Critical Effects of Precipitation on Future Colorado River Flow

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ABSTRACT: Of concern to Colorado River management, as operating guidelines post-2026 are being considered, is whether water resource recovery from low flows during 2000–20 is possible. Here, we analyze new simulations from phase 6 of the Coupled Model Intercomparison Project (CMIP6) to determine plausible climate impacts on Colorado River flows for 2026–50 when revised guidelines would operate. We constrain projected flows for Lees Ferry, the gauge through which 85% of the river flow passes, using its estimated sensitivity to meteorological variability together with CMIP6-projected precipitation and temperature changes. The critical importance of precipitation, especially its natural variability, is emphasized. Model projections indicate increased precipitation in the upper Colorado River basin due to climate change, which alone increases river flows by 5%–7% (relative to a 2000–20 climatology). Depending on the river's temperature sensitivity, this wet signal compensates for some, if not all, of the depleting effects of basin warming. Considerable internal decadal precipitation variability (~5% of the climatological mean) is demonstrated, driving a greater range of plausible Colorado River flow changes for 2026–50 than previously surmised from treatment of temperature impacts alone: the overall precipitation-induced Lees Ferry flow changes span from −25% to +40%, contrasting with a range from −30% to −5% from expected warming effects only. Consequently, extreme low and high flows are more likely. Lees Ferry flow projections, conditioned on initial drought states akin to 2000–20, reveal substantial recovery odds for water resources, albeit with elevated risks of even further flow declines than in recent decades.

SIGNIFICANCE STATEMENT: Increasing temperatures have led to concerns that Colorado River flows will be permanently reduced due to global warming. Here, we analyze precipitation, surface temperature, and streamflow (at Lees Ferry) in the upper Colorado River basin since 1895 revealing precipitation to be the largest contributor to runoff variability while temperature variability has been a much smaller contributor. New climate model projections indicate increased precipitation in the upper basin due to global warming, acting to increase river flows by 5%–7% during 2026–50. This wet signal compensates for some of the depleting effects from further basinwide warming. Critically, the large intrinsic variability in precipitation is demonstrated to yield a wider range of future Colorado River flows than previously foreseen based solely on considering temperature effects.

KEYWORDS: Climate Change; Hydrology; Probability forecasts/models/distribution

1. Introduction

How much water flows in the Colorado River was a foundational question for the 1922 Compact commissioners as they deliberated a century ago to make an equitable division of the use of the river's water. The vision was to write a compact that would settle present and future disputes allowing the expeditious and full development of the river for human purposes. This would be achieved by building large dams and vast water supply infrastructure that would control the notorious peaks and valleys in the annual flows ensuring a degree of water supply certainty and safety (e.g., Hundley 2009; Kuhn and Fleck 2019).

The 1922 Compact divided the beneficial consumptive use of the Colorado River between two basins: upper basin and lower basin. The dividing point is Lees Ferry, a location on the river in northern Arizona about 15 miles downstream of the Glen Canyon Dam. The 1922 Compact apportioned 7.5 million acre-feet per year to the upper basin and 8.5 million acre-feet to the lower basin. Since upper basin watersheds produced about 85% of the flow, to equate the availability of water, the compact requires the upper division states to not cause the flows at Lees Ferry to be depleted below 75 million acre-feet in consecutive 10 years (see Article IIId of the 1922 Compact).

In 1944, the United States and Mexico signed an international water treaty that requires the United States to deliver 1.5 million acre-feet per year to the border with Mexico. Under the 1922 Compact, if there is no surplus system water available for delivery to Mexico, each basin must provide 50% of the deficiency. Thus, the metric for 1922 Compact compliance is commonly described as an average annual flow at Lees Ferry of 7.5–8.25 million acre-feet per year

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(Kuhn and Fleck 2019). The post-Mexican Treaty development laws and reservoir operating rules, including the 2007 Interim Guidelines, have all been designed to meet this flow metric. The total live capacity of federal regulatory storage above Lees Ferry, including Lake Powell, was designed so that the upper basin could have sufficient carryover storage on hand to meet its 1922 Compact obligations during a repeat of the 1930s drought (Kuhn and Fleck 2019).

While Lake Powell's primary purpose is compact compliance, Lake Mead's purposes are flood control and metering out to lower basin water users on the main stem compact deliveries from the upper basin, intervening tributary flow, and occasional surplus flows that come from upper basin wet years. It has been understood since at least the 1960s that compact deliveries and intervening flows alone are not enough to meet the collective needs of Mexico and the lower basin. The difference between Lake Mead inflows without the occasional surplus flows and the annual demands for Lake Mead water is commonly referred to as the lower basin's "structural deficit."

Until only recently, 2022, the water stored in Lakes Mead and Powell, about 4 times the river's annual flow at full capacity, has been sufficient to offset any formal shortage declarations. But that capacity has largely been drawn down in the twenty-first century—their combined storage being only 30% in early 2023 as a multidecadal drought has driven the flows on the river to historic lows (e.g., Udall and Overpeck 2017; Woodhouse et al. 2016; Hoerling et al. 2019). The extent to which human-induced climate change has contributed to this Colorado River water crisis is a matter of intense scientific inquiry though it is generally felt that the river's modern-day crisis is symptomatic of the climate crisis plaguing the planet overall.

What the 1922 Compact commissioners and the authors of the subsequent development laws could not foresee was the threat to water supply arising from anthropogenic climate change. As policymakers, water resource managers, and a vast array of the river's water users now begin deliberations on new post-2026 guidelines for managing river operations (https://www.usbr.gov/ColoradoRiverBasin/post2026/index.html), severe drought, depleted reservoirs, and the potential for significant shortages to existing users are dominating the agenda. The stakes are incredibly high. Perhaps like never before, policymakers are turning to science to ask the basic question "How much water is likely to be in the river?" but now framed in the context of human-induced climate change impacts.

The traditional view of climate change impacts on Colorado River flow argues for a decrease owing to surface temperature rise (e.g., Revelle and Waggoner 1983; Nash and Gleick 1991). This is true notwithstanding uncertainty in the magnitude of the flow's temperature sensitivity—plausible values in the range from $-3\%\ ^\circ\mathrm{C}^{-1}$ to $-10\%\ ^\circ\mathrm{C}^{-1}$ (e.g., Vano et al. 2012, 2014; McCabe and Wolock 2007; Hoerling et al. 2019; Milly and Dunne 2020). It is the high confidence in climate model projections of temperature rise that undergirds arguments for further declines in Colorado River flows. Indeed, when Udall and Overpeck (2017) considered many climate model projections for temperature and convolved those with the range of plausible temperature sensitivities, runoff declines occurred in every realization. The median value of declines drawn from the statistical distribution of all samples was found to be in the range from −10% to −30% by midcentury depending on the assumed temperature sensitivity.

The above perspective on temperature-induced Colorado River flow change, especially its certainty that flows will decline, overlooks the critical effect of precipitation—the primary driver of the river's historical variability. As will be shown herein, observed decadal variations in upper Colorado River basin precipitation have accounted for over 80% of the decadal variability in historical Lees Ferry flows. The range of plausible outcomes for the Colorado River would thus be considerably different than those inferred from temperature constraints alone, under the not unreasonable assumption that a strong precipitation constraint on Lees Ferry flow will continue to operate into the near future. This would be true regardless of any climate change impact on the basin's precipitation. In the situation of no net change in precipitation arising from global warming, the median value of runoff changes would be the same as those inferred from global-warming-induced temperature effects alone. Importantly, however, they would have a broader range of plausible outcomes to the extent that significant natural variations in precipitation occurred. The importance of inherent decadal variations in precipitation on future Colorado River flow has not been extensively addressed, with the emphasis of prior work that treated precipitation being mainly on the climate change component of changes only—either via idealized scenarios (e.g., Revelle and Waggoner 1983; Vano et al. 2014) or by using multimodel ensemble averages from climate simulations and projections (e.g., Nash and Gleick 1991; Christensen and Lettenmaier 2007; Harding et al. 2012; Hoerling et al. 2019). That inherent decadal variations in the region's precipitation can be important is indicated by Lehner et al. (2018) whose attribution study demonstrates that southwest U.S. precipitation decline from the 1980s to the early twenty-first century arose from natural processes associated with the region's climate sensitivity to oceanic decadal variations. It is thus important to assess the extent to which inherent climate variations in coming decades could expose risks of not only much greater Colorado River flow declines if precipitation declined by such natural fluctuations but also of possible flow increases should precipitation increase. Here, we wish to quantify the probabilities for extreme runoff states by taking account of both the natural and climate change–driven fluctuations of precipitation on decadal time scales.

A central question posed in this study is how the consideration of both temperature and precipitation changes (naturally occurring and anthropogenically forced) alters the likelihoods of occurrences for more extreme Colorado River flows at Lees Ferry. As mentioned, this location is the critical divide separating the upper and lower basins at which the legal performance of the 1922 Compact is measured. Our analysis will update Udall and Overpeck (2017) by using data, as described in section 2, from phase 6 of the Coupled Model Intercomparison Project. In addition, several large ensemble model simulations are analyzed to increase sample sizes and

TABLE 1. Models, references, data sources, ensemble sizes, and spatial resolutions.

Model	Reference	Data source	Ensemble size	Spatial resolution
CESM1	Kay et al. (2015)	https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html	40	100 km
CESM2	Danabasoglu et al. (2020)	https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html	50	100 km CMIP6 BMB
CESM2*	Rodgers et al. (2021)	https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html	50	100 km Smooth BMB
SPEAR	Delworth et al. (2020)	https://www.gfdl.noaa.gov/spear_large_ensembles/	30	50 km
MIROC6	Tatebe et al. (2019)	https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html	50	120 km
CMIP6	Eyring et al. (2016)	https://esgf-node.llnl.gov/projects/cmip6/	38	Various

thereby better identify the statistical probabilities for low and high flow outcomes. Empirical analyses of Lees Ferry flow sensitivity to historical temperature and precipitation variations are used to constrain projections of future Lees Ferry flow, following methods of Lehner et al. (2019), and are presented in section 3a. The study uses a policy-relevant window for assessing future flows—comparing in section 3b the immediate quarter-century (2026–50) after the anticipated 2026 new Interim Guidelines against the flow of the recent 2000–20 dry period. The latter period being among the lowest 20-yr averages in the instrumental record, analysis in section 3c will further consider the conditional probability that projected flows in 2026–50 could materially exceed the recent low flow era, and thus potentially lead to storage recovery of Lakes Mead and Powell. A summary and discussion of results appear in section 4.

2. Data and methods

a. Observations

The naturalized flow of the Colorado River at Lees Ferry is based on the Upper Colorado River Commission's monthly data from 1895 to 2022, the same as the flow data used in Hoerling et al. (2019). The analysis is of the water-year flow averages, with the first water year being October 1895–September 1896 and the last being October 2021–September 2022 (see http://www.ucrcommission.com/RepDoc/UCRCAnnualReports/69_UCRC_Annual_Report.pdf). Water-year averages of precipitation and surface temperature for 1895–2022 are based on 5-km gridded analyses (Vose et al. 2014). These data are spatially averaged over the upper Colorado River basin lying above the Lees Ferry gauge. The area corresponds to the USGS upper Colorado River watershed referred to as region 14 of its 2-digit hydrologic unit code [HUC02; see the outline of the upper Colorado River basin (UCRB) watershed in Fig. 5 over which spatial averages are calculated].

b. Climate model simulations

Coupled ocean–atmosphere model simulations from phase 6 of the Coupled Model Intercomparison Projection (Eyring et al. 2016) suite are used. One ensemble is generated based on a single realization from 38 different models (see Table 1). Our analysis is for the 1920–2050 period in which the models are forced by historical variations in atmospheric chemical composition, anthropogenic and volcanic aerosols, and solar variability prior to 2014. Model simulations after 2014 are based on the shared socioeconomic pathway-8.5 (SSP5-8.5) scenario.

In addition to this multimodel ensemble, five different large ensemble simulations (LENSs) are studied. These include the National Center for Atmospheric Research (NCAR) Community Earth System Model, version 1 (Kay et al. 2015) and version 2 (Danabasoglu et al. 2020) (CESM1 and CESM2, respectively); the Model for Interdisciplinary Research on Climate, version 6 (MIROC6; Eyring et al. 2016); and the NOAA Geophysical Fluid Dynamics Laboratory Seamless System for Prediction and Earth System Research (SPEAR) model (Delworth et al. 2020). For CESM2, two separate large ensembles are examined that differ only in their emissions of anthropogenic aerosols related to black carbon. Further details of the LENS experiments appear in Table 1, including their approximate spatial resolutions over the UCRB. For the large ensemble runs, CESM1 forcing after 2005 follows an RCP8.5 protocol, whereas the CESM2 simulations employ SSP3-7.0 (Rodgers et al. 2021), while the other LENS runs are forced by the SSP5-8.5 scenario. Two separate ensembles for CESM2 are used that employ different emissions for anthropogenic aerosol forcing related to biomass burning (BMB), which can affect extratropical climate variability (Fasullo et al. 2022). All model data are interpolated to a 1° latitude/longitude grid, using simple bilinear spatial interpolation, before generating spatial and ensemble averages. Water-year averages of the upper Colorado River basin spatial averages of simulated temperature and precipitation are computed for all model realizations in the same manner as for observations. To ensure that we approximate the borders of this HUC02 scale for the UCRB, the model data are interpolated to 5-km resolution as in the observational data though with no other downscaling adjustments or calibration of the model data.

A key property of the CMIP6 models for the purposes of this study is the realism of simulated decadal precipitation variability over the UCRB. The latter acts as the major driver of Colorado River variability, as subsequently demonstrated. Table 2 compares the observed (OBS) UCRB decadal variability of precipitation to that in each of the five LENS models. The analysis is based on the common period 1950–2020. The variability is calculated from the standard deviation of consecutive overlapping 10-yr averages and is expressed as a

TABLE 2. The coefficient of UCRB decadal precipitation variability (CV; %) during 1950–2020.

	OBS	CESM1	CESM2	CESM2*	SPEAR	MIROC
CV	4.9%	4.3% ± 1%	4.6% ± 1%	4.5% ± 1%	4.1% ± 1%	4.9% ± 1%

percent of each dataset's 1950–2020 mean precipitation. This is a measure of the coefficient of variability (CV). Indicated is the sampling uncertainty in the model based on calculating the standard deviation among the coefficients derived from each ensemble member.

c. *Simulated Lees Ferry flow*

Owing in part to coarse spatial resolutions of the coupled models and due to other potential biases in runoff generated by their land surface models, simulated runoff and its change derived from the direct output of such general circulation models have considerable error (e.g., Vano et al. 2014; Lehner et al. 2019). Here, we constrain the runoff from the climate model projections using a multiple linear regression formulation as in Lehner et al. (2019) and in Hoerling et al. (2019):

$$\Delta Q \sim a_0 \Delta P + b_0 \Delta T, \tag{1}$$

where Q is the total runoff, P is the precipitation, and T is the surface temperature. Here, the interaction term between ΔP and ΔT is assumed to be small, as had been found previously by Lehner et al. (2019). According to Eq. (1), changes in runoff are predicted by changes in precipitation and temperature, with the impact of meteorological changes mediated by the runoff sensitivities to precipitation (a_0) and temperature (b_0), respectively. These latter coefficients are determined from empirical analysis of observations and informed by land surface model sensitivity experiments (e.g., Vano et al. 2014), while the changes in meteorological quantities are derived from the CMIP simulations. We first attempt to derive the coefficients in Eq. (1) based on univariate linear regression between decadal runoff variations and each of the meteorological variables, based on data from 1950 to 2020. The empirical approach yields a robust estimate of a_0, whereas the estimate of b_0 reveals considerable uncertainty consistent with the wide range of published estimates of Lees Ferry flow's temperature sensitivity. We therefore treat the flow response to meteorological forcing by adopting a range of plausible sensitivities informed both by empirical evidence and model sensitivity studies, as discussed further in section 3c.

3. Results

a. *Meteorological drivers of Lees Ferry flow*

Figure 1 shows the 1896–2022 water-year time series of Lees Ferry flow (top) and the UCRB averaged temperature (middle) and precipitation (bottom). Whereas surface temperature variability has been dominated by an upward trend, precipitation and Lees Ferry flow have exhibited pronounced decadal variations, with the latter two superposed on overall downward trends. The period since 1950, when an abundance of gauge data provides for more reliable precipitation analysis (Vose et al. 2014), is characterized by several pronounced hydroclimate swings in the upper basin. Low flow and low precipitation during the period 1950–80 are somewhat comparable to water deficits that reappeared in the post-2000 era. Interspersed have been two wet periods: one in the early 1980s and a second in the late 1990s. These witnessed high Colorado River flows during which reservoir storage at Lakes Mead and Powell were near their full capacities (not shown).

The relationship between meteorological variations and Colorado River flow is assessed for consecutive decadal periods during the post-1950 era of relatively abundant observations. Decadal averaging better captures the link between meteorological driving and runoff production by minimizing the effects of storage on the land surface, an effect important on interannual time scales. Decadal variations of Lees Ferry flow are strongly constrained by precipitation (Fig. 2, left) with a correlation of +0.91. It is such a strong constraint that may explain why a wide range in future Colorado River streamflow projections arises in multimodel climate change scenarios—stemming from differences in future precipitation (e.g., Harding et al. 2012; Lehner et al. 2019; Ficklin et al. 2013; Xiao et al. 2018). We will clarify below that such ranges are more symptomatic of the critical importance played by natural decadal precipitation variability, rather than indicative of different model sensitivities to climate change or to various emissions scenarios.

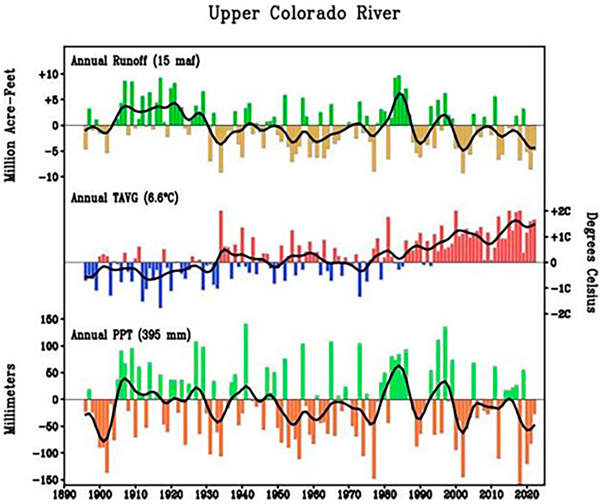

FIG. 1. The 1896–2022 departure time series of (top) water-year Lees Ferry flow (maf) and (middle) UCRB averaged temperature (°C) and (bottom) precipitation (mm). Departures are relative to the entire period mean (values indicated in the upper left). Streamflow is based on the Colorado River Commission data; temperature and precipitation data are based on gridded analyses of Vose et al. (2014). The solid black curve is a 9-point running mean.

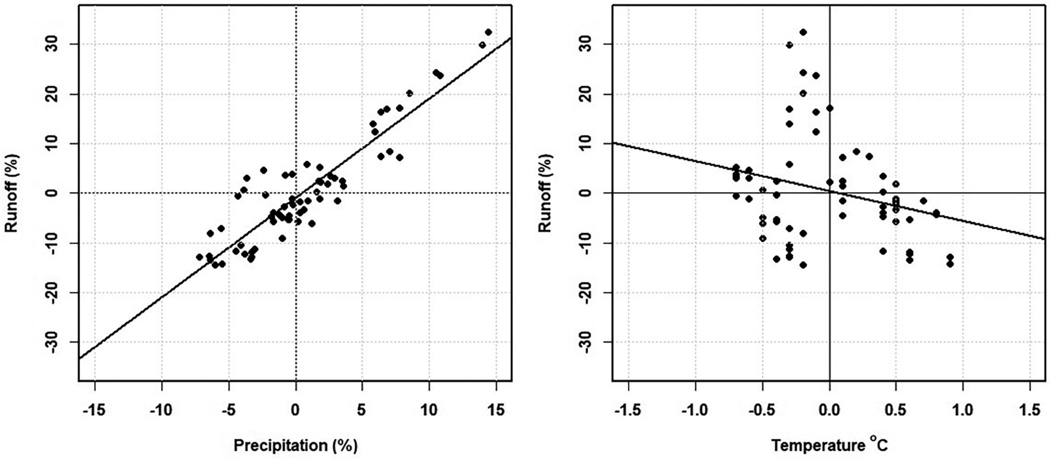

FIG. 2. The scatter relationship of percent departures of Lees Ferry flow and UCRB averaged (left) precipitation and (right) temperature for 1950–2022. Departures are computed from the moving 10-yr averages relative to the 1950–2020 mean. The correlation of decadal departures is 0.91 for Lees Ferry flow and precipitation and −0.26 for Lees Ferry and temperature. The precipitation elasticity of decadal runoff is 1.9 and the temperature sensitivity is −6% °C^{-1}, as determined from the slope of their respective scatter.

Given the high explained variance (83%), the slope of the linear regression provides a very reliable estimate of the precipitation sensitivity of runoff. This value, known as the precipitation elasticity of runoff, is 1.9. This empirical estimate for elasticity from observed decadal variations is appreciably larger than the 1.3 derived from the analysis of observed interannual variability by Lehner et al. (2019) and compares to an average of about 2.5 derived from decadal variations in high-resolution climate models (Hoerling et al. 2019) and in land surface model sensitivity experiments (Vano et al. 2014). Various previous observational estimates of the runoff elasticity indicate a value greater than 1 in this region (e.g., Sankarasubramanian et al. 2001; Sankarasubramanian and Vogel 2003). The relatively lower value derived from year-to-year variability (compared to decadal variations) likely reflects the importance of land surface effects on Lees Ferry flow whose lag-one correlation is about 0.3, indicative of an appreciable land surface memory.

By contrast, observed decadal Lees Ferry flow variations have been almost uncorrelated with decadal temperature variations (Fig. 2, right). The correlation of −0.26 barely statistically significant, from few outliers, and as such, an estimate of the river's temperature sensitivity based on the slope of the linear fit (−6% °C^{-1}) should be viewed as being less reliable. This is evident from the empirical result that a wide range of Lees Ferry decadal flows from +30% to −15% have occurred in the presence of virtually the same decadal temperature anomalies. This result is not evidence against the role of temperature in Lees Ferry flow per se. Rather, it indicates that detectability of the true temperature effect is low and difficult to extract from the short instrumental record, owing in part to the large constraint imposed by precipitation alone. Various modeling (e.g., Vano et al. 2014; Hoerling et al. 2019) and theoretical (e.g., Milly and Dunne 2020) approaches confirm a depleting effect of warming temperatures on Lees Ferry flow, with a probable range of temperature sensitivities between −3% and −10% °C^{-1}. Such a range, and other considerations, will be subsequently used to inform predictions for Lees Ferry flow based on Eq. (1).

b. *Projected meteorological changes in the UCRB*

Figure 3 shows the ensemble mean simulated anomalies for UCRB precipitation (top) and temperature (bottom) during 1920–2050. Departures are relative to each model's 2000–20 climatology, and the model results are compared to observed departures (black dotted curve) in their common periods. The means of each large ensemble exhibit little coherent change in UCRB precipitation throughout the twentieth century. They thus indicate that anthropogenic climate change played little material role in causing the low precipitation during the Millennium Drought. The results are consistent with Lehner et al. (2018) who found, from atmospheric model experiments, that the sharp decline in the region's precipitation from the 1980s to the first decades of the twenty-first century was largely due to natural decadal variability. They are, however, contrary to suggestions by Hoerling et al. (2019) based on diagnosis of idealized forcing experiments, also using atmospheric models, that a centennial scale decline in UCRB precipitation from the early twentieth century into the early twenty-first century may have been partly due to anthropogenic forcing. Instead, the most striking signal in Fig. 3—based on this more complete collection of model experiments in terms of forcing realism, ensemble size, and model diversity—is a precipitation increase over the UCRB beginning in the early twenty-first century and continuing to at least 2050.

The muted response of these large ensemble averages during the twentieth century contrasts with a wide range in observed conditions indicating that the prominent decadal variability in observed UCRB precipitation has not been due to time-varying external radiative forcing but has almost

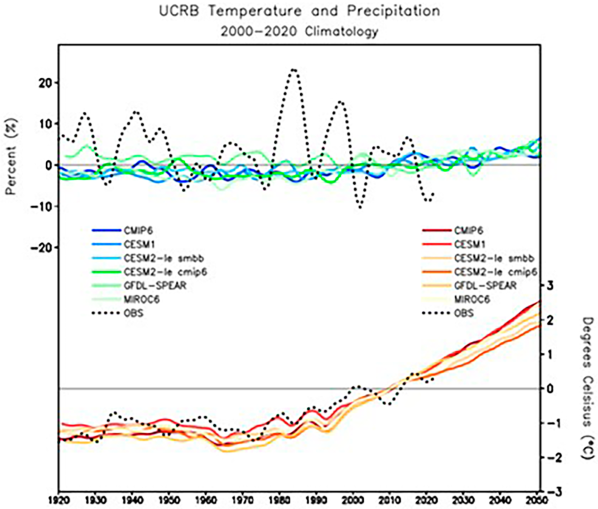

FIG. 3. Time series of (top) 1920–2050 UCRB precipitation departures (%) and (bottom) surface temperature departures (°C). Shown in the dark curves are the multimodel ensemble averages of 38 CMIP6 model simulations, and shown in lighter curves are the multimember ensemble averages of five different LENSs. Departures are relative to a 2000–20 reference. Observed departures for 1920–2020 are shown in a dotted black curve. All curves smoothed with a 9-point running mean.

certainly resulted from natural variability. Consistent with that interpretation, individual members of these ensembles do generate large decadal swings associated with the models' internal fluctuations akin in magnitude to observations (see Fig. S1 in the online supplemental material). Those, however, are not synchronized in time with the observed occurrences as expected if they arise from internally coupled ocean–atmosphere noise. The simulated fluctuations are not coherent in time among ensemble members either, thus leading to the muted time series of the ensemble mean anomalies seen during the twentieth century in Fig. 3.

A more prominent climate change signal in these large ensembles, relative to the noise of their internal variations, is evident in their surface warming. The rise in temperatures begins in the late 1980s and accelerates in the twenty-first century. The simulated UCRB temperature time series resembles the classic hockey stick pattern noted in global averages of observed and CMIP-simulated temperatures. It is evident from the small spread among individual simulations, especially compared to the large spread in precipitation simulations, that temperature is highly constrained by the external forcing (see Fig. S1). This is also suggested by the consistency of the observed time series with the model ensemble averages during 1920–2020. Thus, very different from the UCRB precipitation sensitivity to external forcing, which although trending wetter in the twenty-first century exhibits only a modest signal-to-noise ratio, the UCRB temperature response exhibits a very large signal-to-noise ratio. It is for this reason of high detectability (and high predictability) that temperature has been the focus of studies on the Colorado River's response to climate change forcing. But recognizing the large precipitation constraint on the river's flow (see section 3a), an analysis of temperature's role alone would be omitting the principal agency for the river's variability.

The projected probability distributions for UCRB precipitation and temperature changes (2026–50 relative to 2000–20) are shown in Fig. 4. A higher likelihood of a warmer–wetter UCRB climate (the peaks of the distributions are to the right of the zero line) emerges from the statistics of individual runs drawn from 38 different CMIP6 and likewise from the 220 samples drawn from 5 different large ensemble simulations. The warming signal is approximately 1.5°C, and the precipitation increase is about 2.5%. However, the use of single runs does not permit one to unequivocally interpret the spread of the CMIP6 histograms as resulting from internal noise and thereby also leaves some ambiguity of the forced change signal itself. We will thus focus our subsequent analysis on the LENS data, which also benefit from higher spatial resolution than the majority of CMIP models and thus are deemed more suitable for addressing the regional problem at hand. Critically, these provide a larger and more representative ensemble from which to assess probabilities for projected hydroclimate changes.

Shown in Fig. 5 are the LENS ensemble mean projected changes in precipitation and surface temperature (2026–50 vs 2000–20). Both the warmer and wetter signals of UCRB changes are seen to be part of a coherent regional pattern of like-signed anomalies. In the UCRB, maximum wettening occurs in the central Rockies headwater region (3.0%–3.5%), and a wet signal extends across much of the northern Rockies.

The upper Colorado wettening is part of increased precipitation projected to occur over much of the interior West and the Great Plains. The exception is over the desert Southwest where a change in sign to reduced precipitation occurs, including much of the lower Colorado River basin. Projected warming is especially ubiquitous, spanning the entire United States, with a local maximum over the northern upper Colorado River basin. In the subsequent analysis, only the UCRB averages (calculated over the green region highlighted in Fig. 5) of the projected meteorological changes are utilized for generating projections for Lees Ferry flow.

c. *Projected Lees Ferry flow changes*

Lees Ferry flow changes (2026–50 vs 2000–20) are projected using Eq. (1) based on the statistics of the LENS-projected upper Colorado River basin meteorological changes given in Fig. 4. The various projections for temperature and precipitation thereby provide the probabilistic character for projected Lees Ferry flow and incorporate effects of both natural decadal variations and anthropogenic climate change. Although only a single climate change scenario is employed, the focus on near-future conditions minimizes sensitivity to assumed greenhouse gas emission rates. In addition, in the spirit of Udall and Overpeck (2017), the uncertainty in those predictions is treated by considering a plausible range (or likely scenarios) for the precipitation elasticities and temperature sensitivities.

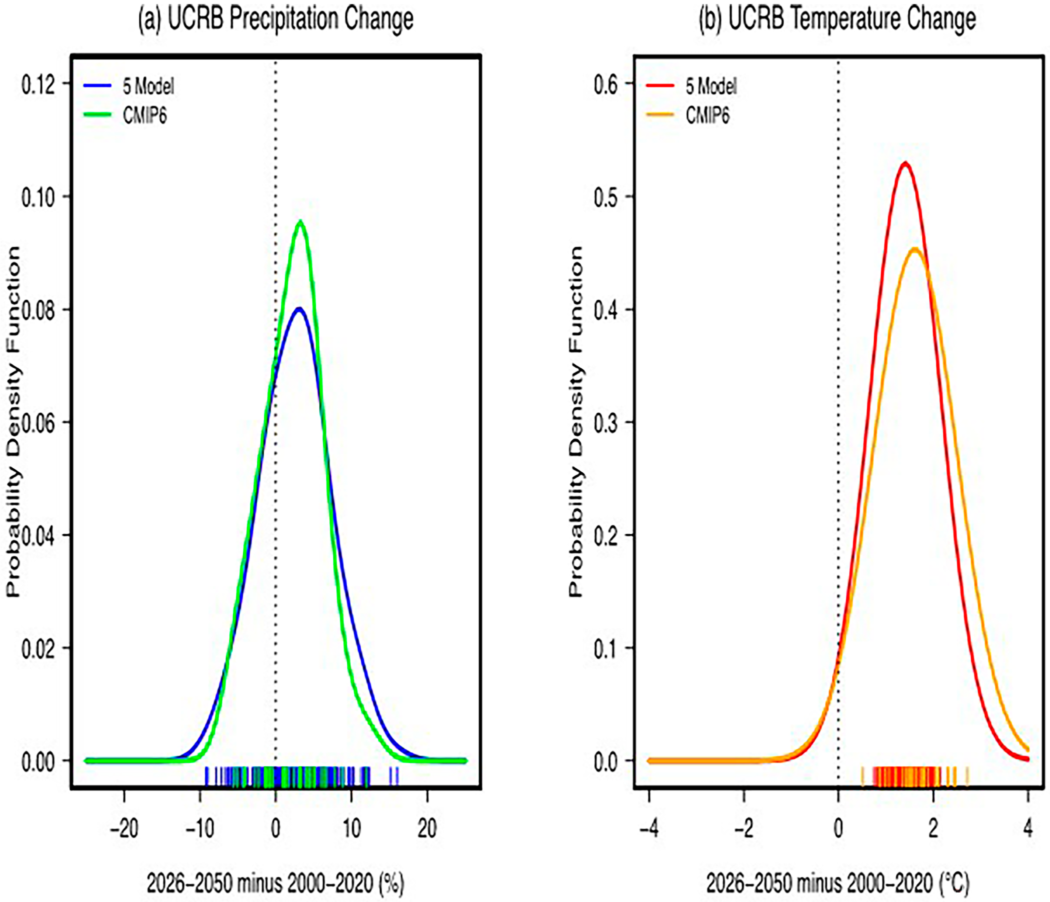

FIG. 4. Simulated changes in UCRB (left) precipitation (%) and (right) temperature (°C). Yellow and green curves are based on the 38 different CMIP6 models, while red and blue curves are based on 220 members of LENSs based on five different models. The probability distributions are smoothed histograms applied to bins using a nonparametric Gaussian filter.

We initially analyze Lees Ferry runoff sensitivity under three assumptions of the elasticity: 1.0, 1.9, and 2.5 (Fig. 6). The 1.0 value is used to simply illustrate runoff response to meteorological forcing if precipitation induced no amplification in runoff responses. The 1.9 value is the empirically derived estimate for decadal variability, which was shown to strongly constrain observed Lees Ferry flow variations in such time scales. We noted in section 3a that a 1.3 value was used in Lehner et al. (2019) though, being based on interannual covariability of runoff and precipitation, it is not as relevant to this study's focus on longer time-scale variations. The 2.5 value reflects an average across various model experiments (Vano et al. 2014; Hoerling et al. 2019). Our subsequent analysis (Figs. 7 and 8) will focus on runoff changes under elasticity assumptions of 1.9 and 2.5.

In contrast to precipitation constraints, the empirical results of Fig. 2 indicate a much weaker constraint of decadal temperature on runoff variations. Our approach is therefore to treat the uncertainty by accommodating a reasonable range based on a wide body of empirical, theoretical, and modeling literature that has examined the problem (we use a range from -5% to -10% $°C^{-1}$). We should add that the temperature sensitivity itself may change as warming acts to progressively reduce the snow cover in the upper basin, thereby modifying the surface energy balance in a way that might suggest a heightened sensitivity, as could be inferred from the Milly and Dunne (2020) theoretical analysis. We therefore also consider the flow changes under a -15% $°C^{-1}$ sensitivity. By incorporating a threefold range of possible temperature sensitivity, our analysis attempts to reflect the uncertainty space, but clearly more research on this problem is required.

To first illustrate the separate effects of precipitation and temperature projections, Fig. 6 shows histograms of the percent changes in Lees Ferry flow based only on the LENS precipitation projections [i.e., assuming $b_0 = 0$ in Eq. (1); left panel] and only on their temperature projections [i.e., assuming $a_0 = 0$ in Eq. (1); right panel]. Owing to the ensemble mean projected increase in UCRB precipitation, the mean value of predicted Lees Ferry flow likewise increases, being greater for larger elasticities. In contrast, owing to the ensemble mean projected temperature rise together with the specified flow depletion rates under the influence of warming, the mean value of projected Lees Ferry flows likewise declines. These latter results mostly reproduce the findings of Udall and Overpeck (2017) based on earlier generations of CMIP models.

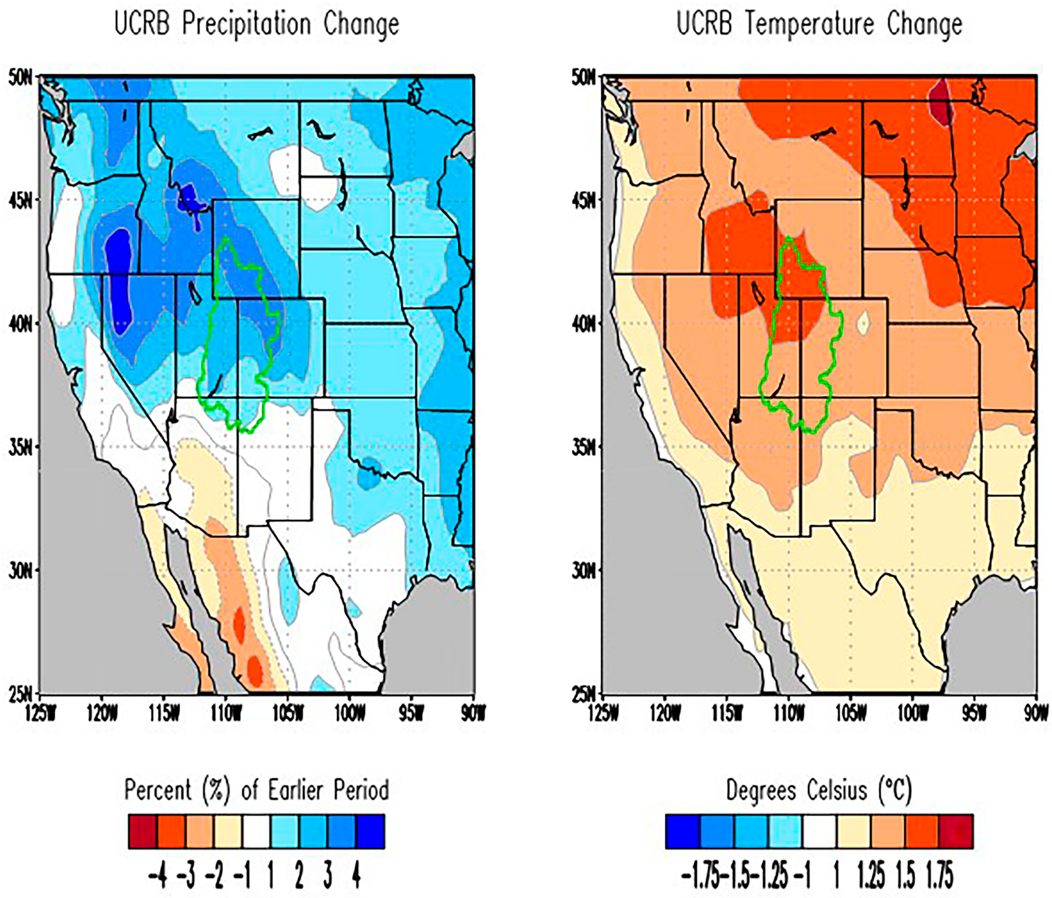

FIG. 5. The (left) ensemble average precipitation departures (%) and (right) surface temperature departures (°C) for 2026–50 relative to 2000–20 based on the multimodel average of five large ensemble model simulations.

Two important features are noteworthy in Fig. 6 that have not been sufficiently emphasized in prior studies. One is the countervailing effects of climate change on Lees Ferry flow due to the signals of mean wetting and mean warming. Traditionally, confidence in the climate change–induced precipitation signal over the UCRB has been low. This is related to different signs in projections found in ensembles of prior generation CMIP models (e.g., Brekke et al. 2014). In contrast, we find a comparatively robust wet signal among the new generation of climate models. Robust in the sense that the estimated climate change signal of a 2.5% increase in precipitation is approximately $1/2$ standard deviation of the natural decadal variability (see Table 2). In addition to the ensemble means trending wetter in each of the six different large ensemble averages studied herein, 70% of individual model realizations across both the 38-model CMIP6 ensemble and the 220-member LENS ensemble yield positive precipitation changes in the UCRB.

Notwithstanding this robustness in the basin's projected precipitation change in new CMIP6 data, the large run-to-run variability in precipitation is perhaps more critical to recognize. In the LENS data, this spread is due to internal variability (we have confirmed that the spread among individual LENS models is very similar to the spread in the 5-model combined histograms). Here, we find such internal noise in precipitation to drive a wide range of future flows, as revealed by the considerable spread in their projected Lees Ferry flow histograms. In particular, the precipitation spread has greater implications for future Lees Ferry flow probabilities than temperature spreads owing to the amplification of the former by the river's large elasticity.

Thus, whereas all temperature-driven projections of Lees Ferry flow indicate declines, both increased and decreased flows arise in the sampling statistics of precipitation-driven predictions (see Fig. 6). A greater range of future Lees Ferry flows arise when considering internal decadal variability of precipitation alone as compared to temperature variability alone, a spread that is further enlarged in the presence of greater assumed elasticity.

Specifically, the spread among the samples of Lees Ferry projected flow when aggregated across the various scenarios for the coefficients a_0 and b_0 is twofold greater in association with precipitation than with temperature variations alone. Such differences are largely independent of the ensemble mean precipitation change itself, being a symptom purely of the magnitude of inherent internal noise (amplified by the elasticity), not of the forced signal per se. Note that the range

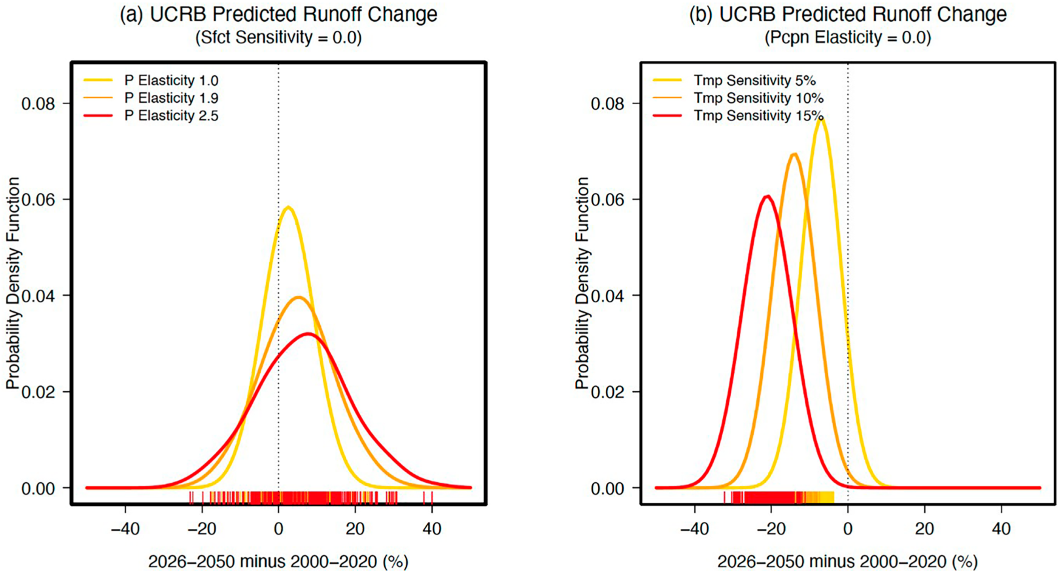

FIG. 6. Histograms of projected Lees Ferry flow changes (%) based (left) on large ensemble model UCRB precipitation changes only and (right) on large ensemble UCRB temperature changes only. Precipitation-related Lees Ferry flow changes are shown for three different elasticities (1.0, 1.9, and 2.5) and for three different temperature sensitivities (−5%, −10%, and −15% $°C^{-1}$). Changes are percent differences of 2026–50 relative to 2000–20. The probability distributions are smoothed histograms applied to bins using a nonparametric Gaussian filter.

of Lees Ferry flow changes, across all three histograms of Fig. 6, is roughly from −25% to +40% for precipitation driving, compared to the narrower range from −5% to −30% associated with temperature driving.

It is thus apparent that to better represent statistics of plausible future Lees Ferry flows, the combined influences of temperature and precipitation changes must be considered, both their externally forced and internally driven components. Indeed, this had been recognized in Lehner et al. (2019), though their projections of Lees Ferry flow were derived from single values of assumed elasticity and temperature sensitivity and thus did not address the uncertainty

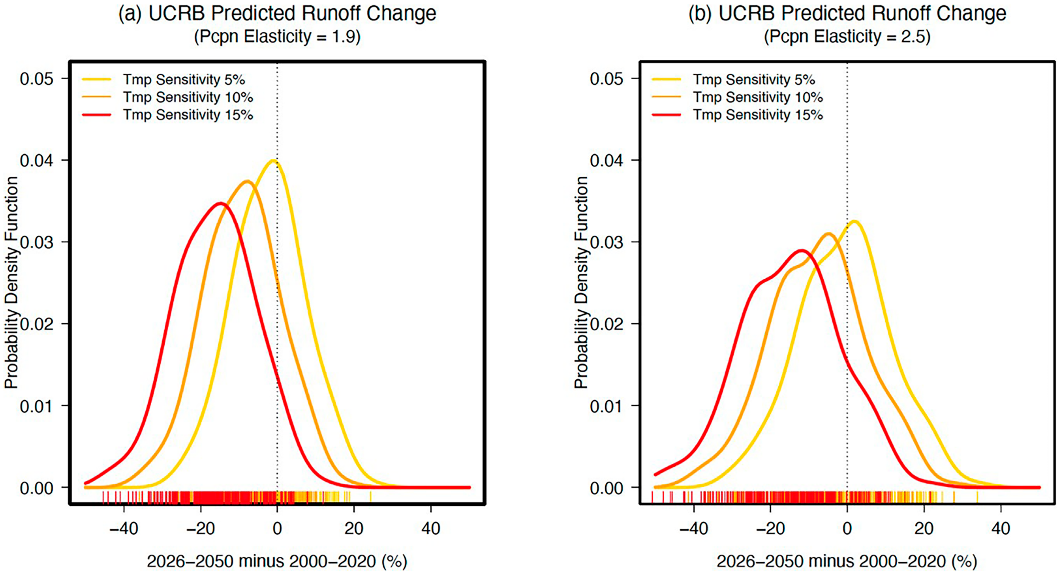

FIG. 7. As in Fig. 6, but for predicted Lees Ferry flow changes (%) based on the combined effects of large ensemble model UCRB precipitation and temperature changes. Results assuming elasticity = 1.9 (2.5) are shown in the left (right) panels. Results are displayed for three temperature sensitivities (−5%, −10%, and −15% $°C^{-1}$). Changes are percent differences of 2026–50 relative to 2000–20. The probability distributions are smoothed histograms applied to bins using a nonparametric Gaussian filter.

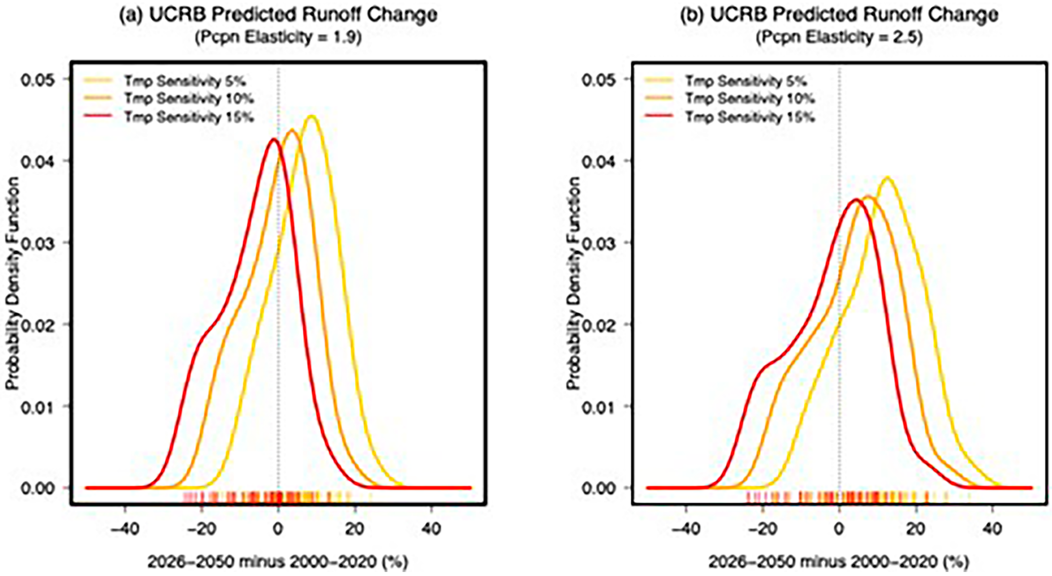

FIG. 8. As in Fig. 7, but for predicted Lees Ferry flow changes (%) based on the combined effects of large ensemble model UCRB precipitation and temperature changes and conditioned on dry initial conditions during 2000–20 in analogy to observations. Results assuming elasticity = 1.9 (2.5) are shown in the left (right) panels. Results are displayed for three temperature sensitivities (−5%, −10%, and −15% °C^{-1}). Changes are percent differences of 2026–50 relative to 2000–20. The probability distributions are smoothed histograms applied to bins using a nonparametric Gaussian filter.

space comprehensively. Here, we apply a range of plausible constraints that better reflect uncertainty in the observed physical relationships of Colorado River flow with the basin's meteorology, more in the spirit of the approach of Udall and Overpeck (2017) as they applied to temperature effects.

In the subsequent analysis of Lees Ferry flow projections, the combined effects of temperature and precipitation driving are considered for three scenarios of temperature sensitivities. To reiterate, the assumption of −5% °C^{-1} is guided by the recent GCM-based analysis of Lees Ferry flow variability that indicated lower-end sensitivity during the historical period (Hoerling et al. 2019). The −10% °C^{-1} value is closer to a recent theoretical estimate (Milly and Dunne 2020) and is at the upper end of LSM sensitivity experiments. The −15% °C^{-1} value, though unlikely to represent the historical sensitivity, could plausibly reflect a future heightened sensitivity as climate change alters the basin's water and energy balance. Henceforth, results will be shown for two assumed elasticities: 1.9, which is informed by the strong constraint determined empirically (see Fig. 2), and 2.5, which is based on LSM and GCM estimates (Vano et al. 2014; Hoerling et al. 2019). The lower value of 1.0 is deemed to be highly unlikely. In comparing the following results to Lehner et al. (2019), note their use of an elasticity of 1.3 and a temperature sensitivity of −11.1% °C^{-1}. Those values for a_0 and b_0, when applied to Eq. (1), have the consequence of enhancing temperature change effects relative to precipitation change effects on runoff.

Figure 7 shows the projected Lees Ferry flow histograms assuming an elasticity of 1.9 (left) and 2.5 (right). For the lower temperature sensitivity, the mean prediction is for virtually no change in Lees Ferry flow. For greater temperature sensitivities, the most probable Lees Ferry flow change is in the range from −7% to −16%. Note that these projected declines by midcentury are smaller than those of Udall and Overpeck (2017) because of the wet signal (i.e., the precipitation response to changes in external radiative forcing) in these new CMIP6 LENS projections.

The management concern is arguably less about the mean than about the probability for extreme states of the river's decadal yield—plausible outcomes in the tails are often of greater interest to risk management than the most probable outcome. In this regard, we note that over 10% of the samples of the combined histograms in Fig. 7 (3 × 220) yield flow declines of greater than 30%. These are relative to an unconditional climate of 2000–20 (as opposed to the observed drought state of 2000–20) and would imply a 2026–50 mean flow of below 11 maf. Such a state of the river would be more severely depleted than during the recent Millennium Drought. On the other hand, it is also worth noting that about 20% of the combined histogram realizations yield increased flow, with a few projections of flow increases occurring even under the scenario of high-end temperature sensitivity. Analysis of the cumulative distribution functions (assuming elasticity = 1.9) indicates the 10th percentile Lees Ferry flow change to be −15%, −22%, and −30% for progressively greater assumed temperature sensitivities, respectively (see Fig. S2). Their corresponding 90th percentile changes are 10%, 5%, and −2%, respectively. The internal decadal variability of precipitation is thus seen to be sufficiently large to render more abundant Lees Ferry flow during 2026–50 even under the more intense warming (and warming impact) scenarios.

The above projections of Lees Ferry flow are unconditional. The 2000–20 reference against which changes were calculated represented a collection of all possible initial states, rather than any particular state. Given that the observed Colorado River basin in 2000–20 has been characterized by especially low precipitation and low runoff, a relevant question for planning is how the river's flow in 2026–50 is likely to differ from that during the Millennium Drought epoch—is water resource recovery from low flows during 2000–20 possible? To address this question, the LENS data for 2000–20 are subsampled to include only those simulations whose initial states rank in the lower quintile of their respective model's 2000–20 distribution—effectively initial drought states. The flow change for 2026–50 is then determined only for these (44) subsamples, which can be viewed as a proxy for the expected change relative to the observed post–Millennium Drought. Figure 8 reveals that when aggregated across all scenarios of temperature sensitivity and for the two assumptions of elasticity, there is a higher probability for Lees Ferry flow to increase (the peaks of the distribution are to the right of the zero line), rather than decrease, relative to the recent low flow epoch. A possible reason for such recovery (partial at least) is the sensitivity of southwest U.S. precipitation to decadal-scale Pacific basin sea surface temperature variations. Given that southwest U.S. precipitation declines from the 1980s to the early twenty-first century have been attributed to a marked swing toward a cold (negative) phase of the Pacific decadal oscillation (PDO) (Lehner et al. 2018), the recovery seen in the model samples could reflect a bounce-back in the region's precipitation if the PDO reverted to normal or a positive polarity during 2026–50. It should be noted that our selection of conditional samples from which future simulated Lees Ferry flows were derived in Fig. 8 has not examined the characteristics of PDO-like variability in those particular model runs. It is plausible that there are other pathways to achieving UCRB decadal dryness than via a PDO mechanism alone, and in principle, our sample would be inclusive of a multitude of possible causes for initial state dryness. Nonetheless, a more refined selection of dry UCRB precipitation subsamples, one that strictly samples the coupled models' ENSO-like PDO fluctuations resembling observations, might offer a better initial state analog to the recent observations (see Ding et al. 2018; Mahmood et al. 2022).

If the 2000–20 drought situation had been mostly caused by human-induced climate change, then the further increase in radiative forcing during the subsequent 2026–50 era would be expected to further starve the basin's water resources. That is clearly not the outcome predicted in Fig. 8. The projections instead point to a greater likelihood of at least partial Colorado River recovery. The cumulative distribution functions (assuming elasticity = 1.9) indicate 50th percentile Lees Ferry flow changes of 7%, 1%, and −3% for the progressively greater assumed temperature sensitivities, respectively. The 90th percentile predictions indicate increases of 15%, 10%, and 5% (see Fig. S3).

It is important to emphasize "partial" recovery since very few model realizations in this conditional subsample produce a greater than 20% increase in Lees Ferry flow, which would be needed to roughly offset water supply losses due to the 20% deficit in flows observed during 2000–20. While this is a more positive view of prospects than has been sometimes feared, one must recognize the appreciable probability for further Lees Ferry flow declines in 2026–50 when compared to even their initial low flow states of 2000–20. Such an outcome is principally realizable under the highest assumed temperature sensitivity. The scenarios thus provide a cautionary tale that even under anticipation for some bounce back in precipitation due to natural variability alone, a possible acceleration in warming-related depletion would act to prolong and intensify the physical roots of the current water crisis.

TABLE 3. Probability of Lees Ferry flow changes for 2026–50 vs 2000–20.

Prediction	<−20%	<−10%	>+10%	>+20%
Unconditional	18%	44%	7%	1%
Conditional	4%	16%	26%	5%

Table 3 summarizes the probabilities for Lees Ferry flow changes. Results for the unconditional (Fig. 7) and conditional (Fig. 8) projections have been aggregated across the three scenarios of temperature sensitivity and the two scenarios of elasticity. Thus, the full range of uncertainties treated herein for Lees Ferry predictions are synthesized in Table 3. The differences between conditional and unconditional probabilities are the key features of the table, indicating much greater odds for Lees Ferry flow recovery when the initial reference state is dry. The result may appear intuitive. However, as mentioned previously, if the 2000–20 low flow era had been largely due to human-induced climate change, then a much smaller probability for recovery would have been expected than what these conditional probabilities reveal. Specifically, no rebound from a natural cycle of dry to wet would be expected if such cyclical drivers had not contributed to the Millennium Drought—i.e., if no natural cycle had operated on the river to cause the 2000–20 drought in the first place. Instead, Table 3 reveals that a natural cycle of at least partial recovery from recent low flows is to be expected for the Colorado River.

4. Summary and discussion

The principal purpose of this study is to generate robust probability forecasts for natural Lees Ferry flow that integrate an expansive suite of projected meteorological changes with known sensitivities of the flow to such drivers. The analysis is informed by new climate model simulations as part of CMIP6, which in addition to the traditional diagnosis of multimodel ensembles also include large ensemble simulations for several selected models. These latter experiments permit a more robust estimate of the range of meteorological outcomes associated with both climate change and climate variability. Recognizing the regional biases in global models, including insufficient spatial resolution that is necessary to properly model the physics of Colorado River basin runoff, this study has used multiple linear regression between the flow and meteorological forcings [Eq. (1)], the latter derived from the large ensembles. Our methods thus follow the tradition of several recent studies (e.g., Udall and Overpeck 2017; Hoerling et al. 2019; Lehner et al. 2019) on projecting future flows of the Colorado River.

Our focus on the role of precipitation is motivated by two considerations. First, it is shown that 83% of the observed decadal variability in Lees Ferry flow is explained by upper Colorado River basin precipitation—it is the principal engine driving the hydrologic variability. Second, the nature of the Lees Ferry–UCRB precipitation relation during 1950–2022 is characterized by an elasticity of 1.9. Thus, a near twofold increase in decadal runoff anomalies per incremental decadal precipitation anomalies exists, indicating that moderate precipitation changes generate outsized Colorado River flow changes. In contrast, decadal flows were found to be only weakly constrained by temperature, explaining less than 5% of the flow's decadal variability during 1950–2022. We estimate a depleting effect of UCRB temperature on Lees Ferry flow when decadal conditions are warm, but its magnitude has low confidence owing to the minimal variance of Lees Ferry decadal flows accounted for by temperature historically.

The study focuses on Lees Ferry flow projections for 2026–50 versus 2000–20. Assessing the probability of the physical supply during this near-term window is especially relevant because water managers and policymakers are currently deliberating the post-2026 guidelines and strategies aimed to protect the Colorado River. Our projections of Lees Ferry flow are probabilistic in that they accommodate several sources of uncertainty. One is the magnitude of the river's sensitivity to temperature, and we use scenarios describing low, mid, and high sensitivity that span a threefold range in their depletion rate magnitudes. Second is the precipitation elasticity of Lees Ferry flow, which, though well-constrained by empirical data, is allowed to span a 25% magnitude range of 1.9–2.5. Third is the magnitude of the inherent internal meteorological variability itself, and we use a 220-member large ensemble suite of simulations to capture the range of possible climate states.

A principal finding is an increase in UCRB precipitation of about 2.5% in the UCRB for 2026–50 due to the effects of climate change alone. The magnitude of this signal is not negligible, being half the magnitude of internal decadal variability. A projected increase of precipitation over the UCRB occurs quite robustly in 70% of model samples. And there is a large spatial footprint of wettening, with increases projected to occur throughout much of the western half of the United States in CMIP6. Owing to the large precipitation elasticity of Lees Ferry flow, this wettening compensates for an appreciable fraction of temperature-induced runoff declines that is associated with the projected anthropogenic warming of about 1.5°C.

A further key result is that the range of plausible Lees Ferry flows in 2026–50 is much expanded when incorporating the effects of inherent decadal precipitation variations relative to considering temperature variability alone. Increases in runoff of over +10% during 2026–50 are projected in some samples, even for the more acute temperature sensitivity scenarios owing to an internal dynamical capacity to generate appreciable decadal precipitation variability in the UCRB. Likewise, extreme low flows for 2026–50 are also predicted with some samples indicating greater than 40% reductions. In sum, while the inclusion of a climate change signal of precipitation ameliorates depleting influences of anthropogenic warming and thereby paints a less dire view of climate change impacts on the Colorado River, precipitation's large inherent variability nearly doubles the range of plausible flow regimes. The latter is especially true relative to projections employing temperature effects alone, which underestimate the prospect of both low and high flow states.

We further constrained the projections of Lees Ferry flow by selecting model ensembles with dry initial conditions (the 2000–20 reference) mimicking the recently observed low flow regime. These projections indicated a much greater probability for flow recovery than those based on the unconditional initial states. Indicated thereby is that some natural bounce back from a low precipitation/runoff regime in 2000–20 is to be expected. However, the depleting effects of ongoing warming curtail this recovery and ensure a less than robust river in 2026–50 than might have occurred under past naturally occurring dry–wet cycles such as seen in paleo-reconstructions of Lees Ferry flow (e.g., Stockton and Jacoby 1976; Meko et al. 2007; Gangopadhyay et al. 2022). Perhaps surprising, given the low flow initial reference state of these projections, is our finding of a roughly 30% probability for even lower flows in 2026–50, a risk that emerges especially under scenarios of high runoff sensitivity to warming.

Our focus has been on annual conditions averaged over decades, with the implicit assumption that Lees Ferry flow changes are well represented by changes in annually averaged meteorological conditions. Further, our application of Eq. (1) assumes that Lees Ferry flow change can be reconstructed from a linear combination of changes in annual averaged temperature and precipitation. On the first matter, it is indeed the case—in this mainly snowpack-driven basin—that cold season precipitation would have the major controlling effect on Lees Ferry annual flow volumes. However, warm season moisture is also relevant. By conditioning soil moisture, precipitation affects the subsequent cold season runoff efficiency (see, e.g., Woodhouse et al. 2016). At least in a qualitative manner, wet (dry) conditions in either cold or warm seasons would both be expected to have positive (negative) impacts on annual runoff volumes. In this sense, the seasonality of changes may not be critical to an annual production of flow though this requires a more careful quantitative analysis.

Regarding the paper's reliance on Eq. (1) to infer Lees Ferry flows, it is useful to note the results of Hoerling et al. (2019) that address this. They contrasted the actual simulated UCRB annual runoff change occurring in three climate models to those reconstructed based on applying Eq. (1) to the model's meteorological changes alone. Note that the former was based on daily simulated land surface model responses to seasonally varying climate change within the coupled global atmospheric model; the latter was only based on considering the additive (linear) effects of the model's annual meteorological changes. The similarity between the two approaches (see their Fig. 10) demonstrates the considerable realism in recreating the complex coupled model runoff responses via the application of the simplified Eq. (1), pointing to the suitability of using such an approach. Of course, lost in such an analysis are the response of the seasonal varying hydrograph and the importance of shifts in the timing of peak runoff, as recently analyzed in some detail by Currier et al. (2023). Related to the latter are seasonal changes in the snowpack itself, the possible effects of which on annual flows have not been studied herein.

Implicit also in the use of Eq. (1) is that Lees Ferry flow can be modeled as a response to the area-averaged meteorological changes over the upper Colorado River basin as a whole. Indeed, it is well known that much of the climatological annual runoff is generated by only a small fraction of the higher elevation portions of the catchment (e.g., Fig. 3 of Hoerling et al. 2019), and as such, climatological runoff production depends on spatial resolution (e.g., Fig. 4 of Vano et al. 2014). Here, we would note that Eq. (1) is concerned with anomalies, superposed on a background climate. We have found that the spatial scale of anomalies in temperature and precipitation based on the multimodel ensemble mean responses are continental and homogeneous across the UCRB (see Fig. 5). However, since our paper's analysis considers all the variations (externally forced and internally generated), it is quite possible that individual samples that reflect strong anomalies from internal variability could yield meteorological changes, which are not as spatially homogeneous or large in scale. As such, the application of Eq. (1) using basin-averaged T and P anomalies could yield somewhat poorer estimates of Lees Ferry flow anomalies in those cases given that runoff efficiency is spatially variable as shown in Hoerling et al. (2019).

Finally, we note that the paper has not accounted for changes in the character of precipitation, such as the intensity of daily events or the frequency of wet day occurrences. Our prior studies using a simple water balance model (see Vano et al. 2014) suggest it is unlikely that changes in those, aside from their reflection in annual totals, would greatly alter the water-year runoff production from the upper Colorado River basin. That model was forced with an observational estimate of only the monthly varying precipitation (and temperature) over a historical period since 1915. The resulting time series of simulated annual mean flow correlated at 0.95 with the actual annual Lees Ferry gauge data (not shown). This does not signify an irrelevance for daily extremes in precipitation. Indeed, statistics of extreme flood events in small river catchments would be expected to be sensitive to changes in extreme precipitation. Yet, to the extent that extreme daily events are reflected in longer time averages, then their contribution to the annual runoff volumes averaged for decades over the entire upper Colorado River as studied herein is likely reasonably captured when using such time-averaged forcings.

Two overarching issues have motivated this study. First, drought conditions have been prevalent in the Colorado River basin for most of the twenty-first century. This situation coupled with basinwide uses, primarily below Lake Mead that have exceeded the available supply, has led to a significant depletion of the two main reservoirs on the river—Lakes Powell and Mead. At the same time, increasing temperatures in the American Southwest, largely associated with global warming, led to many voices asserting that future flows in the Colorado River are now permanently reduced to levels prevalent during the last two decades.

Most of these claims are built on the expectation of continued warming in future decades due to climate change. However, observations of precipitation, surface temperature, and streamflow in the upper Colorado River basin over the past ~100 years indicate that by far, the largest contributor to runoff variability has been due to precipitation variability, with the associated temperature variability contributing a relatively small percentage of the streamflow variability as measured at Lees Ferry.

We have utilized two modeling approaches to analyze the combined effects of projected changes in precipitation and surface temperature over the UCRB, namely, the output from a set of CMIP6 single realization models and from output derived from five LENSs. To determine probabilistic envelopes of future UCRB runoff, we have used different ranges of plausible precipitation/runoff and temperature/runoff sensitivities and have focused on the 25-yr period 2026–50 relevant to the expected Interim 2026 Guidelines for managing Colorado River usage.

The suite of different temperature and precipitation projections along with plausible runoff sensitivities provides a robust and more complete set of future runoff expectations of both natural and external climate change scenarios to midcentury. Just as a beautiful rose flower comes with thorns, so too, on the Colorado River, our findings indicate that the effects of precipitation variability lead to a higher probability of wet periods and also dry periods for 2026–50. Water managers should thus not be surprised and should be prepared for a future where in the next 25 years, there are more wet periods than dry periods akin to the drought of 2000–22. Managing this wide range, especially considering increasing demands, is the pressing challenge for water managers in the basin. As the stakeholders embark on negotiating the post-2026 operating guidelines, this study along with others urges them to recognize and fully appreciate the Colorado River's intrinsic large variability. A framework that incorporates this variability via risk-based management approaches, we believe, can lead the basin and the region toward a future with sustainable water resources.

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Data availability statement. The dataset used in this study, which consists of a time series of historical and projected Lees Ferry flow, precipitation, and temperature, can be obtained from https://www.hydroshare.org/resource/52f57fb7e08d46ffbb8ea65073c9eefc/. This repository also contains data corresponding to each figure in respective files named accordingly.

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