defined as the depth of water required to produce 100 % crop yield.

The calibrated DayCent model used in this study is provided by Zhang et al. (2020), with 293 calibrated sites distributed across the SPRB. The model is run for the calibrated sites for the six crops using the historical and future climates of each region. The mean irrigation depth is then calculated for each crop in each region and multiplied by the irrigated area of each crop to obtain Ag consumptive use (Fig. 3) over time. Additionally, section 4 in the supplementary materials show the comparison of the simulated results from VIC, IUWM, and DayCent compared to their monitored values for the study area.

2.5. Water allocation model parameterization and calibration

This section presents the integration of the water supplies and demands into WEAP-SP and describes the parameterization and calibration of the WEAP-SP. WEAP-SP is manually calibrated from 1985 to 2014 by trial-and-error sequential model runs. Calibration parameters include delivery efficiency, irrigation application efficiency, percent of consumption uses in the urban indoor and CII users, percent of consumptive losses from return flow, and reservoir parameters. Three model outputs are used as main calibration targets: (1) annual water diversions, (2) monthly storage, and (3) annual outflow from the basin. The calibration process starts with comparing the calibration targets' results with their observed values from HydroBase (CWCB, 2019a). WEAP-SP is re-tuned and re-estimated until it imitates the SPRB current conditions.

2.5.1. Required water diversion and model efficiencies

The required water diversion is the total water necessary to be diverted from a stream to fulfill a water demand. Hence, required water diversions needed to achieve the water demands from DayCent and IUWM are estimated considering delivery and irrigation application efficiencies (Fig. 3). Application efficiency is already a component of IUWM and is set at 71 % for the outdoor demand, while the indoor and CII consumption ratios are estimated at 20 %. During the calibration process, delivery efficiencies are set at 80 % for Ag users and 75 % for urban users. The application efficiency for sprinkler irrigation is assumed to be 25 percentage points greater than the flood application efficiency, and flood irrigation efficiency is chosen independently for each year to predict the historical required diversions during the calibration process. A linear regression model of the annual flood application efficiency as a function of the annual Ag consumptive uses per unit area is estimated with an R-Squared value of 0.98. Annual flood and sprinkler application efficiency are then projected for each future scenario. Lower and upper limits for the calculated flood application efficiency are estimated at 35 % and 65 %, so sprinkler application efficiency ranges from 60 % to 90 %.

Fig. 3 summarizes the annual urban water demand from IUWM, the Ag consumptive use from DayCent, and the estimated required diversion from the calibration process for the historical period and the eight climate scenarios. Urban water demand has an increasing trend over the total simulation time, largely driven by population growth. There are minor annual fluctuations reflecting the effects of different climate scenarios on outdoor demands. Ag consumptive use has a slightly declining trend during the historical period reflecting the reduction in irrigated lands and the transition from flood to sprinkler irrigation during the historical period. In the future, the annual mean of Ag consumptive use across the scenarios remains relatively stable as total irrigated land and irrigation technology are fixed after 2015. In general, population growth drives the upward trend in required diversions, while climate effects are represented by the shaded area around each curve (Fig. 3).

In WEAP-SP, as application or delivery efficiencies decrease, more water must be diverted from a stream to satisfy a given demand. The difference between diverted and consumed water is the return flow, a portion of which is lost from the system while the rest re-renters the streams. All water in WEAP-SP is accounted for through consumptive demands, losses from return flow to streams, reservoir evaporation (discussed in the following section), and outflow from the basin. From the calibration process, the percent of water lost from the return flow is estimated at 10 % and 13 % for Ag flood and sprinkler irrigation, 35 % for urban outdoor users, and 15 % for indoor and CII users. The parameter uncertainty is further discussed in Section 2.7.

2.5.2. Representing reservoirs

The SPRB has several reservoirs that store water from high flow season to high demand season and from wet to drought years. Total storage in each subbasin is aggregated to a single reservoir located downstream of the headwater. This representative reservoir is allowed to store all the water supplies connected to this subbasin. Total storage is estimated using recorded monthly reservoir levels from 1975 to 2018 in HydroBase (CWCB, 2019a), which are aggregated to the subbasin level. At the Basin level, the maximum total quantity of stored water was 1.97 BCM, observed in May 1985 (Fig. 4). The sum of the stated maximum storage of each individual subbasin yields 2.25 BCM, implying that the full storage capacity was not reached. In reality, it is difficult to for all reservoirs to reach maximum capacity at the exact time due to physical limitations and operational difficulties. Therefore, each subbasin's maximum storage capacity is modified to match the maximum observed storage. Empirical cumulative distribution functions (ECDF) of the monthly stored water in each subbasin are calculated, and the maximum storage capacity for each subbasin is specified at the non-exceedance probability of 0.97, aggregating to 1.97 BCM storage capacity for the entire study area.

The dead storage (i.e., stored water below the outlet level of the reservoir) is estimated at 28 % during the calibration process, leaving the active storage at 1.42 BCM. As a secondary calibration target, the simulated mean annual evaporation from 1993 to 2013 is compared to the simulated evaporation of the South Platte Decision Support System (SPDSS) (CWCB, 2017). The models have similar evaporation volumes, with values of 0.18 BCM/y and 0.22 BCM/y for WEAP-SP and SPDSS reports, respectively.

2.5.3. Simulating outflow from the SPRB

The South Platte River Compact between Colorado and Nebraska (State of Colorado and State of Nebraska, 1923) regulates the minimum flow of the South Platte River at Julesburg in Colorado, near the states' border. From April 1st to October 15th, the flow is not to drop below 3.4 m^3/s on any given day which accounts for at least 0.06 BCM. For the remainder of the year, the volume of water released to Nebraska should be at least 0.04 BCM with a daily minimum not to drop below 0.28 m^3/s. Although the compact requires only 0.1 BCM/y to be released to Nebraska, the water released is 0.49 BCM on average (CWCB, 2015). According to data from HydroBase (CWCB, 2019a), Julesburg station's annual flow from 1925 to 2017 has a mean, median, and standard deviation of 0.49, 0.36, and 0.48 BCM/y.

The difference between the actual and compact outflow results from several components, including the released water from a reservoir when it is full, the un-stored water when water supplies are expected to be very high, or the return flow of the most downstream users. To combine the compact regulations with the natural flow process, an exponential regression model is estimated to predict the half-monthly outflow discharge as a function of the previous ten months' aggregated native water supply volume and the following six months' aggregated native water supply volume (Eq. S1). This model has an R-Squared value of 0.94. The exponential model predicts the outflow for each future scenario using the VIC native water supply independently from WEAP-SP (Fig. 4). Then, lower and upper bounds of the estimated outflow, 3.4 and 56.6 m^3/s, are used to satisfy the minimum flow requirements and imitate the historical annual outflow to preserve the same environmental conditions.

2.5.4. Water allocation rules

For the baseline scenario, priority numbers are estimated for each demand node using data on actual water rights to best approximate the current makeup of the SPRB. To emulate how water is administered under a prior appropriation doctrine, WEAP allocates water to the nodes with high priority before those with lower priority. Once water is allocated to a particular node, return flows and remaining natural flows are available to downstream nodes. Reservoirs have the lowest priorities, preceded by the outflow from the SPRB with the second-lowest priority.

To estimate priorities for the remaining nodes, priority numbers are aggregated for relevant water rights using data from HydroBase (CWCB, 2019a). The priority number communicates a ranking within the hierarchy of all water rights in Colorado, which is determined by a right's appropriation and court adjudication date. For urban demand nodes, all water rights within a region with relevant uses (e.g., domestic, commercial, or municipal) are identified, and a mean priority number, weighted by each right's decreed flow rate, is calculated. A similar process is used for agricultural nodes, however after isolating agricultural water rights within a region, a weighted-mean priority must first be calculated for all associated irrigation ditches. Priorities are then generated for each agricultural node using the mean priority across irrigation ditches weighted by the area of each crop with flood and sprinkler irrigation. Every demand node has a fixed priority number during the entire simulation time and across simulations.

In the SPRB, most urban communities are upstream of the agricultural communities in all regions. In WEAP-SP, the three urban users exist upstream of the 12 Ag users in each region, where each user has access to the return flow from the upstream users. In each region, the urban users are arranged such that indoor users are upstream, followed by the CII and outdoor users. The outdoor priority number is estimated from HydroBase data, while the priorities for CII and indoor are increased as they are upstream of the outdoor user. Regarding the Ag users, they are located in each region according to their priority numbers; the highest priority crop is located upstream, followed by the lower crops, maximizing the availability of return flows.

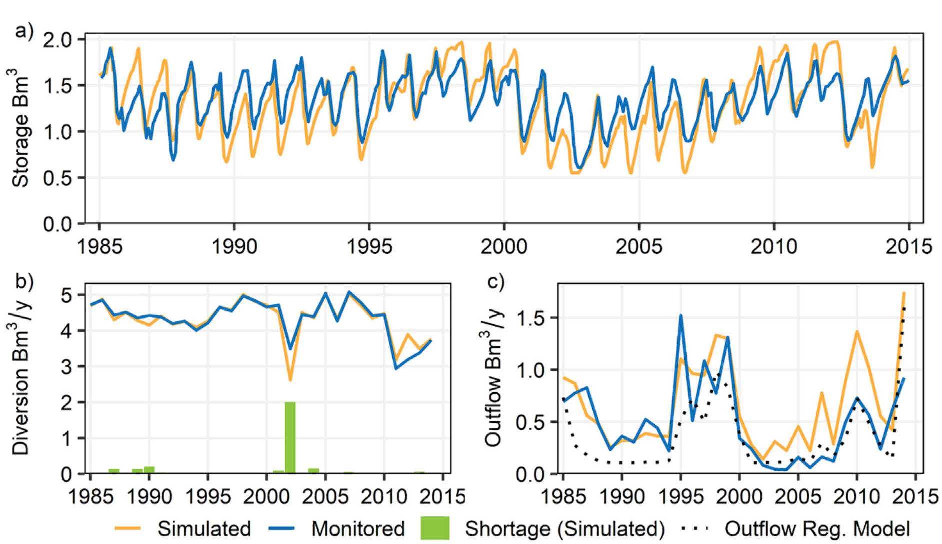

Fig. 4. The three calibration targets of the WEAP-SP calibration process, (a) monthly storage, (b) annual diversions and the simulated shortage, and (c) annual outflow.

2.5.5. Water allocation calibration evaluation

The main calibration target is the annual water diversions, which is the most important variable in the water allocation process (Fig. 4b). The modeled values have <0.5 % Bias, with 0.82 Nash Sutcliffe Efficiency (NSE) and 0.91 Kling-Gupta Efficiency (KGE), which indicates very good model performance (Knoben et al., 2019; Moriasi et al., 2015). Monthly storage (Fig. 4a), the secondary calibration target, also performs well with <4 % Bias and 0.53 KGE. Annual outflow from the model is also evaluated (Fig. 4c), which is overestimated in the model compared to the monitored values (blue line) and the outflow generated from the regression model (dotted line). Higher outflow values likely occur because the demand models estimate net irrigation requirements. In practice, farmers may not know these requirements with certainty. It would therefore be rational for risk-averse farmers to hedge against downside risk by applying water more intensely (Finger, 2013). This behavior could lead to slightly more losses and slightly lower outflows. Despite the difference in predicted outflows, the WEAP-SP successfully imitates the historical water allocation in the SPRB (Fig. 4) and can be meaningfully used in simulations of future scenarios.

2.6. Uncertainty analysis

Three primary levels of uncertainty exist in each modeling system: input, structural or model, and parameter (Cibin et al., 2014; Herrera et al., 2022; Renard et al., 2010; Song et al., 2015). In this analysis, input uncertainty is handled by using eight climate scenarios in the four models used in this framework. Additionally, the effectiveness of alternative strategies and the index-based approach analyses in Sections 3.2 and 3.4 represents uncertainty in the model inputs of water supply, storage capacity, and required diversions as previously described. The structure or model uncertainty occurs because of model simplifications. It could be addressed by using more than one model to simulate the same outputs, which is out of the scope of this manuscript. Additionally, only calibrated models are used in this study.

Parameter uncertainty (Arabi et al., 2007) is then fully addressed by performing Sobol uncertainty analysis for WEAP-SP. Sobol is a variance-based method that uses Monte Carlo methods to perform global sensitivity analysis. Eight parameters are selected to represent the majority of WEAP parameters. The most significant parameters are determined using the SALib python package (Herman and Usher, 2017; Iwanaga et al., 2022) through 2304 runs in WEAP-SP for the historical period, where each run represents a parameter set. Then, a multiobjective optimization for maximizing the three calibration targets KGE is performed to determine the non-dominated parameter sets through Pareto front analysis (Bastidas et al., 1999). The non-dominated sets represent the sets where no other sets are better than them in all dimensions of the maximization problem (Khanmohammadi et al., 2021). Finally, these non-dominated sets are simulated for the future conditions of the DRY4.5 scenario to estimate the confidence interval of the results.

2.7. Scenarios, strategies, and metrics calculation

In this paper, a 'scenario' refers to all simulated baseline results associated with one of eight climate scenarios. A 'strategy' defines a percentage increase to the current storage capacity or decrease in the future baseline required diversions, and an 'alternative starting condition' generalizes the strategies by considering any applied change to the storage capacity or the future baseline required diversions. According to water availability and priority, a simulated diversion is equal to or less than the required diversion. 'Shortage' is defined as the deficit between the required and simulated water diversions.

Section 3.1 presents the model outputs for the baseline scenarios without any changes to the storage capacity or the required diversions. For the baseline scenarios, the gap between the water supply and aggregate consumptive use (if all water requirements were met), annual shortages by model regions and users, and 30-year annual and half-monthly results summaries are all reported.

In Section 3.2, three adaptation strategies of 10 % and 20 % demand reduction across all users and 25 % increase to the current storage are implemented to test their impact on shortages. The demand reduction strategies represent a range of possible future management actions as described in the Colorado Water Plan (CWCB, 2015), such as enhancing water use technologies or reducing irrigated lands. Differences between demand reduction strategies are beyond the scope of this study but warrant attention in future research. Regarding reservoir infrastructure, a 25 % increase in storage capacity, corresponding to 0.49 BCM, represents an arbitrary but achievable goal in the SPRB. The 30-year half-monthly mean shortage is the metric used to compare strategies for future baseline scenarios.

Section 3.3 shows the uncertainty analysis results, and Section 3.4 presents a more generalized analysis of the impact of alternative starting conditions on shortages. Three scenarios and 48 alternative starting conditions of storage and required diversions are examined to generalize results. The DRY-8.5, DRY-4.5, and WET-4.5 represent the worst-case, middle, and optimistic scenarios, respectively (Table S3). Then for these scenarios, storage capacity is varied from 40 % to 160 % of the current storage by 20 % increments and required diversions from 40 % to 130 % of the future baseline demands by 15 % increments, resulting in 147 total simulations. The metrics used in this analysis are dimensionless to facilitate the generalization of results to other basins, as discussed in detail in the Results and discussions section.

3. Results and discussions

3.1. Baseline scenarios

3.1.1. Consumptive uses and the water balance gap

The 10-year running annual mean aggregate consumptive use and water supply across the baseline scenarios are compared to examine how climate change and population growth affect the overall water balance in the SPRB (Fig. S11). The aggregate consumptive use is the total of consumptive demands, losses from return flow, and mean historical reservoir evaporation. The 10-year annual mean provides an overview of the water balance by reducing the effects of extreme single wet or drought years. In SPRB, the consumptive uses plus the mean outflow are expected to continually exceed the mean water supply, on average, after the 2040s without effective adaptation strategies. This gap confirms that population growth substantially impacts potential water shortages more than climate change, as indicated in Fig. 3. This simulated shortage is consistent with the results of previous studies (Brown et al., 2019; Foti et al., 2012; Heidari et al., 2021a; Jaeger et al., 2017; Warziniack and Brown, 2019; Yigzaw and Hossain, 2016) that water shortage is predicted to increase in the areas projected to increased water demands and more variable water supplies.

3.1.2. Annual spatial shortages

WEAP-SP also provides the spatial distribution of expected shortages to help decision-makers prepare specific management plans for the study region. Shortages depend on the spatial location of each user, the priority of allocation, and overall water availability. Given the distribution of water rights, shortages are nearly shared equally between Ag and urban sectors. The annual aggregate urban shortages increase with time as population grows, while Ag shortages are more climate-dependent as irrigated areas are constant across the future simulations. The largest urban shortages occur in the Central region, followed by the North and the South Metro regions, where most urban required diversions exist. Ag shortages also mainly occur in North, East, and North Central regions where most Ag required diversions exist. Supplementary section 7 provides the annual required diversions and shortages by aggregate users, model regions, and basin total.

3.1.3. 30-Year mean results

In addition to the spatial distribution, WEAP-SP provides results at a half-monthly timestep to better understand the effect of climate change on water allocation within a year. Fig. 5 provides the 30-year half-monthly average water supply, storage, outflow, reservoir evaporation, required diversion, and shortage for historical, near-future, and far-future baseline periods. Warming climate trends beget an earlier stream discharge hydrograph with lower future-period means across the scenarios (Fig. 5a). The 30-year annual mean water supply is mostly greater than historical under the WET and WARM scenarios, and it is lower than historical for the HOT and DRY scenarios (Table S3). The simulated outflow from SPRB highly depends on the existing water supply with a wide range across the scenarios. Although the near- and far-future outflow means are close to the historical mean (Fig. 5c), some scenarios (e.g., DRY-8.5) have low outflow (Table S3), meaning that in addition to water shortage, environmental problems from low stream flows could be likely.

Historically, reservoirs in the SPRB store water from the high-flow season to the high-demand season (Fig. 5b). This pattern remains the same in both future periods, allowing for the mitigation of the consequences of earlier water supplies but with lower storage means due to the changes in water supplies and required diversions (Fig. 5b). Less stored water means that the mean evaporation from reservoirs will be lower in the future than in the historical period (Fig. 5d).

Required diversion patterns have a lower peak and thicker tails in both future periods (Fig. 5e) due to less irrigated land compared to the historical mean (Fig. 5i) and increased urban requirements (Fig. 5j). Fig. 5i also shows the mean historical Ag required diversion assuming the same crops of the year 2015 as simulated in the future simulations. Despite the within-season required diversion change, the required annual mean diversions in the near-future are very close to the historical mean (Table S3). However, the far-future required annual mean diversions are much higher than the historical mean (Table S3). Additionally, the near- and far-future shortages have much higher and earlier peaks with a wide range across the climate scenarios (Fig. 5f). The shortage distribution between Ag and urban is shown in Fig. 5h and j. The anticipated summer and early fall shortages indicate that urban outdoor conservation strategies are likely to be effective mitigation strategies (Fig. 5h). Ag shortages increased and shifted earlier following the shift in water supply (Fig. 5j).

Table S3 provides the 30-year mean shortage ratio, a ratio between the annual shortage divided by the annual required diversions. These values indicate that the shortage ratio: (1) is 2.2 % during the historical period, (2) ranges between 0.5 % and 9.9 % in the WARM and WET scenarios that are considered the optimistic scenarios, (3) ranges between 10.7 % and 13.5 % in HOT-4.5 and DRY-4.5, (4) and ranges from 13.9 % to 41.3 % in the HOT-8.5 and DRY-8.5 scenarios (Table S3).

3.2. Effectiveness of alternative adaptation strategies for reducing shortages

Adaptation for future resilience is the desired goal for decision-makers. This section presents the results of three adaptation strategies and the sensitivity of shortages to them. For comparison purposes, Fig. 6a shows the baseline 30-year half-monthly shortage mean for the historical, and near- and far-future periods. The first tested strategy of 25 % additional storage shows modest or negligible effects on decreasing shortages in both future periods (Fig. 6b). However, demand reduction strategies directly diminish the shortages (Fig. 6c and d).

Overall, demand management strategies outperform storage infrastructure investment strategies because increasing demands affect the water balance more than changing the timing of water yields (Fig. 6). Thus, a 10 % demand reduction strategy lets the near-future mean shortage almost match the historical mean except from June to August (Fig. 6b). Additionally, a 20 % demand reduction strategy lets the near-future mean shortage be less than the historical mean and the far-future mean shortage be close to the historical mean except from May to August (Fig. 6d). However, 25 % additional storage has limited effects on decreasing the shortage (Fig. 6b). Moreover, the performances of adaptation strategies do not vary across the climate scenarios (Fig. S16).

3.3. Uncertainty analysis

The two most significant WEAP-SP parameters from the Sobol analysis are the return flow losses and the flood irrigation consumption factor, indicating that they must be precisely estimated. The urban delivery efficiency and the residential indoor consumptive use come next in importance, while the others have limited impacts on the model performance. The calibration targets goodness of fitness for the total Sobol runs are calculated, and sets are reduced to the sets with NSE and KGE >0.1 and Bias <40 %. The Pareto front analysis for the reduced sets yields 108 non-dominated parameter sets through maximizing KGE values. The manual calibration results, as presented earlier, exist within the 95 % confidence interval of the Pareto front sets (refer to supplementary materials section 10 for more details).

The DRY-4.5 is simulated with the 108 sets, and the annual shortage ratio, calculated as the annual shortage divided by the annual required

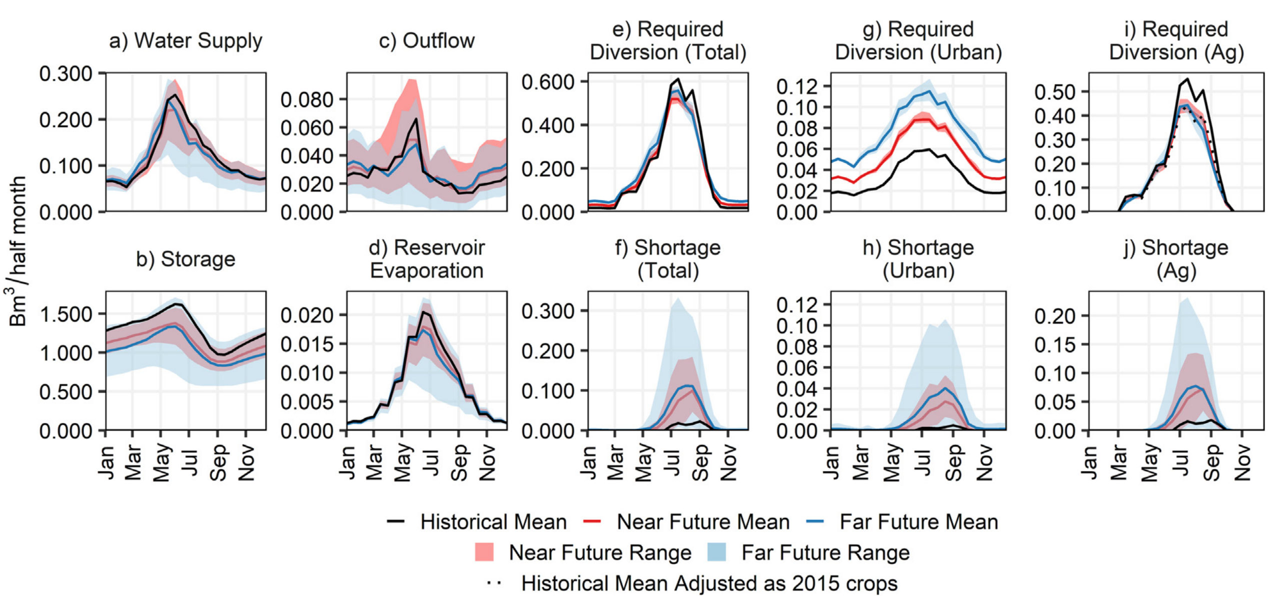

Fig. 5. 30-year half-monthly water supply, storage, required diversions, and shortage means. The solid lines represent the mean across the eight climate scenarios, and the areas represent the maximum and minimum values at each timestep.

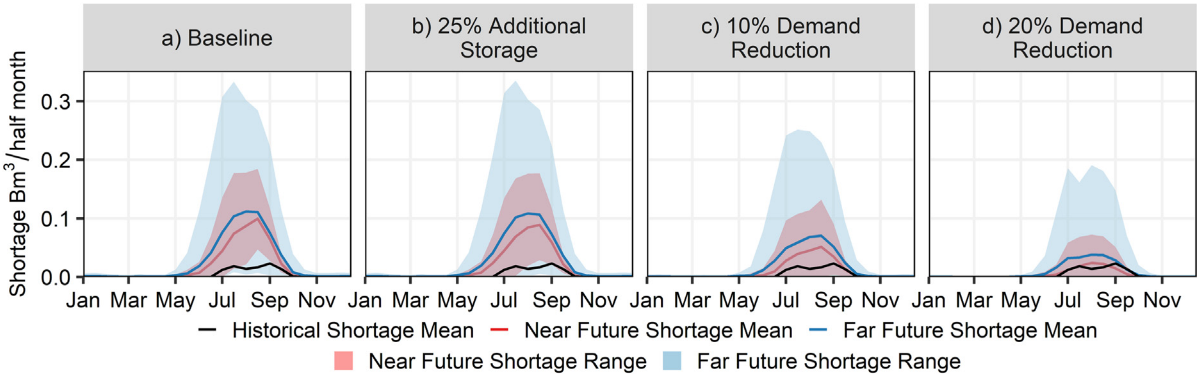

Fig. 6. 30-year half-monthly shortage means of future baseline scenarios and the three alternative adaptation strategies with the historical mean. The solid lines represent the mean across the eight climate scenarios, and the areas represent the maximum and minimum values at each timestep across the scenarios. The results for each climate scenario is presented in Fig. S16.

diversions, exists within the 95 % confidence interval of the Pareto front sets. Finally, the coefficients of variation of the annual shortage ratio for the near future and far future are 0.07 and 0.1, respectively, indicating the low error range for the 108 model results and the feasibility of generalization.

3.4. Generalizing results: an index-based approach

To generalize the results from the present case study, a range of required diversions and storage capacities across three climate scenarios are explored to determine thresholds when adaptation strategies will perform well. Results can inform the likelihood of shortages and how changes in demand and storage capacity may affect shortages in other basins with different initial conditions. Three indices are identified that drive the water allocation process: (X_1) the 30-year annual required diversion mean normalized by the 30-year annual water supply mean (WS), (X_2) the storage capacity normalized by WS, and (X_3) the 30-year annual return flow mean normalized by WS. The four components in these three indices can be measured for any water basin and describe >99 % of the variance of the 30-year annual shortage ratio mean (Y); refer to supplementary materials section 11 for more details. X_3 has a significant role in meeting the required diversions, which describes water use efficiency and ranges from 0.75 to 1.2 in the future baseline scenarios (Fig. S21).

Fig. 7 shows the relationship between X_1, X_2, and Y during the near and far future shortage for the WET-4.5, DRY-4.5, and DRY-8.5 scenarios. Looking at the horizontal axis, demand reductions always diminish shortage regardless of storage and inflow conditions. Also, all subplots in Fig. 7 share the same trend of contour lines being almost vertical when the values of X_2 exceed a threshold of approximately 0.64, above which changes in storage capacity do not affect shortage. However, the contours display curvature below this threshold, reflecting non-linear relationships between Y and X_1 and highlighting the sensitivity of shortages to storage in this condition. Y decreases as X_2 increases until it reaches 0.64 (corresponding to 0.46 considering only active storage), as X_2 becomes insignificant -refer to supplementary materials section 13 of statistical evidence of this threshold existence-. However, if X_2 exceeds 1.2, Y increases as X_2 increases because of more evaporation from a larger storage area, because dead storage volume and surface area increase when storage volume increases, leading to more evaporation losses. The current storage conditions in the SPRB are at or above the identified threshold in the dry scenarios, explaining why additional storage has negligible effects on shortages as discussed in Fig. 6b.

Fig. 8a shows the predicted Y at the mean of X_1 with a 95 % confidence interval (Arel-Bundock, 2022) using the regression model shown in eq. 2

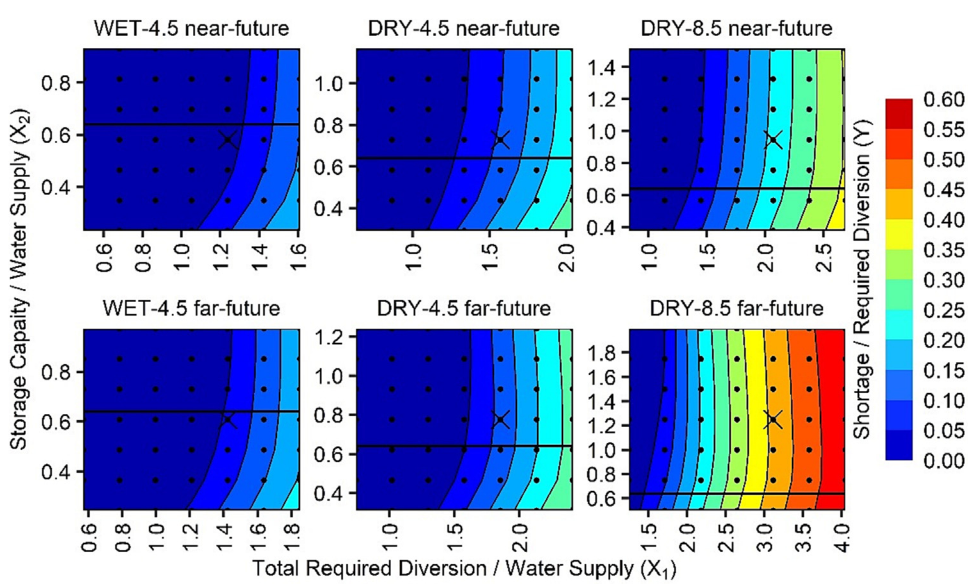

Fig. 7. Shortage (Y) at different starting conditions -the dots- of required diversion (X_1) and storage (X_2); each subplot represents one 30-year period; the cross represents the future baseline conditions for each scenario.

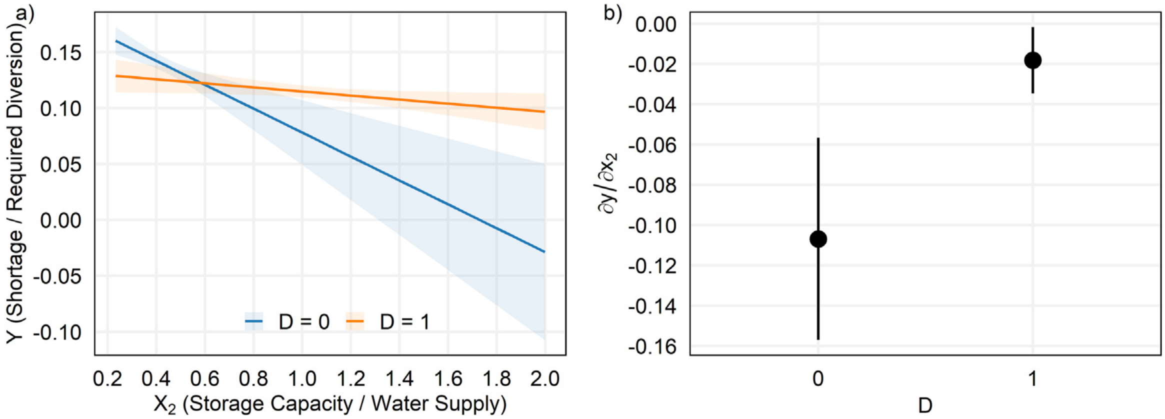

Fig. 8. a) Conditional Adjusted Predictions of Y. b) Marginal effect of X_2 on Y. Both are for the groups above and below the threshold with 95 % confidence intervals (Arel-Bundock, 2022).

(R-squared = 0.94). For the group with D = 0 ($X_2 < 0.64$), Y decreases as X_2 increases, while it is almost horizontal for the other group with a narrower confidence interval (Fig. 8a). Additionally, the marginal effect of X_2 on Y is almost zero for the D = 1 group ($X_2 \geq 0.64$), highlighting that increasing X_2 has a negligible effect on Y (Fig. 8b). This result implies, perhaps counterintuitively, that additional storage has more significant benefits as water inflows increase relative to current capacities (Lower X_2).

$$Y_{c,t,i} = \alpha + \beta_1 * X_{1\ c,t,i} + \beta_2 * X_{2\ c,t,i} + \beta_3 * D + \beta_4 * X_{2\ c,t,i} * D \tag{2}$$

where *c*, *t*, and *i* represent the climate scenario, simulation period (near or far future), and starting conditions, respectively.

From this generalization approach, basins above the 0.64 storage threshold would need to focus on demand reduction strategies to reduce shortages. In this case, investments in storage may not help reduce overall basin shortages. It is important to note, however, that additional storage may impact the shortages of specific users even if total shortages are not affected. While this distributional impact does not appear to occur in the current setup of WEAP-SP, it may be an important consideration for other basins considering expansion of storage capacity. This may be especially true if additional storage is accompanied by other strategies, such as purchasing the water rights of downstream users and storing the water.

4. Conclusions

In this study, a water allocation model (WEAP-SP) was developed and calibrated for the SPRB driven by population growth and climate change through 2100 with a half-monthly timestep. The main goals are to predict the spatial and temporal future water shortage, test the effectiveness of demand reduction and additional storage strategies on reducing shortages, and identify generalized conditions under which each strategy may be beneficial to similar basins. Results indicated that although the reservoirs in SPRB reduce the consequences of the temporal shift of the water supply timing, a continuous shortage nevertheless exists after the 2040s.

In SPRB, the two tested strategies showed very different effects on water shortage mitigation. In all eight simulated climate scenarios, additional storage showed insignificant effects on reducing water shortages. Conversely, a 20 % demand reduction strategy diminished the near- and far-future shortage mean across all eight climate scenarios to be close to the historical half-monthly shortage mean.

To generalize the effect of the two strategies to other basins, 147 scenarios were simulated at different starting conditions of required diversions and storage capacity. A threshold of the ratio between the storage capacity and the 30-year annual mean water supply of 0.64 was identified, above which additional storage does not affect water shortages. This suggests that areas expected to experience increased water inflows (or those with low current storage capacity) are most likely to benefit from additional water storage infrastructure. In contrast, demand reduction strategies always reduce expected shortages.

Although illustrating the impact of storage investment and demand reductions on water shortages is necessary to inform policy decisions, it is insufficient to recommend pursuing a specific strategy. Policymakers should consider the costs of candidate strategies compared with their effectiveness in reducing water shortage and the associated environmental impacts.

CRediT authorship contribution statement

Conceptualization: Gharib, Blumberg, Manning, Goemans, Arabi.
Methodology: Gharib, Blumberg, Manning, Goemans, Arabi.
Investigation: Gharib, Blumberg, Manning, Goemans, Arabi.
Resources: Gharib, Blumberg.
Data curation: Gharib.
Formal analysis: Gharib.
Software: Gharib.
Funding acquisition: Manning, Goemans, Arabi.
Roles/Writing - original draft: Gharib.
Writing - review &editing: Gharib, Blumberg, Manning, Goemans, Arabi.

Data availability statement

The DayCent model and parameters were provided by Zhang et al. (2020). The baseline climate data, the projected MACA climate data, and the VIC model results were provided by Heidari et al. (2020), Naz et al. (2016), and Abatzoglou and Brown (2012).

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

We thank the anonymous reviewers for their constructive criticisms and insightful comments, which helped in improving the paper substantially. This paper is based upon work supported by the National Institute of Food and Agriculture under award 2018-69011-28369 and the National Science Foundation under grants 1444758 and 1828902. We thank Yao Zhang and Stephen Williams for providing the DayCent Model and helping set it up. We thank Hadi Heidari for providing the climate datasets and the VIC model results.

Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.161964.

References

Abatzoglou, J.T., Brown, T.J., 2012. A comparison of statistical downscaling methods suited for wildfire applications. Int. J. Climatol. 32 (5), 772–780. https://doi.org/10.1002/joc.2312.

Aliyari, F., Bailey, R.T., Arabi, M., 2021. Appraising climate change impacts on future water resources and agricultural productivity in agro-urban river basins. Sci. Total Environ. 788, 147717. https://doi.org/10.1016/j.scitotenv.2021.147717.

Arabi, M., Govindaraju, R.S., Engel, B., Hantush, M., 2007. Multiobjective sensitivity analysis of sediment and nitrogen processes with a watershed model. Water Resour. Res. 43 (6), 1–11. https://doi.org/10.1029/2006WR005463.

Arel-Bundock, V., 2022. marginaleffects: Marginal Effects, Marginal Means, Predictions, and Contrasts. R Package Version 0.6.0.9000. https://vincentarelbundock.github.io/marginaleffects/.

Bastidas, L.A., Gupta, H.V., Sorooshian, S., Shuttleworth, W.J., Yang, Z.L., 1999. Sensitivity analysis of a land surface scheme using multicriteria methods. J. Geophys. Res.-Atmos. 104 (D16), 19481–19490. https://doi.org/10.1029/1999JD900155.

Biemans, H., Haddeland, I., Kabat, P., Ludwig, F., Hutjes, R.W.A., Heinke, J., Von Bloh, W., Gerten, D., 2011. Impact of reservoirs on river discharge and irrigation water supply during the 20th century. Water Resour. Res. 47 (3), 1–15. https://doi.org/10.1029/2009WR008929.

Blanc, E., Strzepek, K., Schlosser, A., Jacoby, H., Gueneau, A., Fant, C., Rausch, S., Reilly, J., 2014. Modeling U.S. water resources under climate change. Earth'sFuture 2 (4), 197–224. https://doi.org/10.1002/2013ef000214.

Brown, T.C., Mahat, V., Ramirez, J.A., 2019. Adaptation to future water shortages in the United States caused by population growth and climate change. Earth's Future 7 (3), 219–234. https://doi.org/10.1029/2018EF001091.

Chen, D., Chen, H.W., 2013. Using the Köppen classification to quantify climate variation and change: an example for 1901–2010. Environ. Dev. 6 (1), 69–79. https://doi.org/10.1016/j.envdev.2013.03.007.

Chinnasamy, C.V., Arabi, M., Sharvelle, S., Warziniack, T., Furth, C.D., Dozier, A., 2021. Characterization of municipal water uses in the contiguous United States. Water Resour. Res. 57 (6), 1–18. https://doi.org/10.1029/2020WR028627.

Cibin, R., Athira, P., Sudheer, K.P., Chaubey, I., 2014. Application of distributed hydrological models for predictions in ungauged basins: a method to quantify predictive uncertainty. Hydrol. Process. 28 (4), 2033–2045. https://doi.org/10.1002/hyp.9721.

Cook, B.I., Smerdon, J.E., Seager, R., Coats, S., 2014. Global warming and 21st century drying. Clim. Dyn. 43 (9–10), 2607–2627. https://doi.org/10.1007/s00382-014-2075-y.

CWCB, 2015. Colorado Water Conservation Board. Colorado Water Plan. https://cwcb.colorado.gov/colorado-water-plan.

CWCB, 2017. Colorado Water Conservation Board, South Platte River Basin Water Resources Planning Model User's Manual. retrieved on August, 2021. https://cdss.colorado.gov/resources/modeling-dataset-documentation.

CWCB, 2019. Colorado Water Conservation Board, HydroBase, Colorado's Decision Support Systems (CDSS), version:2019-09-10. url: https://cdss.colorado.gov/software/hydrobase. https://cdss.colorado.gov/software/hydrobase.

CWCB, 2019. Colorado water conservation board, updated population projections for water plan scenarios. Analysis and Technical Update to the Colorado Water Plan (Vol. 2, Issue 2) https://dnrftp.state.co.us/#/CWCB/Technical Update to Water Plan/1. Technical Update Documentation/.

Dai, A., 2013. Increasing drought under global warming in observations and models. Nat. Clim. Chang. 3 (1), 52–58. https://doi.org/10.1038/nclimate1633.

Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtisb, J., Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. International Journal of Climatology 2029 (March 2008), 2011–2029. https://doi.org/10.1002/joc.

Del Grosso, S.J., Parton, W., Mosier, A.R., Ojima, D.S., Kulmala, A.E., Phongpan, S., 2000. General model for N2O and N2 gas emissions from soils. Glob. Biogeochem. Cycles 14 (4), 1045–1060.

Del Grosso, S.J., Parton, W.J., Mosier, A.R., Walsh, M.K., Ojima, D.S., Thornton, P.E., 2006. DAYCENT National-Scale Simulations of nitrous oxide emissions from cropped soils in the United States. J. Environ. Qual. 35 (4), 1451–1460. https://doi.org/10.2134/jeq2005.0160.

Dieter, C.A., Maupin, M.A., Caldwell, R.R., Harris, M.A., Ivahnenko, T.I., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2017. Estimated use of water in the United States in 2015. U.S. Geological Survey Circular. 1441. https://doi.org/10.3133/cir765 Issue 765.

DOLA, 2020. Colorado Department of Local Affairs, State Demography Office. . https://demography.dola.colorado.gov/population/.

Dozier, A., Arabi, M., Wostoupal, B.C., Goemans, C.G., Zhang, Y., Paustian, K., 2017. Declining agricultural production in rapidly urbanizing semi-arid regions: policy tradeoffs and sustainability indicators. Environ. Res. Lett. 12 (8). https://doi.org/10.1088/1748-9326/aa7287.

EPA, 2017. U.S. Environmental Protection Agency. Updates To The Demographic And Spatial Allocation Models To Produce Integrated Climate And Land Use Scenarios (Iclus) (Final Report, Version 2). U.S. Environmental Protection Agency, Washington, DC EPA/600/R-16/366F. In Report (Issue January).

EPA, 2020. ICLUS V2.1.1. U.S. Environmental Protection Agency. https://www.epa.gov/gcx/iclus-downloads.

Finger, R., 2013. Expanding risk consideration in integrated models - the role of downside risk aversion in irrigation decisions. Environ. Model. Softw. 43, 169–172. https://doi.org/10.1016/j.envsoft.2013.02.001.

Flörke, M., Schneider, C., McDonald, R.I., 2018. Water competition between cities and agriculture driven by climate change and urban growth. Nat. Sustain. 1 (1), 51–58. https://doi.org/10.1038/s41893-017-0006-8.

Foti, R., Ramirez, J.A., Brown, T.C., 2012. Vulnerability of U.S. Water Supply to Shortage: A Technical Document Supporting the Forest Service 2010 RPA Assessment. 295. http://www.treesearch.fs.fed.us/pubs/42363.

Foti, R., Ramirez, J.A., Brown, T.C., 2014a. A probabilistic framework for assessing vulnerability to climate variability and change: the case of the US water supply system. Clim. Chang. 125 (3–4), 413–427. https://doi.org/10.1007/s10584-014-1111-6.

Foti, R., Ramirez, J.A., Brown, T.C., 2014b. Response surfaces of vulnerability to climate change: the Colorado River basin, the High Plains, and California. Clim. Chang. 125 (3–4), 429–444. https://doi.org/10.1007/s10584-014-1178-0.

Fry, J.A., Coan, M.J., Homer, C.G., Meyer, D.K., Wickham, J.D., 2009. Completion of the National Land Cover Database (NLCD) 1992 – 2001 Land Cover Change Retrofit Product. U.S. Geological Survey Open-File Report , p. 18. http://pubs.usgs.gov/of/2008/1379/pdf/ofr2008-1379.pdf.

Gleick, P., Bielawski, A., Cooley, H., 2021. The U.S. Infrastructure Plan: Water Components - Pacific Institute. . https://pacinst.org/the-u-s-infrastructure-plan-water-components/.

Hallegatte, S., 2009. Strategies to adapt to an uncertain climate change. Glob. Environ. Chang. 19 (2), 240–247. https://doi.org/10.1016/j.gloenvcha.2008.12.003.

Heidari, H., Arabi, M., Warziniack, T., Kao, S.C., 2020. Assessing shifts in regional hydroclimatic conditions of U.S. river basins in response to climate change over the 21st century. Earth'sFuture 8 (10), 1–14. https://doi.org/10.1029/2020EF001657.

Heidari, H., Arabi, M., Warziniack, T., 2021. Vulnerability to water shortage under current and future water supply-demand conditions across U.SRiver Basins. Earth's Future 9 (10). https://doi.org/10.1029/2021EF002278.

Heidari, H., Arabi, M., Warziniack, T., Kao, S.C., 2021. Shifts in hydroclimatology of us megaregions in response to climate change. Environmental researchCommunications 3 (6). https://doi.org/10.1088/2515-7620/ac0617.

Hering, J.G., Waite, T.D., Luthy, R.G., Drewes, J.E., Sedlak, D.L., 2013. A changing framework for urban water systems. Environ. Sci. Technol. 47 (19), 10721–10726. https://doi.org/10.1021/es4007096.

Herman, J., Usher, W., 2017. SALib : An open-source Python library for Sensitivity Analysis. J. Open Source Softw. 2 (9), 97. https://doi.org/10.21105/joss.00097.

Herrera, P.A., Marazuela, M.A., Hofmann, T., 2022. Parameter estimation and uncertainty analysis in hydrological modeling. Wiley Interdiscip. Rev. Water 9 (1), 1–23. https://doi.org/10.1002/wat2.1569.

Hyndman, Rob J., Khandakar, Yeasmin, 2008. Automatic time series forecasting: the forecast package for R. J. Stat. Softw. 27 (3), 22. http://www.jstatsoft.org/%0Ahttp://www.jstatsoft.org/v27/i03/paper.

Iglesias, A., Garrote, L., 2015. Adaptation strategies for agricultural water management under climate change in Europe. Agric. Water Manag. 155, 113–124. https://doi.org/10.1016/j.agwat.2015.03.014.

Iwanaga, T., Usher, W., Herman, J., 2022. Toward SALib 2.0: advancing the accessibility and interpretability of global sensitivity analyses. Socio-Environ. Syst. Model. 4, 18155. https://doi.org/10.18174/sesmo.18155.

Jaeger, W.K., Amos, A., Bigelow, D.P., Chang, H., Conklin, D.R., Haggerty, R., Langpap, C., Moore, K., Mote, P.W., Nolin, A.W., Plantinga, A.J., Schwartz, C.L., Tullos, D., Turner, D.P., 2017. Finding water scarcity amid abundance using human–natural system models. Proceedings of the National Academy of Sciences of the United States of America 114.

Joyce, L.A., Coulson, D., 2020. Climate scenarios and projections: a technical document supporting the USDA Forest Service 2020 RPA assessment. Gen. Tech. Rep. RMRS-GTR-413. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO https://doi.org/10.2737/RMRS-GTR-413 85 p. https://. In USDA Forest Service - General Technical Report RMRS-GTR (Vol. 2020, Issue 413).

Khanmohammadi, S., Kizilkan, O., Musharavati, F., 2021. Multiobjective optimization of a geothermal power plant. Thermodynamic Analysis and Optimization of Geothermal Power Plants. Elsevier Inc https://doi.org/10.1016/B978-0-12-821037-6.00011-1.

Kim, D., Eum, H.Il, Kaluarachchi, J.J., Chun, J.A., 2019. A sensitivity-based analysis for managing storage capacity of a small agricultural reservoir under drying climate. Agric. Water Manag. 213 (November 2018), 410–418. https://doi.org/10.1016/j.agwat.2018.10.040.

Knoben, W.J.M., Freer, J.E., Woods, R.A., 2019. Technical note: inherent benchmark or not? Comparing Nash-sutcliffe and kling-gupta efficiency scores. Hydrol. Earth Syst. Sci. 23 (10), 4323–4331. https://doi.org/10.5194/hess-23-4323-2019.

Leng, G., Huang, M., Voisin, N., Zhang, X., Asrar, G.R., Leung, L.R., 2016. Emergence of new hydrologic regimes of surface water resources in the conterminous United States under future warming. Environ. Res. Lett. 11 (11). https://doi.org/10.1088/1748-9326/11/11/114003.

Liang, X., Lettenmaier, D.P., Wood, E.F., Burges, S.J., 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. J. Geophys. Res. 99 (D7). https://doi.org/10.1029/94jd00483.

Lukas, J., Barsugli, J., Doesken, N., Rangwala, I., Wolter, K., 2014. Climate change in Colorado: A synthesis to support water resources management and adaptation. A Report for the Colorado Water Conservation Board, 2nd ed. Western Water Assessment, Cooperative Institute for Research in Environmental Sciences, University of. In University of Colorado Boulder https://dnrftp.state.co.us/#/CWCB/Technical Update to Water Plan/1. Technical Update Documentation/.

Ma, X.(Cissy), Xue, X., González-Mejía, A., Garland, J., Cashdollar, J., 2015. Sustainable water systems for the city of tomorrow-a conceptual framework. Sustainability (Switzerland) 7 (9), 12071–12105. https://doi.org/10.3390/su70912071.

Martinsen, G., Liu, S., Mo, X., Bauer-Gottwein, P., 2019. Joint optimization of water allocation and water quality management in Haihe River basin. Sci. Total Environ. 654, 72–84. https://doi.org/10.1016/j.scitotenv.2018.11.036.

Mekonnen, M.M., Hoekstra, A.Y., 2016. Four billion people facing severe water scarcity. Science Advances 2 (2). https://doi.org/10.1126/sciadv.1500323 e1500323–e1500323.

Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P.C., Ebisuzaki, W., Jović, D., Woollen, J., Rogers, E., Berbery, E.H., Ek, M.B., Fan, Y., Grumbine, R., Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., Shi, W., 2006. North american regional reanalysis. Bull. Am. Meteorol. Soc. 87 (3), 343–360. https://doi.org/10.1175/BAMS-87-3-343.

Momblanch, A., Papadimitriou, L., Jain, S.K., Kulkarni, A., Ojha, C.S.P., Adeloye, A.J., Holman, I.P., 2019. Untangling the water-food-energy-environment nexus for global change adaptation in a complex Himalayan water resource system. Sci. Total Environ. 655, 35–47. https://doi.org/10.1016/j.scitotenv.2018.11.045.

Moriasi, D.N., Gitau, M.W., Pai, N., Daggupati, P., 2015. Hydrologic and water quality models: performance measures and evaluation criteria. Trans. ASABE 58 (6), 1763–1785. https://doi.org/10.13031/trans.58.10715.

Muratoglu, A., Iraz, E., Ercin, E., 2022. Water resources management of large hydrological basins in semi-arid regions: spatial and temporal variability of water footprint of the upper Euphrates River basin. Sci. Total Environ. 846 (April), 157396. https://doi.org/10.1016/j.scitotenv.2022.157396.

Naz, B.S., Kao, S.C., Ashfaq, M., Rastogi, D., Mei, R., Bowling, L.C., 2016. Regional hydrologic response to climate change in the conterminous United States using high-resolution hydroclimate simulations. Glob. Planet. Chang. 143, 100–117. https://doi.org/10.1016/j.gloplacha.2016.06.003.

Neale, M.R., Sharvelle, S., Arabi, M., Dozier, A., Goemans, C., 2020. Assessing tradeoffs of strategies for urban water conservation and fit for purpose water. J. Hydrol. X 8 (June), 100059. https://doi.org/10.1016/j.hydroa.2020.100059.

NOAA, 2021. Climate at a Glance: Statewide Mapping. retrieved on August, 2021NOAA National Centers for Environmental Information. https://www.ncdc.noaa.gov/cag/statewide/.

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M., Hoekstra, A.Y., 2019. Water scarcity alleviation through water footprint reduction in agriculture: the effect of soil mulching and drip irrigation. Sci. Total Environ. 653, 241–252. https://doi.org/10.1016/j.scitotenv.2018.10.311.

Ogle, S.M., Jay Breidt, F., Easter, M., Williams, S., Killian, K., Paustian, K., 2010. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Glob. Chang. Biol. 16 (2), 810–822. https://doi.org/10.1111/j.1365-2486.2009.01951.x.

Oubeidillah, A.A., Kao, S.C., Ashfaq, M., Naz, B.S., Tootle, G., 2014. A large-scale, high-resolution hydrological model parameter data set for climate change impact assessment for the conterminous US. Hydrol. Earth Syst. Sci. 18 (1), 67–84. https://doi.org/10.5194/hess-18-67-2014.

Parton, W.J., Hartman, M., Ojima, D., Schimel, D., 1998. Daycent Description and Testing, pp. 35–48.

Paterson, W., Rushforth, R., Ruddell, B.L., Konar, M., Ahams, I.C., Gironás, J., Mijic, A., Mejia, A., 2015. Water footprint of cities: a review and suggestions for future research. Sustainability (Switzerland) 7 (7), 8461–8490. https://doi.org/10.3390/su7078461.

Qin, Y., Abatzoglou, J.T., Siebert, S., Huning, L.S., AghaKouchak, A., Mankin, J.S., Hong, C., Tong, D., Davis, S.J., Mueller, N.D., 2020. Agricultural risks from changing snowmelt. Nat. Clim. Chang. 10 (5), 459–465. https://doi.org/10.1038/s41558-020-0746-8.

Renard, B., Kavetski, D., Kuczera, G., Thyer, M., Franks, S.W., 2010. Understanding predictive uncertainty in hydrologic modeling: the challenge of identifying input and structural errors. Water Resour. Res. 46 (5), 1–22. https://doi.org/10.1029/2009WR008328.

Richter, B.D., Abell, D., Bacha, E., Brauman, K., Calos, S., Cohn, A., Disla, C., O'Brien, S.F., Hodges, D., Kaiser, S., Loughran, M., Mestre, C., Reardon, M., Siegfried, E., 2013. Tapped out: how can cities secure their water future? Water Policy 15 (3), 335–363. https://doi.org/10.2166/wp.2013.105.

Robertson, A.D., Zhang, Y., Sherrod, L.A., Rosenzweig, S.T., Ma, L., Ahuja, L., Schipanski, M.E., 2018. Climate change impacts on yields and soil carbon in row crop dryland agriculture. J. Environ. Qual. 47 (4), 684–694. https://doi.org/10.2134/jeq2017.08.0309.

Rosegrant, M.W., Ringler, C., 2000. Impact on food security and rural development of transferring water out of agriculture. Water Policy 1 (6), 567–586. https://doi.org/10.1016/S1366-7017(99)00018-5.

Roy, S.B., Chen, L., Girvetz, E.H., Maurer, E.P., Mills, W.B., Grieb, T.M., 2012. Projecting water withdrawal and supply for future decades in the U.S. Under climate change scenarios. Environ. Sci. Technol. 46 (5), 2545–2556. https://doi.org/10.1021/es2030774.

Sharvelle, S., Dozier, A., Arabi, M., Reichel, B., 2017. A geospatially-enabled web tool for urban water demand forecasting and assessment of alternative urban water management strategies. Environ. Model. Softw. 97, 213–228. https://doi.org/10.1016/j.envsoft.2017.08.009.

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., Xu, C., 2015. Global sensitivity analysis in hydrological modeling: review of concepts, methods, theoretical framework, and applications. J. Hydrol. 523 (225), 739–757. https://doi.org/10.1016/j.jhydrol.2015.02.013.

State of Colorado, State of Nebraska, 1923. Article 65: South Platte River Compact.

Stehfest, E., Heistermann, M., Priess, J.A., Ojima, D.S., Alcamo, J., 2007. Simulation of global crop production with the ecosystem model DayCent. Ecol. Model. 209 (2–4), 203–219. https://doi.org/10.1016/j.ecolmodel.2007.06.028.

Strzepek, K., Yohe, G., Neumann, J., Boehlert, B., 2010. Characterizing changes in drought risk for the United States from climate change. Environ. Res. Lett. 5 (4). https://doi.org/10.1088/1748-9326/5/4/044012.

Thornton, P., Dinesh, D., Cramer, L., Loboguerrero, A.M., Campbell, B., 2018. Agriculture in a changing climate: keeping our cool in the face of the hothouse. Outlook Agric. 47 (4), 283–290. https://doi.org/10.1177/0030727018815332.

Thornton, P.E., Running, S.W., White, M.A., 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. J. Hydrol. 190 (3–4), 214–251. https://doi.org/10.1016/S0022-1694(96)03128-9.

United States Census Bureau, 2020. COLORADO: 2020 Census. . https://www.census.gov/library/stories/state-by-state/colorado-population-change-between-census-decade.html.

Warziniack, T., Brown, T.C., 2019. The importance of municipal and agricultural demands in future water shortages in the United States. Environ. Res. Lett. 14 (8). https://doi.org/10.1088/1748-9326/ab2b76.

Warziniack, T., Arabi, M., Brown, T.C., Froemke, P., Ghosh, R., Rasmussen, S., Swartzentruber, R., 2022. Projections of freshwater use in the United States under climate change. Earth'sFuture 10 (2). https://doi.org/10.1029/2021EF002222.

Wehner, M.F., Arnold, J.R., Knutson, T., Kunkel, K.E., LeGrande, A.N., 2017. Ch. 8: Droughts, Floods, and Wildfires. Climate Science Special Report: Fourth National Climate Assessment, Volume I. Climate Science Special Report: Fourth National Climate Assessment. Volume I, pp. 231–256. https://doi.org/10.7930/J0CJ8BNN.U.S I.

Yates, D., Sieber, J., Purkey, D., Huber-Lee, A., 2005. WEAP21 - a demand-, priority-, and preference-driven water planning model. Part 1: model characteristics. Water Int. 30 (4), 487–500. https://doi.org/10.1080/02508060508691893.

Yigzaw, W., Hossain, F., 2016. Water sustainability of large cities in the United States from the perspectives of population increase, anthropogenic activities, and climate change. Earth's Future 4 (12), 603–617. https://doi.org/10.1002/2016EF000393.

Zhang, Y., Gurung, R., Marx, E., Williams, S., Ogle, S.M., Paustian, K., 2020. DayCent model predictions of NPP and grain yields for agricultural lands in the contiguous U.S. Journal of geophysical researchBiogeosciences 125 (7), 1–15. https://doi.org/10.1029/2020JG005750.