Assessing the Effects of Climate Change on Middle Rio Grande Surface Water Supplies Using a Simple Water Balance Reservoir Model

ROBYN N. HOLMES,a ALEX MAYER,b DAVID S. GUTZLER,c AND LUIS GARNICA CHAVIRA

a Michigan Technological University, Houghton, Michigan
b University of Texas at El Paso, El Paso, Texas
c University of New Mexico, Albuquerque, New Mexico

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ABSTRACT: The middle Rio Grande is a vital source of water for irrigation in the region. Climate change is impacting regional hydrology and is likely to put additional stress on a water supply that is already stretched thin. To gain insight on the hydrologic effects of climate change on reservoir storage, a simple water balance model was used to simulate the Elephant Butte–Caballo Reservoir system (southern New Mexico). The water balance model was forced by hydrologic inputs generated by 97 climate simulations derived from CMIP5 global climate models, coupled to a surface hydrologic model. Results suggest that the percentage of years that reservoir releases satisfy agricultural water rights allocations over the next 50 years (2021–70) will decrease relative to the past 50 years (1971–2020). The modeling also projects an increase in multiyear drought events that hinder reservoir management strategies to maintain high storage levels. In most cases, changes in reservoir inflows from distant upstream snowmelt is projected to have a greater influence on reservoir storage and water availability downstream of the reservoirs than will changes in local evaporation and precipitation from the reservoir surfaces.

KEYWORDS: Watersheds; Climate change; Water budget/balance; Hydrologic models

1. Introduction

In the southwestern United States, climate change is contributing to a growing risk of water shortage (Garfin et al. 2018; Hicke et al. 2022; Williams et al. 2022). The Rio Grande basin is emblematic of this already water-scarce region. As the primary source of surface water for the basin, decreases in streamflows in the Rio Grande are having major effects on water users, primarily agricultural irrigators that depend on the resource (Hurd and Coonrod 2012). With current water resources already completely allocated to holders of legal water rights and inadequate water available to support in-stream flows to maintain natural habitats, additional reductions in water supply availability in the basin will provide significant challenges for water managers (Llewellyn et al. 2013).

The majority of the flow in the upper Rio Grande originates as snowmelt runoff from the Rocky Mountains in southern Colorado and northern New Mexico (Rango 2006). Historical data indicate that peak snow water equivalent in the headwaters decreased about 25% between 1958 and 2015 (Chavarria and Gutzler 2018). Future projections in the upper Rio Grande basin indicate the volume of snowmelt runoff decreases by 18% or more by the end of the twenty-first century (Elias et al. 2015). Dettlinger et al. (2015) compared several large, snowmelt-driven basins in the western United States and found that climate change is expected to have the greatest impact on Rio Grande flows, with the largest decreases in flows expected in the upper Rio Grande basin.

As the largest surface water user in the region, agriculture is expected to be hardest hit by climate-related declines in water availability. A hydroeconomic model of the middle Rio Grande projected that by the 2030s, regional economic losses due to changes in water availability will range from $15 million to $114 million yr$^{-1}$ across water use sectors, depending on climate and crop pattern scenarios, with the potential for up to $302 million yr$^{-1}$ in 2080 (Hurd and Coonrod 2012).

Modeling water systems under future climate change scenarios is a common approach to better understand how climate change will affect hydrologic systems (Shepherd et al. 2018). Climate change scenarios make assumptions about the future to explore possible outcomes associated with unknown but plausible climate futures. Global climate models (GCMs) provide projections of climatic parameters such as temperature, wind speed, and rainfall based on future climate forcing scenarios. However, they do not directly model surface hydrology, which requires an additional step. Calibrated hydrologic models (i.e., SWAT, Arnold et al. 1998; variable infiltration capacity (VIC), Liang et al. 1994) are forced with inputs derived from GCM-derived climate scenarios (Krysanova et al. 2017).

Most such studies use projections from GCMs forced by prescribed greenhouse gas scenarios developed by the Coupled Model Intercomparison Project (CMIP). The standardization of some aspects of GCMs, such as output formatting, facilitates ensemble analysis from multiple GCMs to probe modeling uncertainties. Since GCMs are run at a global scale,
projections are output on a coarse horizontal grid (typically on the order of 1° latitude and longitude for CMIP5, the generation of CMIP simulations used in our study) and contain regional biases. Projections must undergo spatial downscaling and, typically, regional-scale bias correction before variables can be used as climate inputs to hydrologic models (Chen et al. 2021).

Snowmelt-fed water systems in the western United States depend on large reservoirs to store water during peak runoff season then release water during irrigation seasons. Large reservoirs also increase the reliability of surface water supplies against year-to-year variations in runoff by storing water year to year. A significant concern for storage reservoirs in all semiarid regions is that the warming climate will drive increased evaporative losses (Friedrich et al. 2018). Zhu et al. (2005) projected the impacts of climate change on California’s reservoir storage system with simple water balance models and found that the average volume of reservoir evaporation could increase between 4% and 41% over a 72-yr period. They used a linear regression of historical monthly evaporation rates against local air temperature to estimate future reservoir evaporation. Helfer et al. (2012) projected climate change impacts on a large water supply reservoir in southeast Australia with a lake circulation model and an energy-mass transfer evaporation model. They projected increases in annual evaporation of 8% and 15% for near-term (2030–50) and longer-term future periods (2050–70), respectively; warming air temperature was the primary driver of increased evaporation. Huntington et al. (2015) projected evaporation from 12 reservoirs in the western United States from 2010 to 2099, using an energy-balance-based evaporation model. Increases in projected annual evaporation rates ranged from 5 to 15.2 cm (2–6 in.) by 2080. Maestre-Valero et al. (2013) projected that reservoir evaporation rates will increase by 8% in the semiarid Segura basin (Spain) by 2060 using a temperature-based model to estimate future evaporation rates.

In the Colorado River basin, Barnett and Pierce (2008, 2009) used a water balance model to make probabilistic estimates of Lake Mead and Lake Powell reaching minimum power pool elevation under future scenarios. They found the system to currently have less inflows and outflows, a situation that will increase in severity with warming temperatures. McCabe and Wolock (2007) used tree ring reconstructions to form synthetic streamflow series under two warming scenarios. Results showed warming temperatures would increase the failure rate of reservoir releases meeting the Colorado Compact. Christensen et al. (2004) simulated the upper Colorado River basin with a hydrologic model coupled with a reservoir operating model under three climate change projections for 2085. Their results indicated that, while evaporation rates are projected to increase, lower average reservoir storage levels (and thus smaller surface areas) limited the corresponding increases in the volume lost to evaporation.

In the present work, we focus on climate change impacts on surface water availability from Elephant Butte and Caballo Reservoirs in southern New Mexico, the primary storage reservoirs for water users in southern New Mexico, far west Texas, and the Valle de Juárez in northern Chihuahua, Mexico. The U.S. Department of the Interior, Bureau of Reclamation’s (herein, “Reclamation”) West-Wide Climate Risk Assessment has generated projections of naturalized streamflow (no human interference) along the Rio Grande using the VIC hydrologic routing model, forced by bias-adjusted CMIP5 GCM output (Brekke et al. 2013; Lewellyn et al. 2013; Brekke et al. 2014). Townsend and Gutzler (2020) further adjusted Reclamation’s streamflow projections to account for anthropogenic withdrawals (over 50%) upstream of the San Marcial gauge, representing the inflow to Elephant Butte Reservoir (Fig. 1). These studies have demonstrated the upper Rio Grande’s dependence on snowmelt in the mountainous headwaters region, documented changes in snowpack under warming temperatures, and produced both naturalized and diversion-normalized streamflow upstream of Elephant Butte Reservoir.

This paper builds on these prior investigations to examine how releases from the Elephant Butte–Caballo Reservoir system are projected to be impacted by climate change, using a reservoir water balance model to make release projections driven by Reclamation’s climate simulations. The reservoir model accounts for streamflow, reservoir surface fluxes (especially evaporation), and local runoff, allowing the comparative examination of the effects of climate change on water availability locally and in the headwaters region. The model explicitly includes the current prescribed reservoir operating rules to address the following questions: 1) How will reliability of downstream surface water supplies be affected by projected climate change? 2) How resilient is the current reservoir management algorithm (which determines annual outflow from the reservoir system) to projected climate change? 3) How will changes in local temperatures, which should lead to higher evaporative losses from the reservoirs, compare with climate change impacts on upstream snow-fed flows? Answers

![FIG. 1. Map of the study area in southern New Mexico. The Rio Grande flows from north to south through the study area.](image-url)
to these questions will increase our understanding of how the reservoir storage and releases are affected by climate change, with direct implications for ongoing water management planning and decision making.

2. Data and modeling method

a. Middle Rio Grande Valley, New Mexico

Elephant Butte and Caballo Reservoirs are located in southern New Mexico along the Rio Grande (Fig. 1). These jointly managed reservoirs store water and control releases allocated to 85,000 ha (211,000 acres) of irrigated agriculture and a portion of the water supply for El Paso, Texas (population of approximately 700,000). Elephant Butte Reservoir has a storage capacity of 2498 million cubic meters (MCM) [2025 thousands of acre-feet (kaf)] and is used primarily to store seasonal snowmeltwater originating in the Rio Grande–Rio Bravo headwaters, to be released during the summer irrigation season (Ferrari 2008b). Water released from Elephant Butte Reservoir flows 28 km (17 mi) downstream (south) to Caballo Reservoir, which has a much smaller capacity of 401 MCM (325 kaf) and is used to adjust the timing and volume of deliveries to downstream users (Ferrari 2008a).

Each reservoir has a distinct contributing local subwatershed (see Fig. 1). Average annual precipitation in the two subwatersheds is 31.1 cm (12.2 in.). The region nearby the reservoirs receives around 25 cm (10 in.) of precipitation per year, while the evaporation rate from surface water often exceeds 1.2 m (4 ft) per year (Llewellyn et al. 2013). Evaporative losses from Elephant Butte Reservoir have been estimated to range between 8% and 20% of the volume of water released from the reservoir (Eichinger et al. 2003).

Releases from Elephant Butte and Caballo Reservoirs to downstream water rights holders in Texas and New Mexico in the United States and Chihuahua state in Mexico, are governed by operating agreements that stem from the Rio Grande Compact between Colorado, Texas, and New Mexico and the Rio Grande Treaty between the United States and Mexico. The operating agreement details how available water is distributed annually among water rights holders based on storage in the reservoirs before each year’s irrigation season and the amount of reservoir inflow during the prior year. When sufficient water is available in storage, downstream users receive their full allocation of water rights (974 MCM or 790 kaf), referred to hereinafter as “full allocation.” In dry years, water allocations are reduced proportionally for all users. The quantitative prescription of the operating agreement is described below in section 2g, following the description of our water balance formulation of the reservoir system.

b. Water mass balance model

Elephant Butte and Caballo Reservoir storage are combined into a single storage volume $S$, since Caballo Reservoir storage volume is relatively small, and Elephant Butte and Caballo Reservoir releases are similar in magnitude and timing averaged over yearly time periods. The primary metric whose year-to-year time evolution is the focus of this study is reservoir storage $S$. A simple water balance model is used to calculate annual changes in $S$ (see Fig. 2):

$$\frac{dS}{dt} = Q_{in} + P - E + RO - Q_{out},$$

where $Q_{in}$ is the volume of Rio Grande streamflow into the combined reservoir system, $P$ is the volume of direct precipitation onto the combined reservoirs’ surfaces, $E$ is the volume of water that evaporates from the combined reservoirs’ surfaces, $RO$ is runoff from the subwatersheds surrounding the two reservoirs, and $Q_{out}$ is the volume of water released downstream from the combined reservoirs. All terms are annual averages, that is, Eq. (1) is solved for current storage with a forward (implicit) finite-difference approximation with annual time steps. Groundwater seepage into or out of the reservoirs is assumed to be negligible. Equation (1) is solved iteratively at each time step, since the terms $P$, $E$, and $Q_{out}$ in Eq. (1) depend on reservoir storage.

Volumetric precipitation and evaporation are calculated by multiplying respective rates by the total surface area for the two reservoirs. Reservoir surface areas $SA$ for each reservoir are simulated with a fourth-order polynomial regression between surface area and volume for each reservoir, based on hypsometric data from 2007 (Ferrari 2008a,b):

$$SA = a_0 + a_1S + a_2S^2 + a_3S^3 + a_4S^4.$$

Coefficients $a_0$, $a_1$, $a_2$, $a_3$, and $a_4$ are fitted to the hypsometric data (see Table S2 in the online supplemental material).

c. Climate model projections of reservoir inflows

The inflow, term $Q_{in}$ in Eq. (1), is the streamflow in the Rio Grande–Rio Bravo at the influent to Elephant Butte Reservoir, where there are gauges with historical streamflow data (USGS 08358400 Rio Grande Floodway at San Marcial, New Mexico, and USGS 08358300 Rio Grande Conveyance Channel at San Marcial). The two gauges are located on parallel channels leading to Elephant Butte Reservoir.

Reclamation prepared simulations from 1950 to 2099 of naturalized streamflows along the Rio Grande–Rio Bravo driven by CMIP5 output. CMIP5 specifies future scenarios through four representative concentration pathways (RCPs): RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The number associated with each RCP denotes the increase in radiative forcing of the surface in the year 2100 associated with additional
atmospheric greenhouse gas concentrations (van Vuuren et al. 2011).

Monthly averages of CMIP5 output fields were adjusted by Reclamation using the bias correction, spatial disaggregation (BCSD) method that generates monthly projections of atmospheric variables at a 1/8° resolution (Brekke et al. 2013). This output was coupled by Reclamation to the VIC hydrologic model (Brekke et al. 2014) to derive surface hydrology and routed streamflow projections. The BCSD-projected streamflows used in this study were obtained from the “Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections” archive (https://gdo-dcp.ucar.edu/downscaled_cmip_projections/dcpInterface.html). All available BCSD CMIP5 projections with “r1i1p1” initial conditions were used, giving a total of 97 streamflow projections generated from 31 different GCMs. See Table S1 in the online supplemental material for a list of the 31 models.

The BCSD streamflow projections are simulated under naturalized conditions and thus do not account for the human retention and diversion of water from the Rio Grande that occurs upstream of our study area. Therefore, the BCSD projections need to be modified to simulate realistic inflow volumes past San Marcial into Elephant Butte Reservoir. Townsend and Gutzler (2020) developed and applied a statistical normalization procedure to account for human impacts upstream of Elephant Butte Reservoir. The resulting “normalized streamflow” time series were used in our study as the projected annual streamflow into Elephant Butte Reservoir.

d. Direct and local watershed precipitation

Local precipitation time series were constructed for the Elephant Butte and Caballo subwatersheds, using the same 97 CMIP5 projections used for the inflow projections. Monthly, 1/8° gridded BCSD CMIP5-projected precipitation rates (available at https://gdo-dcp.ucar.edu/downscaled_cmip_projections/dcpInterface.html) were spatially averaged over each subwatershed to obtain annual time series for precipitation that falls directly onto the reservoir water surface and “local” precipitation onto the Elephant Butte and Caballo subwatersheds.

e. Evaporation

Projections of future reservoir evaporation rates can be estimated with available climate parameters from downscaled GCMs, but the reliability and availability of GCM-simulated variables can limit the options for the mathematical forms used to estimate evaporation. Temperature-based evaporation rate methods neglect known factors that influence evaporation rates such as solar radiation, humidity, wind speed, and water temperature, but many investigations have found calibrated temperature-based models to be adequate for estimating evaporation when additional data are unavailable. (Xu and Singh 2001; Zhu et al. 2005; Maestre-Valero et al. 2013; Huntington et al. 2015; Majidi et al. 2015).

We used a simple, temperature-based evaporation model to project future reservoir evaporation rates. This approach was chosen over more complex, energy-based methods of evaporation modeling because of the lack of solar radiation projections in the BCSD CMIP5 dataset. The relationship between temperature and reservoir evaporation rate was established through a linear regression of reservoir evaporation rates as a function of anomalies in local temperature:

\[ E = \bar{E} + b_0(T - \bar{T}) + b_1, \]

where \( E \) is surface water evaporation depth, \( \bar{E} \) is the average annual evaporation depth over the period of the dataset, \( b_0 \) and \( b_1 \) are fitted coefficients, \( T \) is local temperature, and \( \bar{T} \) is the average local temperature over the period of the dataset.

The coefficients in Eq. (3) were fitted using a time series of synthetic, projected annual evaporation depths for Elephant Butte Reservoir (Huntington et al. 2015). The synthetic evaporation depths were estimated with a calibrated reservoir evaporation model based on the Complementary Relationship of Lake Evaporation (CRLE), an energy-based model that has been used widely to estimate reservoir evaporation in the southwest United States (Friedrich et al. 2018). Huntington et al. (2015) used a CRLE model calibrated for Elephant Butte Reservoir to simulate reservoir evaporation depth time series over the period 2010–99, using forcings from 112 CMIP3 climate projections (CMIP3 is the generation of CMIP simulations preceding the CMIP5 simulations that we use in this study).

The fitted coefficients in Eq. (3) were derived from the ensemble of the 112 projections of annual reservoir evaporation depth and corresponding annual subwatershed-averaged temperature over the period 2021–70. We note that evaporation rates are much greater in the hot summer months, so the annual time step employed in our water balance model limits the precision of the parameterized temperature-evaporation relationship in Eq. (3).

The parameters and fit statistics are as follows: \( b_0 = 31.9 \pm 0.3 \text{ mm yr}^{-1} \text{ C}^{-1}; b_1 = -1.30 \pm 0.67 \text{ mm yr}^{-1}; R^2 = 0.76 \), where the values of the coefficients are given as best estimate ± standard error. We note that we did not use the projections of reservoir evaporation directly from Huntington et al. (2015) because we wanted to avoid mixing results from CMIP3 and CMIP5 driven simulations. The projected, local temperature time series [term \( T \) in Eq. (3)] were constructed by spatially averaging monthly 1/8° gridded 97 BCSD CMIP5 simulated values across the Elephant Butte and Caballo subwatersheds. Figure 3 shows the evaporation rates fitted to the regression model against the CRLE generated values. The slope, intercept, and \( R^2 \) for the linear fit in Fig. 3 are 1.001, 2.30, and 0.997, respectively, indicating that the regression model successfully fits the CRLE results, extending the range of temperatures through the projected warmer decades of the twenty-first century and providing some post hoc justification for using annually averaged climate variables in Eq. (3). In general, the linear fit is justified, but it is worth noting that the fit underestimates reservoir evaporation at the high end of evaporation rates (\( E > 1500 \text{ mm yr}^{-1} \)), which suggests that evaporative losses might be underestimated under conditions of extreme warming late in the study period.
f. Runoff

Annual runoff RO from the two subwatersheds into the reservoirs is calculated as a fraction of the precipitation that falls on the Elephant Butte and Caballo subwatersheds using

\[ RO = cpA, \]  

where \( c \) is a fitted constant, \( p \) is the annual precipitation depth averaged over a given subwatershed, and \( A \) is subwatershed area. Equation (3) was calibrated by running the water balance model over the period 1993–2014 with historical inflow, releases, precipitation, and evaporation time series as inputs to produce predicted annual reservoir storage. The constant \( c \) was estimated by minimizing the sum of the squares of the residuals between the predicted and actual reservoir storage.

g. Releases from Caballo Reservoir

Targeted annual reservoir releases from the outlet of Caballo Reservoir (Fig. 1), \( Q_{\text{out}} \), are based on an equation that closely approximates reservoir operations according to the 2008 Rio Grande Project Operating Agreement [Ward et al. (2019), developed in units of acre feet]:

\[ Q_{\text{out}} = \min(d_0, d_1 Q_{\text{in}} + d_2 S^{-1}), \]  

where constants \( d_0 = 875 \text{ kaf yr}^{-1} \), \( d_1 = 0.567 \) 08 for units of \( Q_{\text{in}} \) in thousands of acre feet per year, and \( d_2 = 0.46873 \) for units of \( S \) in thousands of acre feet; \( Q_{\text{in}} \) is the current year inflow to the reservoirs; and \( S^{-1} \) is the combined reservoir storage in the previous year. The reservoir release rule is illustrated schematically in Fig. 4. The release, \( Q_{\text{out}} \), is referred to as “targeted” because when reservoir storage is too low to fulfill the “targeted” release, as defined in Eq. (5), only the water that can be released to keep the reservoir at its minimum storage is released. If the reservoir is too full, additional water over the targeted value estimated by Eq. (5) is released to keep the reservoir from exceeding its maximum storage (2450 MCM or 1990 kaf).

3. Water supply resilience in the middle Rio Grande basin

a. Projected reservoir water balance

The annual contributions to the water balance in Eq. (1) and represented schematically in Fig. 2, averaged over the entire projection period (Fig. 5), exhibit several characteristics typical of large storage reservoirs located in arid regions. Streamflow in \( (Q_{\text{in}}) \) and outflow (releases, \( Q_{\text{out}} \)) are by far the largest terms, with releases less than inflows due to evaporative losses during storage. Evaporation is more than 13% of release volume, indicative of substantial water loss. Reservoir inflows from runoff and direct precipitation are small relative to losses from evaporation. The huge disparity between evaporation and direct precipitation (about a factor of 5) illustrates why the reservoir water balance is potentially so sensitive to increases in evaporation associated with warmer temperature in a changing climate (Fig. 3).

Figure 6 summarizes the projected changes of annual precipitation, mean temperature, and reservoir inflows \( (Q_{\text{in}}) \), which are local climatic controls of net reservoir recharge. The projections are summarized by comparing distributions across all available CMIP5 simulations for historical and future 50-yr averaging periods: 1971–2020 and 2021–70. Median local precipitation decreases slightly by 2.0 mm yr\(^{-1}\) (0.079 in. yr\(^{-1}\)), a change that is not significantly different from zero (\( p \) value for single-tail test = 0.20). The spread of the distribution of local annual precipitation change is very large for the future period, as has been found in many previous assessments of CMIP5-projected
climate change in southwestern North America (Garfin et al. 2018).

All simulations project increased local annual average temperatures, with median temperature increasing from 12.3 to 14.0°C (Fig. 6b), which is significant with a $p$ value for single-tail test < 0.001. The most extreme future simulation projects an average 2021–70 temperature of 15.4°C (upper whisker in Fig. 6b), a half-century increase of more than 3°C over the historical period. It is clear from Fig. 6 that increasing temperature is a much more robust and confident projection than any corresponding change in local precipitation or river inflow to the reservoir.

Median reservoir inflow is projected to decline by 12%, from 1018 MCM yr$^{-1}$ (827 kaf yr$^{-1}$) to 898 MCM yr$^{-1}$ (728 kaf yr$^{-1}$) (Fig. 6c; $p$ value for single-tail test = 0.005). As with precipitation, there is an especially wide spread of projected inflows among the simulations. However, the distribution is skewed toward lower reservoir inflows, with the extreme low inflow projection,

![Figure 5](image)

**Fig. 5.** Relative magnitudes of inflow and outflow terms in the water balance [Eq. (1)] averaged across all projections over the period 1971–2070.

![Figure 6](image)

**Fig. 6.** Box-and-whisker plots of the distributions across the climate simulations of annual average (a) precipitation, (b) temperature, and (c) streamflow into the reservoir, averaged over two periods: 1971–2020 (green) and 2021–70 (light blue). Colored boxes cover the 25th–75th percentile, with the center line being the median. Whiskers have a maximum length of 1.5 times the interquartile range. Values outside the whiskers are plotted as dots.
481 MCM yr\(^{-1}\) (390 kaf yr\(^{-1}\); see lower whisker in Fig. 6c), indicating a decrease of more than 50% from the median inflow over the historical period, 1018 MCM yr\(^{-1}\) (827 kaf yr\(^{-1}\)). The projected trend toward more frequent low inflow years poses a critical challenge for water management associated with Elephant Butte Reservoir.

The distributions of projected future precipitation and inflow (Figs. 6a,c) span a huge range; simulated changes do not agree even on the sign of projected change, unlike the temperature projections in Fig. 6b. This high level of uncertainty is mostly derived from tremendous regional variability from one climate model to another in simulations of future precipitation across southwestern North America (Garfi

b. Resilience of the water supply from the Elephant Butte Reservoir system

An important metric for assessing the impacts of these climate changes on water management is the probability that water users will not receive a full allocation under the operating agreement [Eq. (5)]. Results are presented as the fraction of projections (of 97 total) indicating ranges of levels of failure (releases less than a given fraction of full allocation) each year (Fig. 7). The 50% and 25% levels of failure indicate moderate and severe drought conditions, respectively. For comparison, 27% of full allocation was released from the reservoirs during a recent severe drought (2012–13). The frequency of each failure level increases with time (Fig. 7), with the most severe failure level not appearing until after 2020. In the future period, on average, 59%, 22%, and 2% of the projections indicate failure to provide 100%, 50%, and 25% of full allocation, respectively.

An alternative presentation of these results shows the fraction of years in which a given allocation level failed to be met, over the historical and future periods, for each individual simulation (Fig. 8). This plot shows the wide variation across the projections in terms of the fraction of years with failures in the future period. For 100% allocation, the extreme fractions of years with failure (measured by 1.5 times the high interquartile range) in the future period are 85%, 54%, and 4% at the 100%, 50%, and 25% of full allocation failure levels, respectively.

The failure to provide fractions of full allocation in consecutive years is presented in Fig. 9, with the maximum number of consecutive failure years within the 50-yr historical and future periods shown for each individual simulation and for the three failure levels. In the 1971–2020 period, the medians of the maximum consecutive years are 10, 3.5, and ≤1 years for the 100%, 50%, and 25% failure levels, respectively. The lengths of these consecutive shortage year streaks increase in the future, with maximum consecutive years of 14, 4.4, and ≤1 years for the 100%, 50%, and 25% failure levels, respectively. The shift toward longer consecutive periods below each failure threshold indicates it is likely that multiyear droughts will become longer and more common in the future. In the extreme, there outlier projections that predict at least 30, 10, and 2 or greater consecutive-year spells with less than 100%, 50%, and 25% of full allocation, respectively.

c. Climatic causes of diminished water supply

In Fig. 10, results are presented to assess the impact of projected climate change at the local, subwatershed scale relative
to projected impacts from upstream climate change that determine the reservoir inflows. The dashed lines in each panel of Fig. 10 indicate the median changes over the 97 projections. We reiterate here that inflows \( Q_{in} \) were reduced from the natural flows generated in the model simulations by imposing a prescribed relationship designed to mimic historical management associated with upstream withdrawals from the river (Townsend and Gutzler 2020). Their parameterization of withdrawals implicitly assumed no changes to the policies governing water management upstream.

As noted already in connection with Fig. 6, previous studies of both the Colorado (Udall and Overpeck 2017) and upper Rio Grande (Bjarke 2019) river systems have presented evidence that projections of increased streamflow (positive values along the \( y \) axes in Fig. 10) should be considered skeptically. Among the projections of negative streamflow change, decreases exceeding \( -200 \) MCM yr\(^{-1}\) represent long-term changes comparable to the worst multidecadal “megadroughts” in paleoclimatic reconstructions of upper Rio Grande flow (Meko et al. 2010; Gutzler 2013).

In Fig. 10a, local, subwatershed scale climate change impacts are measured by determining average annual net reservoir recharge \((P - E + RO)\). The results in Fig. 10 indicate, first, that potential changes in reservoir inflows are about an order of magnitude greater than changes in precipitation or runoff at the subwatershed scale. Median reservoir inflows are projected to decrease by 72.5 MCM (58.8 kaf yr\(^{-1}\)) between the historical and future periods, but this average change obscures a tremendous range of inflow changes among the individual projections. The net reservoir recharge is projected to change by a substantially smaller amount, with a median change of 5.6 MCM (4.5 kaf yr\(^{-1}\)), and, surprisingly, the change is positive. Since 96 of 97 projections predict that average decreases in reservoir inflow will not be offset by

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**Fig. 9.** As in Fig. 8, but showing the longest streak of consecutive years in which reservoir releases fall below threshold volumes (100%, 50%, and 25% of full allocation) during historical (1971–2020) and future (2021–70) time periods for each simulation. Note that boxes for 25% of full allocation are compressed.

**Fig. 10.** Change in average annual reservoir inflow between past (1971–2020) and future (2021–70) periods (\( y \) axis) plotted against (a) change in net reservoir recharge, where net reservoir recharge is the sum of direct precipitation, evaporation, and runoff from the Caballo and Elephant Butte subwatershed, (b) change in average annual local temperature, where local temperature is the projected temperature spatially averaged across the Elephant Butte and Caballo subwatersheds, and (c) change in annual average local precipitation, where local precipitation is the average annual precipitation over the Caballo and Elephant Butte subwatersheds. In (a), (b), and (c), each point represents an individual climate projection. Dashed lines show the median change over all projections for each axis.
increases in net reservoir recharge, most drought years upstream will be not compensated by wet years downstream.

Figure 10a indicates that roughly one-half of the simulations project increasing net reservoir recharge and that a strong, negative correlation seems to exist between change in reservoir inflow and change in net reservoir recharge. This result can be explained by the feedback between surface area and reservoir inflows. As reservoir inflows decline, surface area also decreases, described by Eq. (2). Thus, increases in the difference between reservoir evaporation and precipitation rates can be offset by decreases in reservoir surface area, resulting in positive changes in net reservoir recharge (which has volumetric units), as illustrated in Fig. 10a.

In Fig. 10b, the same changes in reservoir inflows are plotted against changes against local, subwatershed temperature between the historical and future periods. There is poor correlation between these two variables, indicating that climate changes driving reservoir inflows (primarily associated with headwaters climate change) and with local temperature change are decoupled.

On the other hand, there is a positive correlation between reservoir inflows and local precipitation (Fig. 10c). However, since the reservoir evaporation rate is substantially higher than the local precipitation rate (Fig. 5), the lack of correlation between reservoir inflows and temperature is more important in deducing coupling between climate change in the headwaters and the local subwatersheds. In other words, the relationship in Fig. 10c suggests that projected changes in precipitation are large in scale, such that simulations generating increasing or decreasing precipitation tend to project consistent changes along the entire length of the river, from its headwaters downstream to Elephant Butte Reservoir. However, Fig. 10b demonstrates that there is no such consistency between projected temperature and Rio Grande streamflow; simulations that exhibit more pronounced warming in the vicinity of the reservoir do not systematically generate either more or less streamflow.

4. Discussion

The ensemble projects a decrease in surface water availability across all metrics. The yearly release volume of the median simulation decreases by 11.4% between historical (1971–2020) and future (2021–70) averaging periods (Fig. 6c). The probability that the system will release at or above 50% and 100% of full annual allocation under the median scenario decreases by 10% and 6%, respectively between these same periods (Fig. 7). In the median simulation, the maximum number of consecutive years with releases below full allocation—a measure of multiyear drought duration—increased from 10 to 14 years between the 1971–2020 and 2021–70 averaging periods (Fig. 9).

This overall decline in surface water availability is primarily due to decreased streamflow, which in turn is primarily due to diminished snowmelt runoff in the Rio Grande headwaters (Chavarria and Gutzler 2018). Change in water availability in our study area was far more dependent on upstream (headwaters) climate change than on change in the immediate Caballo and Elephant Butte subwatersheds. Diminished snowpack in the high-elevation headwaters is a widespread twenty-first century projection across western North America (Easterling et al. 2017; Ranasinghe et al. 2021), but as shown in Fig. 6, there is still a huge range in CMIP5 model-projected streamflow associated with uncertain headwaters precipitation projections in the Rio Grande headwaters. Even considering these uncertainties, the heavy reliance on Rio Grande inflows for surface water availability in our study area increases the future risk of water shortages, particularly given the suggestions from previous research that projections of higher twenty-first century streamflow should be considered skeptically (Udall and Overpeck 2017; Bjarke 2019).

The increased risk of low-flow years calls for adaptations to current water management. The feasible space of management options will be further constrained by climate change. Increased risk of low-flow years will make it more desirable to maintain a higher storage volume to act as a buffer during low-flow years. Simultaneously, increasing temperature will increase evaporative losses making it more difficult to maintain a high storage volume. Since evaporation is such a big part of the local water balance, changing policy to purposely operate the reservoir at a low volume could reduce losses but would limit the capacity of the reservoir to act as a buffer during dry periods.

While the projections described here indicate that the Rio Grande surface water supply in the study region is likely to be less reliable, it is important to point out that water users in region, including agricultural irrigators, also have access to groundwater supplies. These users have compensated for poor surface water years with groundwater for at least 50 years. However, aquifers in the region are already at risk because pumping substantially exceeds recharge (Sheng 2013; Fuchs et al. 2018). Less surface water in the region due to climate change in the headwaters means that local groundwater supplies will be depleted sooner (Mayer et al. 2021).

While this research provides valuable insight into the future of releases from Elephant Butte and Caballo Reservoirs, there are significant uncertainties in our modeling that limit confidence in the projections and, therefore, the usefulness of the results for policy makers. Notably, the ensemble average of projected changes in climate variables clearly yields a trend toward declining water availability, but there is enormous variability within the ensemble of projections (Figs. 6, 10a). Increasing temperature, with a corresponding increase in evaporation rate from open water, is projected with high confidence (albeit with considerable quantitative uncertainty; Figs. 6, 10b). However, precipitation projections, which also affect Rio Grande streamflows, are projected with much less confidence (Figs. 6, 10c; Garfin et al. 2018).

Precipitation projections, in particular, vary widely both in terms of the magnitude and even the sign of change (Figs. 6a, 10c), which reduces confidence in hydrologic projections on a regional scale, a well-known limitation of current climate modeling (Palmer and Stevens 2019; Udall and Overpeck 2017). The policy usefulness of model-based simulations such as those used in this study could be tremendously enhanced by the improvement of techniques for determining which
global model simulations to place most confidence in for specific regional applications.

Our simplified parameterization of evaporation, based solely on temperature [Eq. (3)], ignores the well-understood physical effects of variable solar radiation, relative humidity, and wind speed. The latter variables were not readily available to us from the BCSD dataset, but estimating annual evaporation as a function of annual temperature provided a reasonably effective simplification (Fig. 3). Equation (2) would be harder to justify over shorter averaging periods (such as a month or a season).

The operating equation used in the model also presents limitations because there is no way to account for users choosing to “bank” water in the reservoir for future years. The annual time step used in the release equations facilitates the evaporation parameterization but limits its applicability to reservoir management adaptation. Reservoir storage is generally highest during the summer when the evaporation rate is also highest. A more detailed reservoir operations model could be implemented at subannual scale, allowing consideration of strategies to maximize available water and minimize evaporative losses throughout the year. Such a model would need to incorporate flows and reservoirs throughout the Rio Grande system, as is done operationally to manage flow on the river by the Bureau of Reclamation (Sabzi et al. 2017). Adapting model-projected streamflows to such a modeling system is far beyond the scope of this study but could represent a big step forward in water resources projection research.

This study assumed constant management practices upstream of (Townsend and Gutzler 2020) and within the study area by applying the same equations during the entire study period (1971–2070). This procedure allowed us to isolate the effects of climate change on water availability in the basin served by the Elephant Butte–Caballo Reservoir system. Realistically, releases from Caballo were allocated under different rules prior to 2008 and operation strategies will likely change before 2070. Our results should be interpreted as a starting point for discussion of how reservoir management might be changed as an adaptation strategy to minimize water supply risks in a changing climate.

The water balance model has been ported to an online host with a simple user interface (http://purl.org/swim) to facilitate stakeholder-controlled changes to management strategies that incorporate the same climate projections used here. The Sustainable Water through Integrated Modeling (SWIM) interface connects the reservoirs system model described here with simple groundwater aquifer models to allow the simulation of conjunctive surface and groundwater use.

5. Conclusions

This study modeled a reservoir water balance in the middle Rio Grande basin under 97 future climate scenarios, focusing on water availability represented by storage in and releases from Elephant Butte Reservoir. A prescribed formula for outflows from the reservoir, based on the present-day agreement that is the basis for reservoir operations, is maintained through the study period (the next half century).

Future projections show a general decline in surface water availability across all parameters explored, consistent with many previous studies of climate change throughout southwestern North America. Temperature increased across all simulations. Streamflow and precipitation varied between simulations, but the majority of simulations project these variables to decrease with time over the long term, subject to pronounced interannual variability. The projected reservoir release volume of the median simulation is 10% lower in 2021–70 than it was in 1971–2020. The longest consecutive run of annual releases below full allocation for 2021–70 is 14 years, as compared with the median simulation for 1971–2020 of 10 years.

Despite increasing evaporation rates associated with warmer temperatures, there was little change in the volume lost to reservoir surface evaporation between the two time periods in our simulations. This is because the prescription for releasing water from the reservoirs results in continuously low reservoir surface area under decreased inflows. Maintaining the current operating agreement for releases in a climate of decreased streamflow input yields lower downstream water availability, as described above in the statistics of releases below the full allocation level.

The magnitude of change in reservoir input from streamflow was far greater than the change due to local precipitation and evaporation. Future water supply in the middle Rio Grande basin is relatively insensitive to projected changes in local precipitation (occurring mostly in summer). Instead, the water supply is projected to be strongly determined by diminishing snowmelt runoff occurring far upstream. Unfortunately, this implies that local water users would have limited ability to supplement their water supply through local water capture or storage policies, because such policies are unlikely to compensate for diminishing river flows feeding the main storage reservoir.

Instead, our results imply that water availability will need to be addressed through policy governing reservoir releases and water demand. For this study, reservoir management practices are assumed to be constant throughout the whole study period, which allowed us to isolate the hydrologic effects of climate change on water availability. Given the high likelihood of decreased water inputs from upstream, water managers and users will need to find ways to adapt to changing conditions by reconsidering reservoir operating policies, which will affect the demand for water that the reservoir system can reliably support.

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Irrigation Demand and Reservoir Evaporation Projections dataset.

Data availability statement. Preprocessed scenario data and model source code are available online (https://github.com/rnh0lmes/rg-wat-bal). Source code of SWIM integration with the water balance model is available online (https://github.com/iLink-CyberShARE/SWIM-IT/tree/master/Services/Python%20Model%20Processor). NetCDF preprocess source code is available online (https://github.com/rnh0lmes/netCDF-spatial-avg).

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