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A sensitivity-based approach to evaluating future changes in Colorado River Discharge

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Abstract

Projections of a drier, warmer climate in the U.S. Southwest would complicate management of the Colorado River system – yet these projections, often based on coarse resolution global climate models, are quite uncertain. We present an approach to understanding future Colorado River discharge based on land surface characterizations that map the Colorado River basin's hydrologic sensitivities (e.g., changes in streamflow magnitude) to annual and seasonal temperature and precipitation changes. The approach uses a process-based macroscale land surface model (LSM; in this case, the Variable Infiltration Capacity hydrologic model, although methods are applicable to any LSM) to develop sensitivity maps (equivalent to a simple empirical model), and uses these maps to evaluate long-term annual streamflow responses to future precipitation and temperature change. We show that global climate model projections combined with estimates of hydrologic sensitivities, estimated for different seasons and at different change increments, can provide a basis for approximating cumulative distribution functions of streamflow changes similar to more common, computationally intensive full-simulation approaches that force the hydrologic model with downscaled future climate scenarios. For purposes of assessing risk, we argue that the sensitivity-based approach produces viable first-order estimates that can be easily applied to newly released climate information to assess underlying drivers of change and bound, at least approximately, the range of future streamflow uncertainties for water resource planners.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment reported unequivocal evidence that climate change was occurring and global climate models (GCMs) showed general agreement that temperature will increase and runoff will decrease across the southwestern U.S. in the coming century (IPCC 2007; Bates et al. 2008). These changes will make managing water supplies for human consumption and healthy ecosystems more challenging, yet notwithstanding the IPCC statement, there remains much uncertainty as to the nature of regional and local impacts (Vano et al. 2013). A major challenge is that GCMs operate at coarse spatial scales (mostly around ~200 km x 200 km, although the resolution has been increasing over time) relative to the river basin scale where management decisions are made. To respond to this scale mismatch, various approaches have been developed which translate global scale information to more local scales (Barnett et al. 2004; Wood et al. 2004; and others), although the extent these methods capture basin-specific hydrologic characteristics differs considerably (WWA 2008; Vano et al. 2013).

In recent years, a common "end-to-end" approach to integrating climate information into management has been to use an ensemble of downscaled GCM output using methods such as those outlined in Wood et al. (2004), run through a hydrology model to generate streamflow sequences which are then used to explore future changes in reservoir operations (e.g., Payne et al. 2004; Christensen and Lettenmaier 2007; USBR 2011; and others) (Fig. 1, schematic on left). This approach, which we refer to as the "full-simulation approach", is widely used and is generally the preferred approach for inferring local effects of climate change. It is also useful because it provides sequences of future streamflows that are similar with respect to temporal aggregation and record length as the historical streamflow sequences that water managers often use in planning studies. It also allows managers to understand the nuances of future simulations (e.g., two-thirds of the 112 USBR (2011) simulations show streamflow declines while one-third show no change or increases (Harding et al. 2012)). It does, however, require considerable computing and data management, as each scenario is its own realization, which might be viewed as only one ensemble member of many that provide a representation of possible future conditions. Furthermore, each time new climate model runs are released the entire process has to be repeated (e.g., at the approximately five-year interval of the IPCC reports – the fourth Assessment Report (AR4) GCMs, generated through the Coupled Model Intercomparison Project (CMIP) results were made available around 2005 and AR5 models are becoming available as this paper is written). In most past studies, the end-to-end approach has used a single land surface model, but this ignores the uncertainty in the land-surface response simulated by a range of models, which can be considerable (see Vano et al. 2012).

Although the linking of models is arguably an approach that encompasses best-available science, it often focuses more on data processing than underlying mechanisms that control hydrologic change. Models are imperfect representations of land-surface hydrologic processes, and thus each step of the modeling cascade requires decisions on how best to span space and time. Too often, there are so many modeling steps between the climate change projections and their potential impacts (each with unquantified uncertainties) that it is difficult to assess aggregate uncertainties and hard to judge which approaches are appropriate for which questions (Hamlet et al. 2010; Abatzoglou and Brown 2012). These unquantified uncertainties result from various decisions including what models (e.g., GCMs, hydrology models) are used, what is the spatial resolution of the analysis, and what is and is not preserved in the downscaling of climate information (Vano et al. 2013). Increased computing capacity has allowed scientists to generate more scenarios, increasing the stream of data from one model to the next, but with this increase in volume, it has become harder to control the quality of the simulations. The implementation of the end-to-end approach also requires bias-correction procedures that can be difficult to explain, and are therefore often viewed with skepticism by the water resource management community.

We present here a sensitivity-based approach to scenario planning (Fig. 1, schematic on right) that leverages our best understanding of the hydrological processes within the atmosphere-hydrosphere-biosphere continuum. It can produce first-order estimates to help bound the uncertainties in estimated long-term hydrologic response to changes in climate forcings. It can also provide complementary information to other downscaling approaches to help assess sources of uncertainties (e.g., whether streamflow change is more sensitive to precipitation (P) or temperature (T) change in a particular river basin). The approach uses precipitation elasticity (ε) and temperature sensitivity (S) as defined in Vano et al. (2012) to translate climate forcings into changes in streamflow, which can be used to generate cumulative distribution functions (CDFs) of future change. This provides a simplified way of incorporating climate change information into planning by making the process less computationally intensive and more accessible, yet still based on physical processes. That said, it is *extremely* important to match the nature of the management questions to be addressed with the temporal scale of the hydrologic sensitivities. For example, the ε and S we use here are average responses (e.g., they are descriptive of changes in mean streamflow) that do not capture extremes and therefore are not appropriate for management questions related to extremes. This new approach is intended to help understand the range and central tendencies of annual-average basin-wide streamflow responses to long-term annual and seasonal changes in P and T (30-year averages), providing a sense of expected changes prior to conducting more detailed end-to-end simulations.

2. Site description

The Colorado River basin (map included as Fig. S1 in supplementary materials) has been, and will continue to be, an area of great interest with respect to projected climate change (Barnett and Pierce 2008; WWA 2008; Brekke et al. 2009). The Colorado River and its tributaries are the primary water supply for much of the Southwest and provide an important source of electricity to the region through operation of numerous hydropower facilities (Fulp 2005). The water resources of the basin are distributed according to water allocations set by the Colorado River Compact of 1922. In retrospect, the allocations were based on a relatively wet period, before much was understood about the basin's inter-decadal variability, resulting in the overallocation of water resources according to the best current estimates of the river's average flows (Woodhouse et al. 2006). Aggregate storage capacity of the Colorado River's reservoirs is large (about four times the river's annual naturalized flow; in contrast, the Columbia River's reservoirs have a capacity of only about one-third of the mean annual flow). The reservoir system, therefore, allows for carry over from wet to dry years, although multi-year sustained dry periods are problematic. Because of the large storage capacity of the reservoir system, climate change implications on management are typically focused on annual (as contrasted with seasonal) responses, and the sensitivity-based approach we describe here is well suited to this basin characteristic.

As a result of drought and the resultant low reservoir levels in the 2000s, the Colorado River has been the focus of many studies that have attempted to estimate future streamflows (Vano et al. 2013). The modeling framework we describe here builds on this previous work, including Christensen and Lettenmaier (2007), USBR (2011), and Vano et al. (2012). In particular, the USBR study reflects the interest of the basin's water managers in understanding the nature of future streamflows. As such, the basin provides an opportunity to evaluate the sensitivity approach's usefulness, and we use the USBR (end-to-end) results to test our method. In developing the method, we performed comparisons between the full-simulation results of Christensen and Lettenmaier (2007) and the sensitivity-based approach for annual average runoff (surface runoff + drainage) from all 4518 grid cells in the basin (Table A1 and A2 in Christensen and Lettenmaier (2007)), as well as streamflow at Lees Ferry, and the outlets of the Green and Navajo Rivers, the results of which were qualitatively similar. We focus on and show results for Lees Ferry, the primary control point for water allocation purposes in the basin (and which defines the Upper and Lower basins; see map Fig. S1 in supplementary materials), but our method can be applied to other locations within the basin. We calculate sensitivities using routed streamflow, but these values differ little from sensitivities calculated using 30-year average grid-cell runoff.

3. Methods

We use precipitation elasticity (ε) and temperature sensitivity (S) to represent the land-surface response to precipitation (P) and temperature (T) change and then use these concepts to provide first-order estimates of future hydrological changes from GCM output. This essentially creates a tool, equivalent to a nomogram, that can be used to bound future runoff change across the Colorado River basin.

ε (Eq. 1) is a measure of how an incremental (e.g., percentage) change in precipitation (ΔP) results in a percentage change in streamflow (Q). Similarly, S (Eq. 2) is a measure of how an incremental temperature increase (ΔT) results in a percentage change in Q.

$$\varepsilon = \frac{\frac{Q_{hist+\Delta P} - Q_{hist}}{Q_{hist}}}{\Delta P} \qquad (1)$$

$$S = \frac{\frac{Q_{hist+\Delta T} - Q_{hist}}{Q_{hist}}}{\Delta T} \qquad (2)$$

These sensitivities have been explored throughout the Colorado basin by Vano et al. (2012). Values calculated here vary slightly from values reported there because we use a fixed (historical) reference for different increments of change. In other words, we use a single reference (historical) and change the perturbation magnitude (0.1°C, 1°C, 2°C, 3°C). In contrast, Vano et al. (2012) kept the perturbation magnitude constant (0.1°C), but calculated ε and S from different references (0°C, 1°C, 2°C, 3°C). Therefore Vano et al. (2012) describes the local functions while Figure 2a&b show the integral (total change) of the local values. Our motivation in so doing is that we want to infer hydrologic changes associated with the total changes in T and P as simulated by the GCMs (ΔT_{GCM} and ΔP_{GCM}) relative to historical values. We also calculated monthly S and ε in which we incremented T (by 0.1°C) and P (by 1%) for each month.

To estimate streamflow sensitivities (ε, S), we used the Variable Infiltration Capacity (VIC) macroscale hydrology model (Liang et al. 1994). VIC has been used extensively at regional and global scales in numerous studies, mostly in off-line simulations where gridded surface P, T, wind speed, downward solar and longwave radiation, and vapor pressure (humidity) are prescribed (e.g., Nijssen et al. 2001; Christensen et al. 2004; Christensen and Lettenmaier 2007; Elsner et al. 2010; and many others). In this study we used VIC, as applied by Christensen and Lettenmaier (2007) and USBR (2011), although this same approach can be used with other land surface models. We used the Maurer et al. (2002) historical gridded data set and vegetation and soil parameter files as in Christensen and Lettenmaier (2007) and USBR (2011) all at one-eighth degree latitude-longitude resolution. We ran simulations from 1970-1999 using initialized conditions from Vano et al. (2012) and calculated hydrologic sensitivities for 1975-1999, although as tested in Vano et al. (2013) the period of analysis and dataset have little effect on hydrologic sensitivity values. Sensitivity results are roughly equivalent if we use another historical dataset (e.g., Wood and Lettenmaier 2006) or averaging period.

To estimate future streamflow changes with the sensitivity-based approach, we multiplied ΔP_{GCM} and ΔT_{GCM} changes (Fig. S2 in supplementary materials) by their related hydrologic sensitivity measures (ε, S) to estimate the long-term average percent change in streamflow (ΔQ) at a specific location and future time period. GCM output (T_{GCM} and P_{GCM}) was regridded to a common 2° lat-lon grid (see Fig. S1) using the same approach as in Christensen and Lettenmaier (2007), then 30-year monthly averages for both historical and future periods were averaged spatially across the nine 2° latitude-longitude grids cells that encompass the area upstream of Lees Ferry. These values were used to calculate the difference in T (ΔT_{GCM}) and percent change in P (ΔP_{GCM}) between the historical (1970-1999) and three future periods (2010-2039, 2040-2069, 2070-2099).

We first calculated ΔQ according to Eq. 3, where ΔP_{GCM} is the long-term average *percent change* in P and ΔT_{GCM} is the *difference* in long-term average T between the future and historical GCM simulation. $d(P,T)_{int}$ is the interaction between P and T changes which was neglected, due to the additive nature of S and ε in the Basin reported by Vano et al. (2012).

$$\Delta Q_{est} = \Delta P_{GCM} * \varepsilon + \Delta T_{GCM} * S + d(P,T)_{int} \qquad (3)$$

where:

$\Delta P_{GCM} = (P_{GCMfut} - P_{GCMhis})/P_{GCMhis}$

$\Delta T_{GCM} = T_{GCMfut} - T_{GCMhis}$

To improve the performance of this sensitivity-based approach, we made three adjustments (Eq. 4) which account for: (1) variations in annual ε and S values as a function of ΔP_{GCM} and ΔT_{GCM} respectively (Fig. 2a,b), (2) seasonal T by applying monthly $\Delta T_{GCM.mon}$ and monthly S_{mon} values (Fig. 2c, black line), and (3) seasonal P by applying monthly $\Delta P_{GCM.mon}$ and monthly ε_{mon} (Fig. 2c, orange line). Section 4.1 provides more details on these adjustments.

$$\Delta Q_{adj\_est} = \sum_{mon=1}^{12} (\Delta P_{GCM,mon} * (\frac{\varepsilon_{mon} * \varepsilon(\Delta P)}{\sum \varepsilon_{mon}})) + \sum_{mon=1}^{12} (\Delta T_{GCM,mon} * (\frac{S_{mon} * S(\Delta T)}{\sum S_{mon}})) + d(P,T)_{\mathrm{int}} \quad (4)$$

Full-simulation approach streamflow changes (ΔQ_{sim} in Eq. 5) were calculated using routed, bias-corrected future streamflows from VIC model simulations (Q_{fut}) from Christensen and Lettenmaier (2007) and the USBR Colorado River Basin Water Supply and Demand Study (data provided by James Prairie, May 2012) and historical naturalized streamflows from USBR (2012) (Q_{obs}).

$$\Delta Q_{sim} = (Q_{fut} - Q_{obs})/ Q_{obs} \quad (5)$$

We used the bias-corrected streamflows from the 22 "full-simulations" of Christensen and Lettenmaier (2007) (11 GCMs x 2 global emission scenarios) calculated for three future time periods to develop the adjusted estimation method (Eq. 3, Fig 3a (prior to adjustment) vs. Eq. 4, Fig 3b (post adjustment)). In these figures, the abscissa values are percent changes from

Christensen and Lettenmaier (2007) calculated with Eq. 5 and the ordinate values are estimated streamflows using the sensitivity-based approach calculated with Eq. 3 and 4 respectively. 95% confidence intervals were estimated for predicted values. We then used the USBR (2011) full-simulation approach to test the adjusted estimation method, using the same 30-year time periods. The USBR study produced 112 monthly (mean) streamflows for three emission scenarios (A2, A1B, B1) (Fig. 3c). These data were generated as part of the USBR Colorado River Basin Water Supply and Demand Study; see USBR (2011) and Harding et al. (2012) for details.

4. Results and Discussion

4.1. Development and testing of the sensitivity-based approach

Fig. 3a is our estimate of projected runoff change (ΔQ_{est}, from Eq. 4) prior to adjustment. The calculation uses a single ε and S (ε=2.23, S=-6.47% per ºC, values generated from 1% ΔP and 0.01ºC ΔT differences applied to historical simulations respectively, Fig. 2a,b) value for Lees Ferry for 30-year annual average GCM estimates of P and T change (n=66, 2 emission scenarios by 3 time periods by 11 GCMs). We focus on aggregate changes at Lees Ferry; as such it makes little difference if we apply grid cell changes or the aggregate since GCM prediction differences across the 9 grids are small. Therefore, we opted to do the more straightforward basin-wide approach. Each dot corresponds to a unique ΔQ_{sim} (Eq. 5) from bias-corrected streamflows taken from Christensen and Lettenmaier (2007). The proximity of responses to the 1:1 line reflects how well the methods compare for the 66 simulations. The linear relationship between ΔQ_{est} and ΔQ_{sim} has a R^2=0.58, which reflects considerable scatter, where ΔQ_{est} is biased towards overestimating ΔQ_{sim} (the y-intercept of the regression is -5.6%).

An extreme example of this bias is GFDL's A2 scenario in 2070-2099, which simulates a decline in streamflow of -22% whereas the sensitivity-based approach estimates a -63% decline.

We made three adjustments (below) to the sensitivity-based approach to reduce bias and scatter; the influence of each independently and in combination is noted in Table 1.

Adjustment 1, ε(ΔP) and S(ΔT): As ΔP and ΔT change, their sensitivities also change (Fig. 2a,b). Therefore, instead of a single value for ε and S, we varied the long-term annual changes according to ΔT_{GCM} and ΔP_{GCM} values based on two regression equations generated using VIC hydrology model simulations at different perturbations (Fig. 2a,b). These perturbations were selected to cover the range of climate change projections (shown in Fig. S2 in supplementary materials). At Lees Ferry, both ε(ΔP) and S(ΔT), when calculated using a fixed (historical) reference, result in values that can be approximated with a linear equation (Fig. 2a,b). As mentioned in Section 3, these values can also be calculated by taking the integral of changes reported in Vano et al. (2012), which captures the instantaneous change function (tangent of the change) instead of the total change which is required for the method we use here. To get the total change, we calculated ε and S as functions of ΔP and ΔT increments from the fixed historical values (this captures the secant of the change, where changes can be taken directly from the figure without integrating) and also requires a smaller (half) number of simulations.

Adjustment 2, S_{mon}: Simulation experiments by Das et al. (2011) found that annual streamflow responses at Lees Ferry differ according to seasonal warming patterns, where greater decreases in annual streamflow occur for warming in the warm season, as opposed to warming in the cool season. To capture this in our sensitivity-based approach, we apply T changes on a seasonal basis according to the values in Fig. 2c (black line), which were determined through 12 model simulations where we perturbed a single month's T by 0.1ºC in each simulation and calculated how warming in that month affects annual S values. These values when added together equal -6.46%, which is very close to -6.47%, the sensitivity for annual T changes of our unadjusted estimate. We weight these values according to the long-term annual S(ΔT) value as described in the preceding paragraph. Seasonal S range from -0.10% in December to -1.14% in May, with warm season (April-September) sensitivities about three times higher than cool season (October-March) (Fig. 2c). With this adjustment, GCMs that have more warming in the summer than the winter will have greater streamflow changes.

Adjustment 3, ε_{mon}: this adjustment also accounts for seasonal changes, specifically how changes in monthly P (ΔP_{mon}) affect annual streamflow by applying monthly ε values. Monthly ε values (ε_{mon}; Fig 2c orange line) range from 0.09 in Jun and Aug to 0.27 in Mar, a seasonal pattern that coincides with monthly average precipitation (R^2=0.39) which is also highest in Mar and lowest in Jun. Because ε_{mon} is calculated as a 1% P change perturbation in each month, a 1% change in wetter months should have a greater effect on annual streamflow than a 1% change in drier months; accounting for ΔP_{mon} for individual GCMs improves the ability of the sensitivity-based approach to capture full-simulation results (when applied independently of the other adjustment it increases the R^2 from 0.58 to 0.70 and reduces the y-intercept from -5.6 to -1.5, Table 1). An alternative would be to adjust ΔP_{GCM} to coincide with the bias-corrected change applied in the bias-correction spatial disaggregation (BCSD) downscaling technique used in the full-simulation approach (Fig. S3). This alternative adjustment improves results, but not as much as adjustment 3 and is not effective when monthly ε values are applied. More details of this alternative approach are included in the supplementary materials.

When all three adjustments were applied, the ability to reproduce end-to-end results improved considerably (Fig. 3b). The R^2 in the linear relationship between $\Delta Q_{est,adj}$ and ΔQ_{sim}

improved from 0.58 to 0.78, and, there was considerable improvement in the ΔQ_{est} bias towards underestimation of ΔQ_{sim} (y-intercept of the regression is -0.2% vs. -5.6%). Also, the slope of the relationship was closer to one (see Table 1 for comparisons of each adjustment). The GFDL A2 scenario in 2070-2099 (highlighted in Fig. S3, left panels) is an example of how an estimate can improve, from an unadjusted estimate of -63% to an adjusted estimate of -32%, which is considerably closer to the -22% projected using the full-simulation method. The 95% confidence intervals for predicted values are within +12% and -13% of those from the full-simulation method (Fig. 3b).

We also evaluated the sensitivity-based approach using full-simulation results from USBR (2011), for which 112 simulations from three emission scenarios were available, totaling 336 comparisons (36 A2, 39 A1B, and 37 B1 GCMs by three time periods each) (Fig. 3c). These values, which incorporate the three adjustments discussed above, also have a negative bias (y-intercept of the regression is -1.7%) and slope of 1.0. The 95% confidence intervals for predicted values are similar to those estimated from Christensen and Lettenmaier's (2007) full-simulation results; our estimated values were within +12% and -16% of the USBR (2012) full-simulation values (Fig. 3c).

4.2. Assessing risk with the sensitivity-based approach

Water managers' main interest in future streamflow projections is to assess risks associated with climate change. To test whether sensitivity-based results provide similar ensemble distributions to full-simulation results, we compared the cumulative distribution functions (CDFs) of streamflows generated using both approaches. In the development of the sensitivity-based approach (section 4.1), we combined time periods and scenarios; this is appropriate for testing how T and P change can be used to estimate streamflow change, where each 30-year segment can be treated independently. In practice, however, the particular emission scenario and (especially) the future time period are important considerations in planning – where planning horizons are typically several decades (hence the difference between emissions scenarios is usually less than the differences among GCMs). Fig. 4 shows the CDFs for the two approaches using the USBR simulations (as in Fig. 3c) for three future time periods (columns) and three emission scenarios (rows). Differences between emissions scenarios become greater through time, becoming more pronounced in the mid 21st century (IPCC 2007); therefore in 2010-2039 emissions scenarios have no noticeable influence.

Across emission scenarios and future time periods, the ensemble range is captured well (Fig. 4). The magnitudes of changes are similar in earlier periods, however the ensembles show more discrepancies between approaches further in the future and associated with more extreme emissions scenarios. Discrepancies are most likely because at these more extreme values, linearization of the sensitivity-based approach breaks down and the sensitivity-based values, relative to the full-simulation, show greater streamflow declines. Notably, in CMIP3 GCM output for the Colorado River basin, neither emission scenario nor time period are significant predictors for P but both are for T. Therefore T is likely driving these discrepancies, which is also evident in Fig. 3d&e as ΔT_{GCM} influences the magnitude of the regression more than ΔP_{GCM}.

From a climate risk standpoint, the agreement or lack thereof among the CDF is more important than whether the inferred changes associated with any specific GCM agree. Fig. 4 shows that in general, the distributions are consistent, especially at modest change levels (first 30-year period in particular), although there is a bias in the sensitivity-based approach towards overestimating streamflow declines for periods farther in the future and/or for scenarios with large (in absolute value) T and P changes.

4.3. Added value of the sensitivity-based approach

In addition to providing a "shortcut" method for estimating future flows, the sensitivity-based approach allows the influence of T and P changes to be segregated, and in so doing encourages better understanding of the factors that will drive changes in the hydrologic system. For instance, values of ε and S can be used as evaluation tools. As an example, Fig. 3d&e shows the same results as in Fig. 3c, where effects from P change (ΔP_{GCM}) and T change (ΔT_{GCM}) are plotted independently. The plot shows that both ΔP_{GCM} and ΔT_{GCM} are important factors that will affect future streamflow changes at Lees Ferry. On average, ΔP_{GCM} contributes more to the slope (0.74 of 1.01), while ΔT_{GCM} has a considerable effect on the total magnitude and some effect on slope (0.27).

The adjustments outlined in section 4.1 and supplementary materials highlight key elements that are important for prediction of the effects of climate change on streamflow: a) how streamflow responds to both T and P changes at different reference conditions and b) the seasonal effects of T and P change, and c) how P changes are downscaled. These elements suggest ways end-to-end prediction methods might be evaluated. For example, do LSMs used in climate change studies accurately capture streamflow responses to changes in P and T (ε and S values), and do the values change appropriately as the climate becomes drier and warmer? How should downscaling methods capture P changes, especially when the GCM P seasonality does not match that of the historical? For instance, the BCSD approach used in Christensen and Lettenmaier (2007) and USBR (2011) does not preserve the magnitudes of P change as predicted by the GCM, but rather captures the change relative to historical P in each season (see supplementary materials for more details). This subtlety has little effect when future and historical simulations have similar seasonal cycles, but when future seasonality differs from historical, it can affect projected P magnitudes.

Values of ε and S can also be useful tools in evaluating model performance. As demonstrated in Vano et al. (2012), these measures can be used to compare hydrologic model performance to other models and observations. Spatial ε and S maps can help to identify locations where there is more uncertainty as well as areas more sensitive to future change, and imply locations that might be targeted for *in situ* observations. While a body of research has evolved that estimates ε from observed streamflows (e.g., Schaake 1990; Dooge et al. 1992; Dooge et al. 1999; Sankarasubramanian et al. 2001; among others), methods for calculating S values from observations are less clear and arguably more challenging as they depend more on current conditions (which depend on prior weather conditions, e.g., snowpack). A better understanding of observed S would be valuable in model evaluation, as it is a common input variable to land-surface hydrology models in climate studies. This ultimately requires a better understanding of evaporative demand, which is the key driver for which T is just an index (see Dooge et al. 1992; Dooge et al. 1999). Further research into how best to express these evaporative changes would be beneficial and could be done within this sensitivity framework.

4.4. Considerations for application of the sensitivity-based approach

Our approach effectively uses a process-based macroscale land surface model to develop sensitivity maps (equivalent to a simple empirical model) to represent nonlinear hydrologic processes. As such, the applicability of the approach depends on (1) departures from linearity of the underlying functions of T and P change, (2) the superposition of changes, (3) the physical context (location), and (4) the management context. Linearity can be tested by comparing, for instance, whether a 3°C change is predicted to have a similar effect to a 0.1°C change multiplied by 30, or a 30% change in P is predicted to have a similar effect to a 1% change multiplied by 30. Superposition can be evaluated as in Vano et al. (2012) where the sum of independent changes in streamflow from T and P perturbations are compared to changes in streamflow of a simulation where both T and P are changed. In locations where the differences between these comparisons are small, the sensitivity-based approach is more valid (see Vano et al. (2012) figure 10). Additionally, superposition tests can be applied to seasonal changes; the sensitivity-based method is more robust when annual streamflow changes from ΔT and ΔP applied in individual months (Fig 2c) add together to equal annual streamflow changes for the same ΔT and ΔP applied throughout the year.

Physical context matters as different locations respond differently to P and T changes (resulting in different patterns in ε and S values). For example, in a comparison of four major western U.S. river basins (Colorado, Columbia, North and South Sierra), Das et al. (2011) found that annual changes in Colorado River discharge had the greatest declines to 3°C warming annually, and that warm season warming had the greatest influence on these annual changes.

The applicability of the approach also depends on management concerns – the approach outlined here evaluates long-term annual responses, not seasonal responses or their temporal sequencing of changes. In locations where the shape of the hydrograph is more important than annual flow values, the approach may not be appropriate. This method could in principle be applied to a time sequence of changes, but it would change flows only by small increments, which nonetheless over time accumulate could have a large impact. This is different from changing the sequencing of flows, which could have a more immediate impact. In essence, this approach is adding the effect of climate change to a natural flow sequence – where the extent to which you capture variability depends on the natural flow sequences used. In other words, whether sensitivity perturbations are appropriate depends on the management system and specific questions the experiment is intended to address.

5. Conclusions

We have described a sensitivity-based approach that generates estimates of annual average future streamflow change and the dominant causal factors, without detailed simulations. The method uses a process-based model (VIC) to develop a simple empirical model (sensitivity values) and is especially appropriate for producing initial estimates of future streamflow to accompany alternative global model future projections of precipitation (P) and temperature (T), key drivers of land surface hydrology. Our work shows that:

- The sensitivity-based approach produces plausible estimates of future annual mean streamflow change, which are mostly within ±15% of those estimated from a full-simulation approach. Performance of the sensitivity-based approach was improved by three adjustments: (1) accounting for varying P elasticity (ε) and T sensitivity (S) as a function of P and T changes, (2) incorporating monthly variations in S, and (3) incorporating monthly variations in ε. In test applications to predict future mean annual flows at Lees Ferry, the sensitivity-based approach produces estimates that consistently estimate larger streamflow declines (with an average bias of up to -2%, y-intercept in Fig. 3c). Whether this tendency to overestimate declines, as seen in the CDFs of Fig. 4 where the blue line is typically above the gray line, is universal or unique to the Colorado River basin remains to be determined.

• For purposes of assessing risk, the sensitivity-based approach produces viable initial estimates that can be used to bound future streamflow uncertainties for water management purposes. The CDFs of ensemble GCM scenarios (e.g., Fig. 4) match well for the relatively near future (first three decades of the next century), however values further into the future and for severe emissions scenarios mostly overestimate the magnitude of future streamflow changes (mostly reductions in the case of the Colorado River system).

• The sensitivity-based approach helps to focus attention on the causal factors driving future change, and their relative importance, as contrasted with the full-simulation approach which tends to lead to a focus on managing ever-larger quantities of model output. For example, the sensitivity-based approach facilitates evaluation of contributions from P and T change separately. While this can be done with the simulation approach as well, it further compounds the data management problem, and in practice, often is not investigated.

The sensitivity-based approach should be appealing to water managers in that it is computationally efficient, and hence can be used to generate ensembles of hydrologic simulations, which can help in selecting a representative range of simulations for further analysis. For example, it can be easily applied to newly released climate scenarios (e.g., from the Coupled Model Intercomparison Project 5th Assessment), and help provide context as to why results differ. In the comparisons we report here, we used the Variable Infiltration Capacity (VIC) hydrologic model, but these methods are applicable to any other hydrology/land surface model, and can be used to better quantify uncertainty from hydrologic simulations of multiple models.

The approach has limitations, and is best thought of as complementary to other approaches. It is intended for evaluating long-term (e.g., 30-year) average annual changes and does not provide information on daily values, extreme events, or land cover change. We have focused on annual responses, which are of greatest importance to management in the Colorado basin. For other systems, seasonal responses are critical, and understanding how to best capture these responses is currently being investigated.

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TABLE

Table 1. Sensitivity-based adjustments at Lees Ferry

	Slope	y-intercept	R^2
Prior to adjustments	1.08	-5.6	0.58
only adjustment 1[a]	0.98	-4.4	0.63
only adjustment 2[b]	1.13	-5.5	0.61
only adjustment 3[c]	1.06	-1.5	0.70
only altern. adjustment[d]	1.02	-3.0	0.60
adjustments 1 and 2	1.02	-4.4	0.66
adjustments 1 and 3	0.97	-0.3	0.75
adjustments 2 and 3	1.12	-1.4	0.73
all three adjustments	**1.02**	**-0.2**	**0.78**

[a]adjustment 1: $\varepsilon(\Delta P)$ *and* $S(\Delta T)$

[b]adjustment 2: S_{mon}

[c]adjustment 3: ε_{mon}

[d]alternative adjustment: ΔP_{GCMadj} (see supplemental materials)

FIGURES

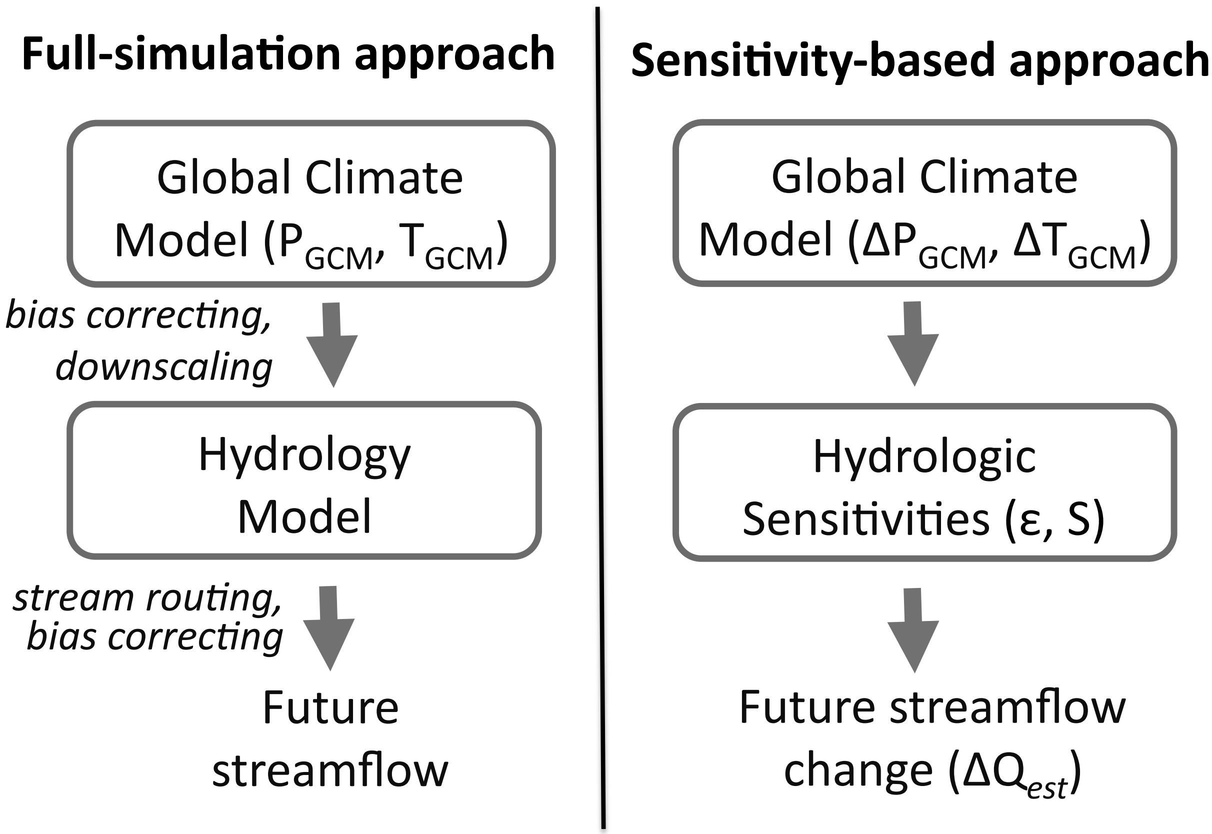
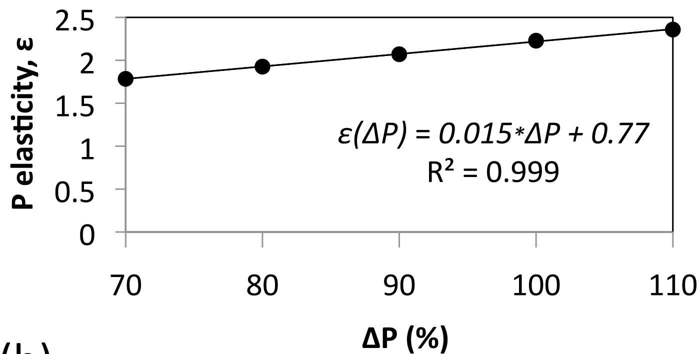


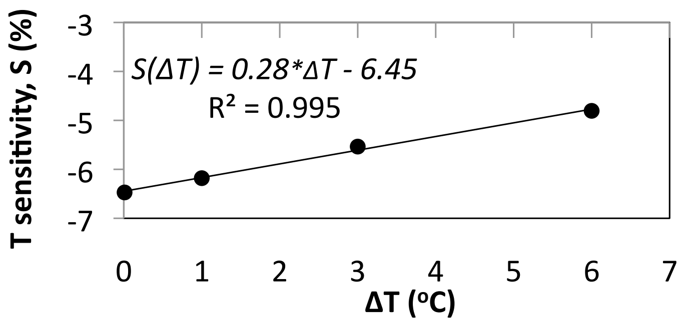
FIG 1 Schematic of two approaches. The full-simulation approach produces a daily time series of future streamflow, whereas the sensitivity-based approach produces only a change in mean streamflow.

(a)



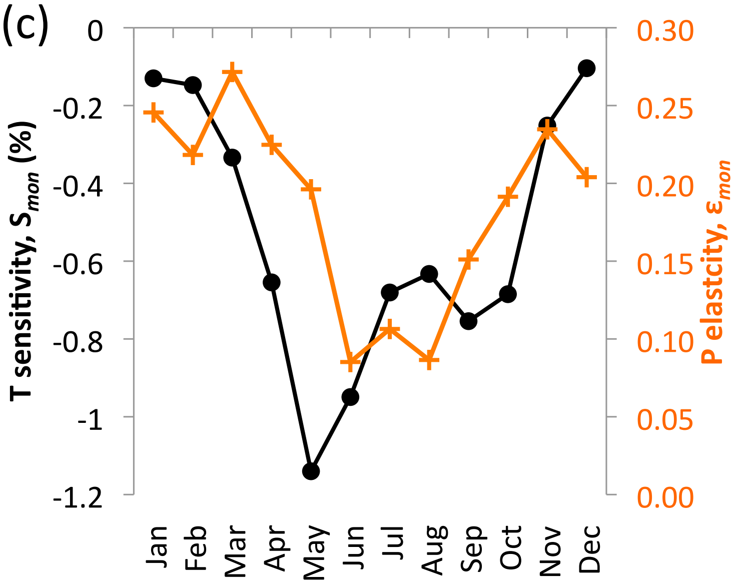
ΔP from Historical Simulation	P Elasticity (ε)
-30%	1.78
-20%	1.93
-10%	2.07
1%	**2.23**
10%	2.36

(b)



ΔT from Historical Simulation	T Sensitvity (S)
0.01 °C	**-6.47%**
1 °C	-6.18%
3 °C	-5.54%
6 °C	-4.81%

(c)



month	T Sensitivity by month (S_{mon})	P Elastcity by month (ε_{mon})
Jan	-0.13%	0.25
Feb	-0.15%	0.22
Mar	-0.33%	0.27
Apr	-0.66%	0.22
May	-1.14%	0.20
Jun	-0.95%	0.09
Jul	-0.68%	0.11
Aug	-0.63%	0.09
Sep	-0.76%	0.15
Oct	-0.69%	0.19
Nov	-0.25%	0.23
Dec	-0.10%	0.20

FIG 2 Variable long-term annual and monthly precipitation elasticities (ε) and temperature sensitivities (S) at Lees Ferry from VIC simulations. Values in the tables correspond to points in the figures. Bold values are used for single ε and S calculations prior to adjustments. (a) ε calculated using Eq. 1 as a function of changing P at 70%, 80%, 90%, 101% and 110% of historical values. (b) S calculated using Eq. 2, using 0.1, 1.0, 3.0, and 6.0 °C increases. (c) S (black dots, left y-axis) and ε (orange crosses, right y-axis) of annual streamflow to increases in temperature or precipitation respectively in each month. For example, a 1°C increase in January results in a -0.14% decrease in annual flow.

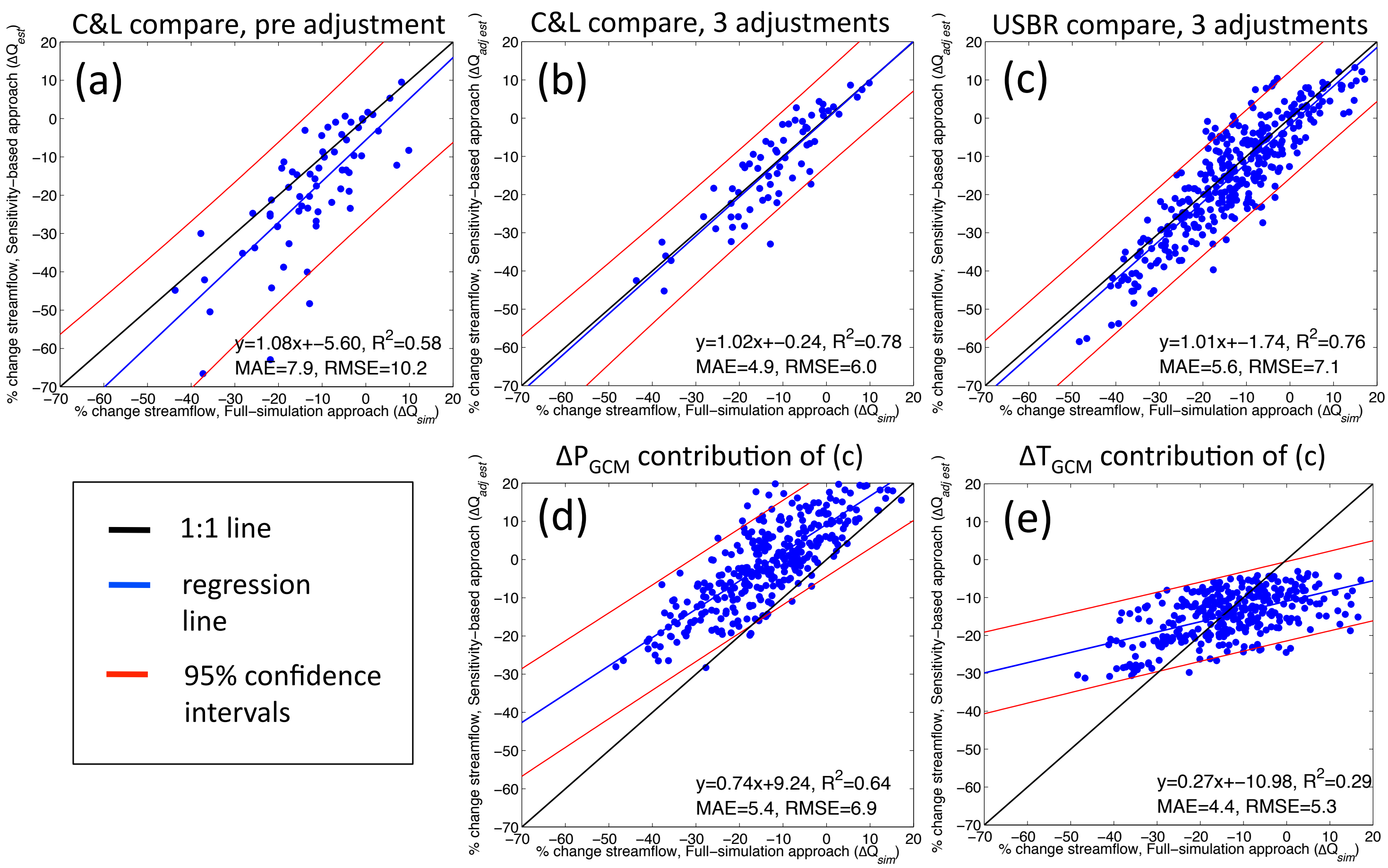


FIG 3 Comparisons of predicted changes in Colorado River annual average discharge from the full-simulation and sensitivity-based approaches. (a) Using full-simulation results from Christensen and Lettenmaier (2007) and a single value for ε and S for the sensitivity-based approach (Eq. 3), (b) using Christensen and Lettenmaier (2007) and the adjusted sensitivity-based approach (Eq. 4), (c) using USBR (2011) full-simulation results and the adjusted sensitivity-based approach (Eq. 4), (d) contributions of precipitation of panel c predicted changes, and (e) contributions of temperature of panel c to predicted changes. 95% confidence intervals in (b) and (c) indicate the two methods are within ±15%.

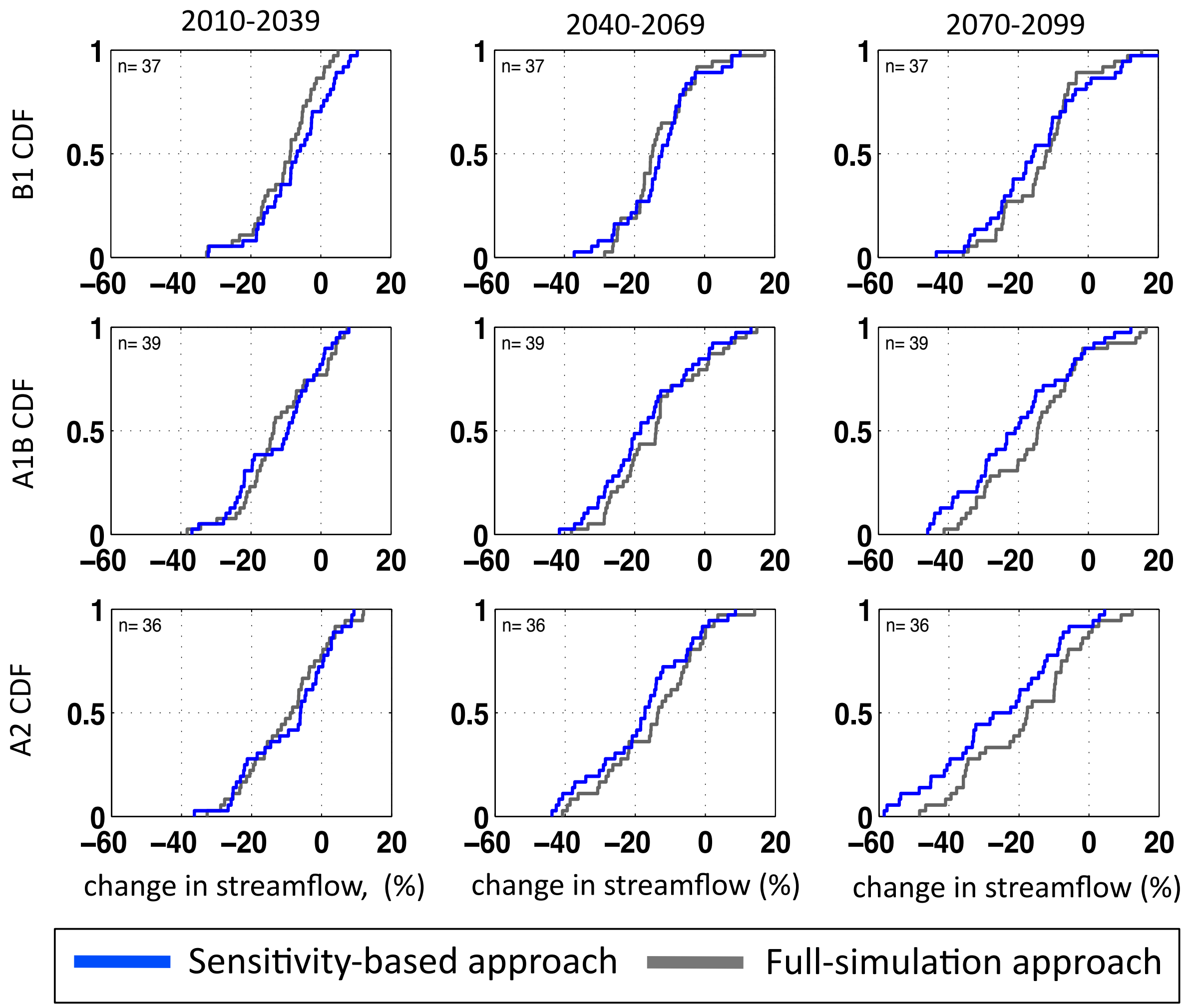


FIG 4 Cumulative distribution functions (CDFs) of 112 USBR simulations of streamflow change from sensitivity-based (ΔQ_{est_adj}) and full-simulation (ΔQ_{sim}) approaches by future time period and emission scenarios.

Supplemental Materials

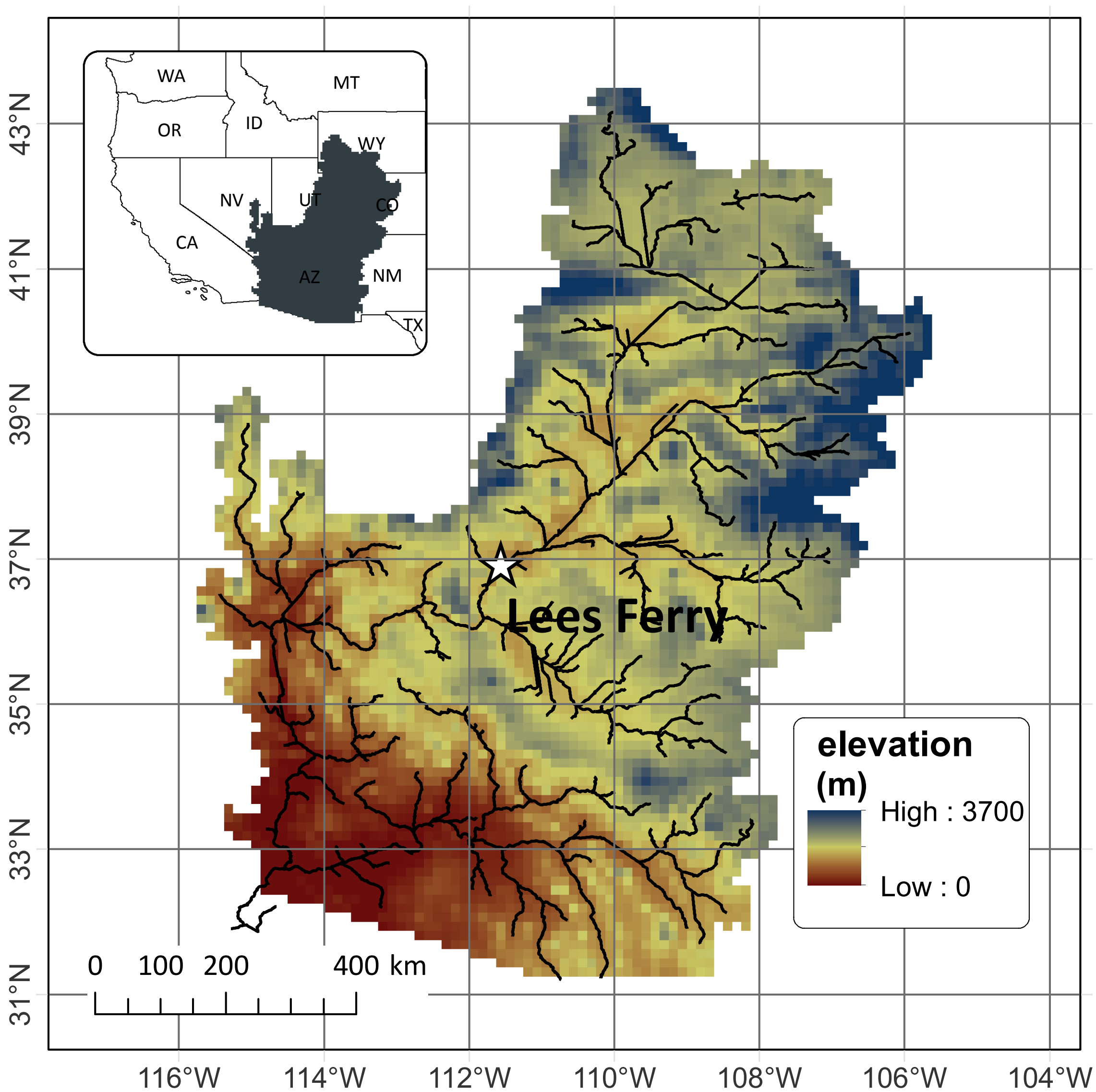


FIG S1. Colorado River basin showing elevation for the 1/8° resolution of the hydrology model. The resolution of the GCM output is approximately 2° resolution, which is indicated by the larger grid overlay.

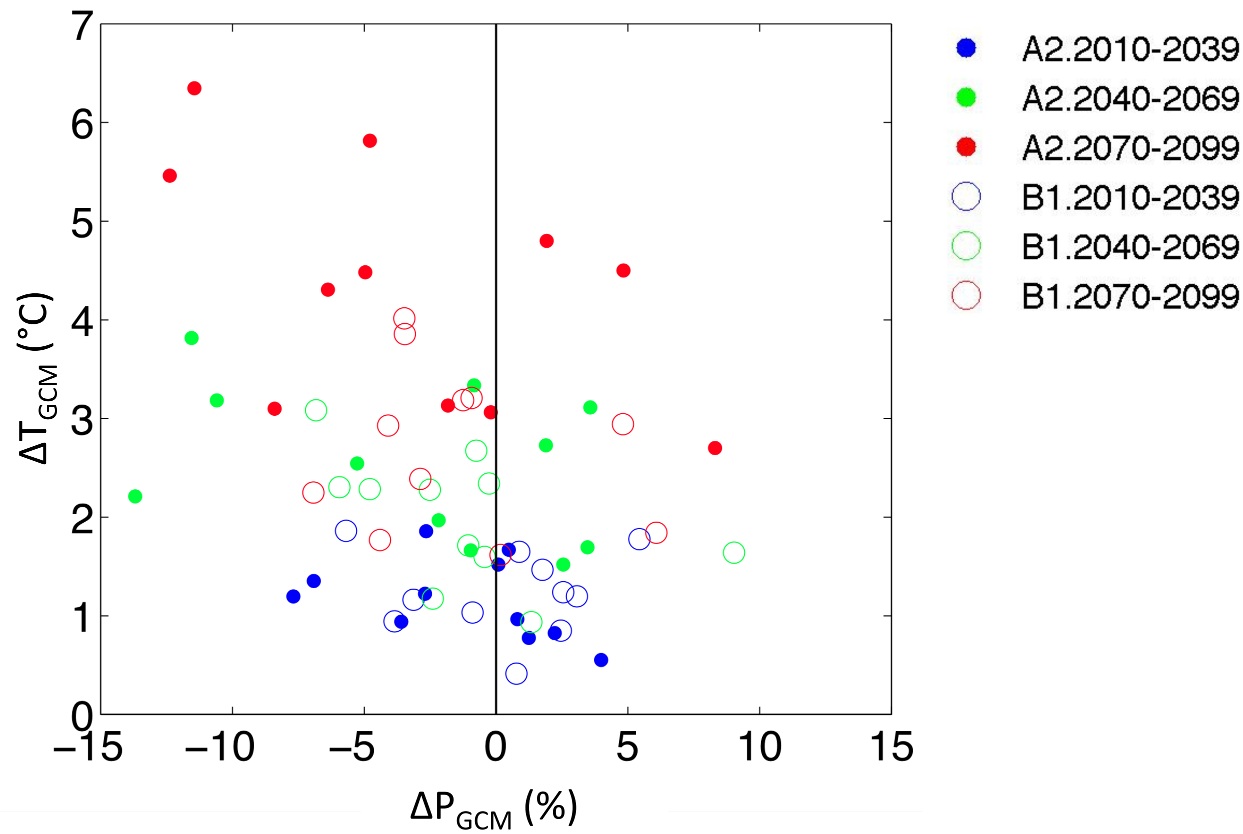


FIG S2. Temperature (ΔT) and Precipitation (ΔP) changes for GCMs used in Christensen and Lettenmaier (2007)

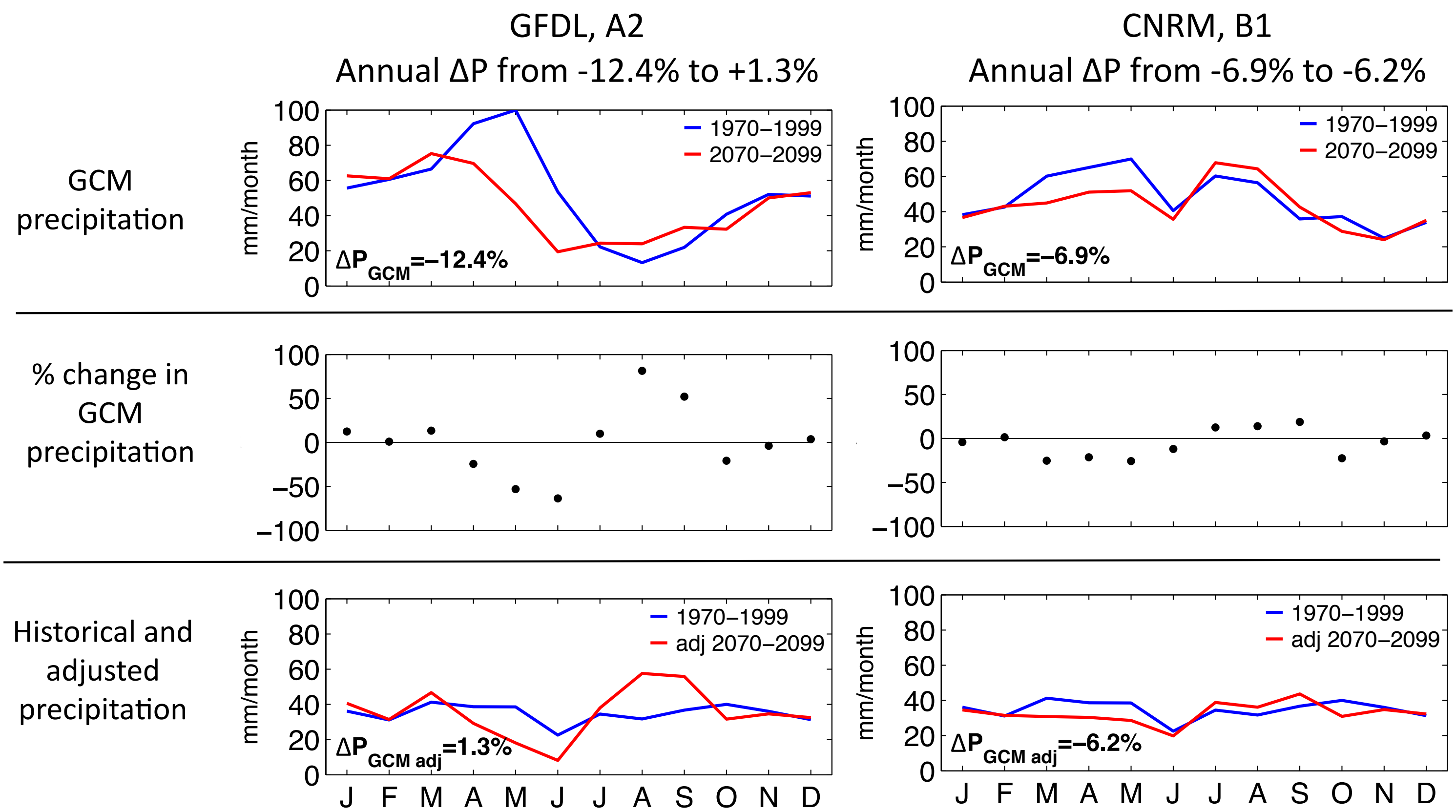


FIG S3 Two examples of the alternative adjustment ($\Delta P_{GCM\ adj}$). Prior to adjustment (top panels) annual ΔP_{GCM} is calculated directly from raw GCM output. The adjustment calculates the % change in monthly GCM precipitation (middle panel) and applies this to the historical precipitation dataset (blue line lower panel, from Maurer et al. (2002) over the Colorado River basin), resulting in adjusted monthly values of future precipitation. From this, the annual $\Delta P_{GCM\ adj}$ (bold values on figures) is calculated. This adjustment has a large effect on GFDL A2 scenario, but little effect on CRNM B1 scenario, which relates to how well each GCM captures observed precipitation seasonality.

Alternative to adjustment three (ΔP_{GCM})

We also tested an alternative approach to adjusting seasonal precipitation that focuses on ΔP_{GCM} values instead of seasonal ε values as in adjustment 3 in section 4.1. This alternative adjusts monthly P changes to be a percentage of historical P (instead of from raw GCM output). This is more consistent with downscaling methods in the full-simulation approach, which adjusts GCM P values with historical precipitation using quantile mapping on a monthly (not annual) timescale. We found that this alternative adjustment is less effective than adjustment 3 (Table 1). However it requires no additional VIC simulations to calculate monthly ε values and highlights an aspect of P downscaling that may be of interest.

The BCSD statistical downscaling approach used in Christensen and Lettenmaier (2007) adjusts P according to the probability distribution of historical observations (e.g., the Maurer et al (2002) gridded dataset), this adjustment, in essence, projects the percentage change between GCM future and GCM historical P values of each month onto historical observations. We performed a simplified adjustment that mimics this bias-correction step through a simple rescaling. Instead of using the direct percentage differences between long-term annual future and historical GCM P as our ΔP_{GCM} values (as in the unadjusted estimate), we calculated monthly percentage differences for GCM P and applied those (percent) differences to the historical observations to calculate a new estimate for future P. Then, these two values (the historical observations and the new estimate for future P) were used to calculate ΔP_{GCM_adj}, which was then multiplied by ε as in Eq. 3. In most cases, this adjustment had little effect on ΔP values. In the 66 adjustments performed, 51 made ΔP more positive, although most ΔP values (73%)

changed by less than 2%. There were, however, a few cases where the changes were substantial. These occurred mostly when the GCM P did not capture the observed seasonality. For example, in GFDL's A2 scenario P is greatest in the spring, not in the fall (Fig. S3, left panels), therefore a relatively small increase in average fall P in 2070-2099 translates to a much larger increase in P when the percent difference is applied to the observed P, changing ΔP from -12.4% to -1.3%. In contrast, in CRNM B1 scenario P has a seasonal cycle that is similar to climatology, and therefore the percent differences applied to historical observations does not change ΔP by much (-6.9% to -6.2%) (Fig. S3, right panels). If the BCSD correction is not desired, this adjustment should not be applied.