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Application of synthetic scenarios to address water resource concerns: A management-guided case study from the Upper Colorado River Basin

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ABSTRACT

Water managers are increasingly interested in better understanding and planning for projected resource impacts from climate change. In this management-guided study, we use a very large suite of synthetic climate scenarios in a statistical modeling framework to simultaneously evaluate how (1) average temperature and precipitation changes, (2) initial basin conditions, and (3) temporal characteristics of the input climate data influence water-year flow in the Upper Colorado River. The results here suggest that existing studies may underestimate the degree of uncertainty in future streamflow, particularly under moderate temperature and precipitation changes. However, we also find that the relative severity of future flow projections within a given climate scenario can be estimated with simple metrics that characterize the input climate data and basin conditions. These results suggest that simple testing, like the analyses presented in this paper, may be helpful in understanding differences between existing studies or in identifying specific conditions for physically based mechanistic modeling. Both options could reduce overall cost and improve the efficiency of conducting climate change impacts studies.

Practical Implications

The results here suggest that both initial conditions within the basin and differences in the timing and duration of wet, dry, warm, or cool periods in the driving climate data are important sources of uncertainty in streamflow simulations that should be considered in evaluating projections of future flows. These results also underscore the importance of using multiple approaches to evaluate the impacts of climate changes. Top-down study designs, where climate model data is selected, downscaled and used to drive an impacts model, provide valuable information, but they have the potential to integrate multiple influences on streamflow because model-derived climate scenarios may differ in many ways (e.g., mean change, seasonality of change, temporal characteristics of the data, spatial pattern of change), and initial basin conditions are not always well characterized because of the need for model spin-up. Different studies use different years of climate data to initialize hydrological models, leading to slightly different initial conditions. The approach used here is capable of deconstructing the influence of initial basin conditions, mean climate change, and differences in the pattern and timing of climate change in a way that a top-down study cannot. Moreover, the methods used in this study, which make it easy to evaluate the effects of mean climate changes and initial conditions, provide a framework for evaluating and prioritizing more intensive hydrological modeling efforts. A synthetic scenario strategy like the one used here facilitates using a bottom-up research approach that allows for a more comprehensive assessment of the types and ranges of hydrological and climatic conditions that can impact future flows.

1. Introduction

1.1. Colorado River flow projections

The Colorado River provides water for most of the major metropolitan areas and agricultural producing regions in the southwestern U.S., with the Upper Colorado River Basin generating the vast majority of the flow (about 90% according to Christensen et al., 2004) (UCRB,

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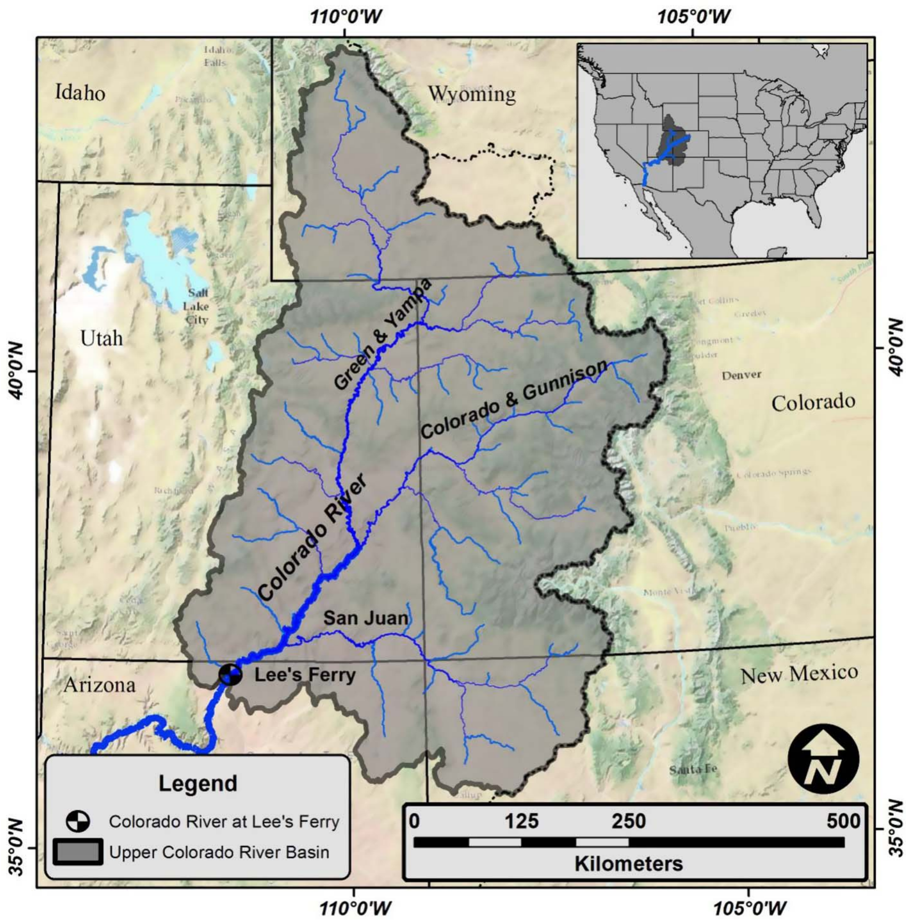

Fig. 1. Map of the Upper Colorado River Basin. The location of the Lees Ferry gauge is indicated.

Fig. 1). Proxy-based streamflow reconstructions have documented long duration low-flow periods in the distant past (e.g., Meko et al., 2007; Gangopadhyay et al., 2015) that would have significantly impacted municipal, industrial, and economic activities in the region. Projections for warmer and possibly drier conditions in the coming century (IPCC, 2013; Ayers et al., 2016; Udall and Overpeck, 2017) have raised concern about future flows in the basin, and the fate of Colorado River has been the focus of numerous streamflow projection studies. These have ranged from statistical estimates of flow, such as Hoerling and Eischeid's (2007) estimates based on projected values of the Palmer Drought Severity Index, to complex studies that use downscaled projections of future temperature and precipitation with a range of hydrological models (Vano et al., 2014).

Results have ranged from predictions of minimal storage in Lake Mead by 2021 (Barnett and Pierce, 2008), to more modest decreases in flow (Christensen et al., 2004; Cook et al., 2004; Milly et al., 2005; Christensen and Lettenmaier, 2007; Hoerling and Eischeid, 2007; McCabe and Wolock, 2007; Seager et al., 2007; Gao et al., 2011; Rasmussen et al., 2011; USBR, 2011a, b; Gao et al., 2012; Seager et al., 2013; Udall and Overpeck, 2017), to projections of little to no change (Harding et al., 2012), with the potential for increases in flow volumes when more recent climate projections are used (Ayers et al., 2016).

1.2. Sources of uncertainty in flow projections

The diversity of flow projections has been largely attributed to the choice of climate scenarios (Harding et al., 2012; Vano et al., 2014), downscaling methods (Vano et al., 2014; Mendoza et al., 2016), and hydrological model parameters (Vano et al., 2014; Mizukami et al., 2016). Other potential sources of uncertainty in flow projections have also been assessed in other contexts. For example, forecast models are regularly run using the best estimate of initial basin conditions (i.e., soil moisture, snowpack or groundwater storage) or with ranges of initial basin conditions to provide better seasonal projections (Harpold et al., 2016; Franz et al., 2003). Starting longer term climate projection-based hydrological simulations under different climatic regimes (i.e., wet or dry and hot or cold periods) can also result in different outcomes (Koczot et al., 2011), yet it is not always clear how comparable initial basin conditions are, given the need for hydrological model spin-up (see Vano et al., 2012; Mizukami et al., 2016 for two initialization strategies).

In addition, the timing and duration of wet/dry/cool/warm periods in input climate data can vary substantially. Clark et al. (2016) suggest that this is an important source of uncertainty to consider (see their Fig.1). Within climate models, climatic persistence can derive from initial atmospheric or oceanic conditions and/or from unforced variability within the model itself, and these two sources of uncertainty are not entirely independent (Hawkins et al., 2016; Deser et al., 2014). Over multi-decadal periods, internal variability can influence the direction of trends (Deser et al., 2012a), and at regional scales, internal variability contributes to projection uncertainty for up to a century (Hawkins and Sutton, 2009). Moreover, many climate models do not skillfully simulate all of the processes that influence multi-annual to multi-decadal variability (Ault et al., 2012, 2014; Deser et al., 2012b), adding a further layer of complication.

1.3. Addressing water manager concerns

Thus, despite the large and growing suite of studies evaluating changes in Colorado River flow, planning for the impacts of climate change on the UCRB is still a significant challenge for water resource managers (Clark et al., 2016). Identifying a way to assess the potential impacts of climate change that is meaningful, useful, and relevant to resource management requires interaction between scientists and water management practitioners (Wall et al., 2017). Collaboration between scientists, engineers, and policy-makers often requires the exploration of new approaches to provide appropriate answers to questions regarding future water resources.

Over the course of a recent workshop focused on discussing the influence of temperature on streamflow in the Colorado River, water managers in the UCRB identified key questions and concerns, ranging from the scientific to the practical. Some of the questions included (1) whether similar climate scenarios can produce substantially different flow characteristics, (2) whether fairly distinct future climate changes can produce similar flow, (3) what characteristics of the input data can drive flow diversity, given similar input climate data, (4) how temperature changes can influence future flows, and (5) how efficient preliminary studies can be used to inform more intensive hydrological modeling efforts. Water managers also identified two specific timescales of drought that had significance for resource management, 4-year periods of intense drought and 7-year periods of moderate drought conditions

Moreover, managers at this meeting expressed interest in a study taking a "bottom-up" approach wherein researchers attempt to identify the range of climate conditions that could produce hydrologic conditions of concern in contrast to the usual "top-down" method where a set of climate projections are downscaled and then used to run a hydrological model (Wilby and Dessai, 2010). One underappreciated weakness of a top-down approach is that sources of uncertainty may be bundled in ways that are difficult to disentangle. For example, in the ensemble members served on the National Climate Change Viewer (https://www2.usgs.gov/climate_landuse/clu_rd/nccv.asp; Alder and Hostetler, 2013; Hostetler and Alder, 2016), MIROC-ESM projects 8.0 °C warming in mean annual maximum temperature over the UCRB between 1981–2000 and 2075–2099, with the rate of warming increasing throughout the 21st century. In contrast, GFDL-CM3, which warms slightly less (7.3 °C), simulates a greater rate of warming during the middle of the 21st century than later. FIO-ESM projects the least warming overall (3 °C by 2075–2099), but, like MIROC-ESM, warms at a greater rate later in the 21st century than earlier (USGS, 2017; Alder and Hostetler, 2013; Hostetler and Alder, 2016). In this example, differences in the magnitude and temporal pattern of warming are conflated, but there can also be difficulties disentangling the magnitude and seasonality of climate change or in separating the magnitude of change from its spatial pattern. Performing bottom-up analysis in a way that can unravel the influence of these differences can require running large ensembles of climate scenarios, something that may be computationally expensive and time-consuming using standard hydrological modeling experiments.

1.4. Statistical flow models

Here we demonstrate a way of responding to water manager concerns regarding possible future Colorado River flow using synthetic climate time series in a statistical modeling framework. Recent work by Woodhouse et al. (2016) suggests that statistical relationships based on basin-average climate can be used to estimate water-year flow with reasonable skill. Although this simple statistical model cannot account for changes in basin ecohydrologic characteristics that can impact flow (e.g., rain-snow partitioning (Knowles et al., 2006; Harder and Pomeroy, 2014), precipitation rate (Dunne et al., 1991), dust-loading (Painter et al., 2010), vegetation change (Bosch and Hewlett, 1982), soil moisture status (Harpold et al., 2016), spatial patterns in temperature (Woodhouse et al., 2016), or in precipitation distribution (Patil et al., 2014)), it does provide a way to disaggregate the contributions of initial basin conditions, changes in mean climate, and the natural variability of climate to changes in flow. Thus, it provides a first order analysis of the potential range of hydro-climatic effects of climate change in the Colorado River basin in a way that water managers felt would be useful.

A statistical approach in no way replaces more physically based models, but it does allow us to transparently, rapidly, and economically simulate a very large ensemble of future water-year flow projections under a large number of unique combinations of climate change for different initial basin conditions. It provides a resource for simultaneously investigating the roles that climate changes, initial basin conditions, and internal climate variability could play in introducing uncertainty to Colorado River flow projections. More importantly, it meets manager needs in three important ways. First, this type of large ensemble approach allows managers to estimate the range of water-year flows that are possible under a given climate change scenario and model. Second, it provides information on climate data characteristics other than mean change (i.e., variability, sequencing, and persistence) that can induce low or high flows. With this information, water managers can evaluate simple metrics describing the input climate data to understand whether projections made with a more traditional "top-down" approach are likely optimistic or conservative. Finally, this efficient and cost-effective analysis offers water managers an opportunity to prioritize climate scenarios that produce concerning flow results, or particularly wide ranges of future flow conditions, for analysis with more costly and time-consuming mechanistic modeling studies similar to the way in which the assessment by Vano et al. (2015) allows managers to assess changes in flow expected for mean changes in climate. While efficiency is not always the end-goal of scientific inquiry, time and cost savings are certainly valuable in management contexts.

2. Methods

2.1. Data

Monthly average temperature and monthly total precipitation from the Precipitation-elevation Regression on Independent Slopes Model (PRISM) 4-km data set (Daly et al., 2008, http:www.ocs.orst.edu/prism/) were averaged over the UCRB for each year from 1906 through 2014. Basin-average monthly temperature was then averaged over the period May through July (sumT), and basin-average monthly precipitation was summed over the months October through April (winP) and May through September (sumP), informed, in part, by the findings of Woodhouse et al. (2016) and described in detail below. While there is concern about the potential for biases in PRISM temperatures, particularly at higher elevations (Oyler et al., 2015a), McCabe et al. (2017) found minimal differences between average monthly temperature estimates from PRISM and TopoWx (Oyler et al., 2015b) over the UCRB. Naturalized flow estimates for the water-year Colorado River flow at Lees Ferry from 1906 to 2014 were provided by the U.S. Bureau of Reclamation (https://www.usbr.gov/lc/region/g4000/NaturalFlow/index.html).

2.2. Statistical flow model

Woodhouse et al. (2016) found a reliable statistical relationship between UCRB naturalized water-year flow and observed basin-average winP, melt-season (March–July) temperature, and fall (November) soil moisture, which was derived from the McCabe and Wolock (2011) water balance model. Here we develop and test a slight modification of the Woodhouse et al. (2016) model, using sumP in place of fall soil moisture to reduce the number of necessary modeling steps.

We built regression models using all combinations of current and previous year climate variables and previous water-year flow (no interactions) over the period 1941–1990 and then compared them on the basis of Akaike Information Criteria (AICc), Bayesian Information Criteria (BIC), autocorrelation in the residuals, and their ability to predict observations over two validation periods (1906–1940 and 1991–2014). The top 25 models are shown in Table 1. There were

Table 1
Top 25 statistical models of Upper Colorado River water-year flow based on a models including all combinations of current and prior year winter precipitation, summer precipitation, and summer temperature, and prior year flow over the training period, 1941–1990. An intercept was included in every model, but is not shown here to save space. Coefficients are not standardized. BIC refers to Bayesian Information Criterion, R^2adj is calculated based on the likelihood-ratio (Bartoń, 2016), AICc is the Akaike Information Criterion, df, the degrees of freedom, ACF.lag1, the lag-1 correlation of the residuals over the training period. In addition, we show the correlation (r), root mean squared error (RMSE), and mean error (ME) over both the early (1906–1940) and late (1991–2014) validation periods.

													Validation 1906–1940			Validation 1991–2014		
Model	flow.lag1	sumP	sumP.lag1	sumT	sumT.lag1	winP	winP.lag1	BIC	R^2adj	df	AICc	ACF.lag1	r	RMSE	ME	r	RMSE	ME
1	0.190	0.020	0.021	−1.247	NA	0.068	NA	203.39	0.895	7	192.68	0.051	0.854	2.417	−1.075	0.940	1.504	−0.096
2	0.229	0.019	0.021	−1.285	NA	0.068	−0.004	207.15	0.895	8	195.37	0.015	0.854	2.384	−0.995	0.939	1.529	−0.164
3	0.195	0.019	0.022	−1.250	0.064	0.068	NA	207.27	0.895	8	195.485	0.053	0.854	2.416	−1.079	0.941	1.485	−0.062
4	NA	0.023	0.025	−1.022	NA	0.070	0.014	207.27	0.886	7	196.55	0.200	0.851	2.627	−1.453	0.944	1.446	0.273
5	0.240	0.019	0.021	−1.293	0.086	0.067	−0.004	211.00	0.895	9	198.29	0.014	0.854	2.381	−0.992	0.940	1.505	−0.125
6	NA	0.023	0.025	−1.028	−0.148	0.070	0.013	210.98	0.886	8	199.20	0.188	0.850	2.615	−1.422	0.942	1.475	0.171
7	0.208	NA	0.018	−1.614	NA	0.068	NA	209.767	0.870	6	200.25	0.115	0.831	2.629	−1.221	0.920	1.754	−0.434
8	0.333	NA	0.016	−1.697	NA	0.067	−0.012	212.22	0.874	7	201.50	0.013	0.830	2.517	−0.945	0.918	1.846	−0.620
9	0.140	0.026	0.021	NA	NA	0.074	NA	211.08	0.866	6	201.56	−0.106	0.878	2.425	−1.305	0.949	1.532	0.875
10	NA	0.028	0.024	NA	NA	0.075	0.012	211.32	0.866	6	201.80	0.036	0.867	2.620	−1.570	0.948	1.624	1.024
11	**0.237**	**0.016**	**NA**	**−1.232**	**NA**	**0.070**	**NA**	**211.67**	**0.865**	**6**	**202.15**	**0.037**	**0.863**	**2.451**	**−1.262**	**0.932**	**1.561**	**−0.165**
12	NA	0.022	0.027	−0.896	NA	0.071	NA	211.88	0.864	6	202.36	0.128	0.845	2.643	−1.425	0.941	1.491	0.383
13	0.225	NA	0.019	−1.615	0.236	0.067	NA	213.26	0.871	7	202.539	0.115	0.832	2.623	−1.230	0.925	1.650	−0.296
14	0.378	0.014	NA	−1.376	NA	0.069	−0.014	213.67	0.870	7	202.95	−0.089	0.858	2.332	−0.939	0.927	1.683	−0.413
15	NA	0.023	0.024	−0.933	−0.444	0.071	NA	214.03	0.869	7	203.31	0.106	0.845	2.595	−1.337	0.936	1.532	0.060
16	0.363	NA	0.017	−1.703	0.285	0.066	−0.013	215.50	0.875	8	203.71	0.007	0.830	2.508	−0.937	0.923	1.726	−0.465
17	0.085	0.027	0.022	NA	NA	0.074	0.006	214.71	0.867	7	203.99	−0.048	0.875	2.492	−1.411	0.949	1.565	0.933
18	0.140	0.026	0.021	NA	0.000	0.074	NA	214.99	0.866	7	204.27	−0.105	0.878	2.425	−1.305	0.949	1.532	0.876
19	NA	0.028	0.023	NA	−0.111	0.075	0.012	215.13	0.866	7	204.42	0.011	0.867	2.600	−1.548	0.947	1.591	0.950
20	0.431	NA	NA	−1.677	NA	0.068	−0.019	214.00	0.858	6	204.48	0.047	0.840	2.437	−0.911	0.913	1.916	−0.718
21	0.222	0.016	NA	−1.222	−0.185	0.070	NA	215.33	0.865	7	204.61	0.032	0.861	2.455	−1.245	0.930	1.612	−0.263
22	0.246	NA	NA	−1.537	NA	0.070	NA	213.32	0.848	5	205.12	0.242	0.847	2.598	−1.357	0.917	1.752	−0.434
23	NA	0.027	0.025	NA	NA	0.075	NA	213.34	0.848	5	205.143	0.006	0.847	2.702	−1.532	0.945	1.667	1.040
24	0.366	0.014	NA	−1.366	−0.083	0.069	−0.014	217.53	0.870	8	205.75	−0.088	0.858	2.336	−0.943	0.927	1.703	−0.448
25	NA	NA	0.022	−1.405	NA	0.070	0.013	215.86	0.852	6	206.336	0.235	0.827	2.878	−1.660	0.923	1.625	−0.063

relatively minimal differences in BIC, AICc, and correlation with naturalized flow in the validation periods for all of the top 25 models, suggesting that there are many reasonable ways to statistically model flow in the UCRB. Table 1 demonstrates that all models fit using data from the middle of the 20th century under-predict flow during the first validation period. Models that do not include temperature tend to overestimate flow during the second validation period. This, in combination with water manager desires to evaluate the effects of projected temperature on future UCRB flow and the growing body of evidence suggesting that temperature already is adversely affecting UCRB flow (Udall and Overpeck, 2017; Woodhouse et al., 2016) led us to favor models that include temperature.

Given the plethora of reasonable models to choose from, we chose to use model 11 (bolded in Table 1), which used all current year climate and previous water-year flow as predictors. We chose this model because it (1) is well supported with good statistical fits over test and validation periods, (2) is parsimonious and thus relatively easy to interpret, and (3) has limited autocorrelation in the residual time series, suggesting that low-frequency variability in the flow is being adequately reproduced. While several models incorporating lagged climate variables had lower AICc and BIC values than model 11, we felt that lagged flow was a more straightforward proxy for basin conditions, as it is unclear how prior year climate can impact flow without mediating basin conditions. We also chose to re-generate the model for the full period of record analyzed (i.e., 1906–2014) to get a more robust temperature coefficient. The final model is outlined in Table 2.

2.3. Construction of synthetic climate series

Anomaly series (time series of departures from the respective long-term means) were synthetically generated for winP, sumP, and sumT. The synthetic series were 109 years in length and were made by resampling the measured series in blocks of 10–15 years (with replacement). Blocked resampling was chosen in an attempt to preserve observed sequences of high- and low-flow years, allowing for better representation of year-to-year and decade-to-decade patterns of serial correlation and persistence (Rajagopalan and Lall, 1999; Hirsch et al., 2015). The process was repeated 500 times to produce 500, 109-year long anomaly series for each variable. The means of the resampled time series were checked, and they varied by up to about 15 mm for winP (6.5% of the observed mean precipitation), 5 mm for sumP (3.2% of the mean) and 0.4 °C for sumT. To resolve the variability in means, we then normalized each resampled anomaly time series to its mean. The final, normalized anomalies all had means within 3×10^{-15} of 0. The observed mean values were added back to the anomaly traces to produce synthetic climate traces for each variable. To account for projected changes in climate (i.e., temperature and precipitation) the means of the synthetic time series were adjusted to include warming (+0 °C, +1 °C, +2 °C, +3 °C, +4 °C) and changes in seasonal precipitation totals (80%, 90%, 100%, 110%, and 120% of observed seasonal precipitation), providing 125 unique combinations of changes in temperature and precipitation (e.g., +2 °C sumT, 80% sumP, 110% winP) with 500 replicates each (Table 3). This range of precipitation and temperature changes encompasses most of the CMIP5 projections for the UCRB as outlined in Vano et al. (2015).

Table 2
Regression model summary describing current water-year Colorado River flow at Lees Ferry regressed against total winter (October through April) precipitation (winP, in millimeters (mm)), total summer (May through September) precipitation (sumP, in mm), mean summer temperature (May through July) (sumT, in degrees Celsius (°C)), and the previous water-year flow at Lees Ferry (pflow) in million acre feet (maf). Coefficients were determined using data for the entire period of record (1906–2014).

	b	s.e.	*t*	*p*
Intercept	5.09463	4.430789	1.150	0.2529
winP (mm)	0.07067	0.004548	15.537	< 0.0001
sumP (mm)	0.01897	0.005448	3.481	0.0007
sumT (°C)	−0.86258	0.228159	−3.781	0.0003
pflow (maf)	0.27067	0.041781	6.478	< 0.0001
	$R^2 = 0.8203$			
	R^2a = 0.8133 ($p < 0.0001$)			

2.4. Construction of synthetic flow series

The flow model (Table 2) was used with all 125 combinations of climate series (Table 3) as inputs using three sets of initial flow values representing initiation basin conditions. The three sets of initial flow values included (1) dry or low flow conditions (25th percentile of observed flow during 1906–2014), (2) moderate flow (50th percentile of observed flow), and (3) wet or high flow conditions (75th percentile of observed flow). A minimum water-year flow value of 0.5 million acre-feet, close to the lowest annual values reconstructed by Woodhouse et al. (2006), was imposed to resolve the potential for zero or even negative flow values being produced by the model. This analytical format provided 375 unique scenarios, with 500 replicates each, leading to a full ensemble of 187,500 future flow trajectories.

2.5. Analysis of synthetic flow

We calculated average flow over the full record, as well as during the beginning (years 1–30), middle (years 40–69), and end (years 80–109) of the period. This allowed us to evaluate the duration of impacts from initial basin conditions, as well as the impact of climate variability.

While changes in the average flow are of concern, effects of climate change on temporal flow patterns and the persistence of low and high flow periods are also important for water management in the UCRB. Low flow period definitions were identified through discussion with water managers about their concerns regarding impacts of changes in future UCRB flow on water management operations. To address concerns regarding low flow periods, we investigated the number of periods when UCRB flow was below the 1906–2014 average for seven years with no more than one year above average (henceforth “low-flow periods” or LFPs) and the number of periods when flow was less than 75% of the 1906–2014 average for four years with no more than one year above average (henceforth “very-low-flow periods” or VLFPs). The frequency of LFPs was evaluated by investigating all possible runs of seven years (years 1–7, 2–8, etc.) and tallying the number of seven-year periods during which flow did not exceed the 1906–2014 average in more than one year. The frequency of VLFPs was evaluated by investigating all possible runs of four years and tallying the number during which flow did not exceed 75% of the 1906–2014 average flow in more than one year. Using periods of defined length (seven and four years) rather than setting a minimum threshold (e.g., seven or more years) allowed for more direct comparison between series that might have few periods below the 1906–2014 average, and those where flow was below the long-term average in most or all years, which would produce only one (very long) low-flow period when assessed using a minimum threshold.

2.6. Drivers of flow variability

To evaluate the impact of initial conditions on mean flow, the frequency of LFPs, and the frequency of VLFPs, we performed repeated measures one-way Analysis of Variance (ANOVA) for each of the 125 distinct climate change scenarios (e.g., +1 °C sumT, 80% winP, and 110% sumP). Repeated measures ANOVA allowed us to account for the fact that synthetic series 1 (2, 3, etc.) was identical under each initial flow condition. This was especially critical when looking at sub-periods of the data because, while the average change was consistent over the full period, there were substantial differences in average temperature or precipitation over a 30-year window of the input data.

Table 3
Summary of precipitation change scenarios and codes used to identify them. Each precipitation change scenario was evaluated in combination with mean summer temperature increases of 0, +1, +2, +3, and +4 °C.

Winter precipitation change (%)	Summer precipitation change(%)				
	80%	90%	100%	110%	120%
80	wP080;sP080	wP080;sP090	wP090;sP100	wP080;sP110	wP080;sP120
90	wP090;sP080	wP090;sP090	wP090;sP100	wP090;sP110	wP090;sP120
100	wP100;sP080	wP100;sP090	wP100;sP100	wP100;sP110	wP100;sP120
110	wP110;sP080	wP110;sP090	wP110;sP100	wP110;sP110	wP110;sP120
120	wP120;sP080	wP120;sP090	wP120;sP100	wP120;sP110	wP120;sP120

We then identified the synthetic flow series with the 25 highest (≥95th percentile) and 25 lowest (≤5th percentile) overall average flow and LFP/VLFP frequencies under moderate initial flow within each climate change scenario and investigated the synthetic climate series to assess what climate characteristics might drive the "best case" (highest average flow or lowest number of LFPs or VLFPs) versus "worst case" (lowest average flow or highest number of LFPs or VLFPs) within a climate scenario. These were identified separately for each variable (average flow, number of LFPs, and number of VLFPs), as the series with the lowest average flow did not necessarily have the highest numbers of drought periods. We looked at characteristics describing the variability of the input climate data (minimum value, maximum value, and standard deviation) and the average climate during the first and last 10 years of the series. Climate conditions during the best and worst case simulations were compared with a two-sided *t*-test. Because the impacts of initial conditions on average flow and drought frequency were relatively modest (see Section 3.2), analysis was limited to moderate initial flow conditions. This also simplified analysis and data presentation.

All computation was performed in R (R Core Development Team, 2008), using the MuMin (Bartoń, 2016), vioplot (Adler, 2015), raster (van Hijmans et al., 2016), rgdal (Bivand et al., 2016), ez (Lawrence, 2016), and sp (Pebesma et al., 2016) packages.

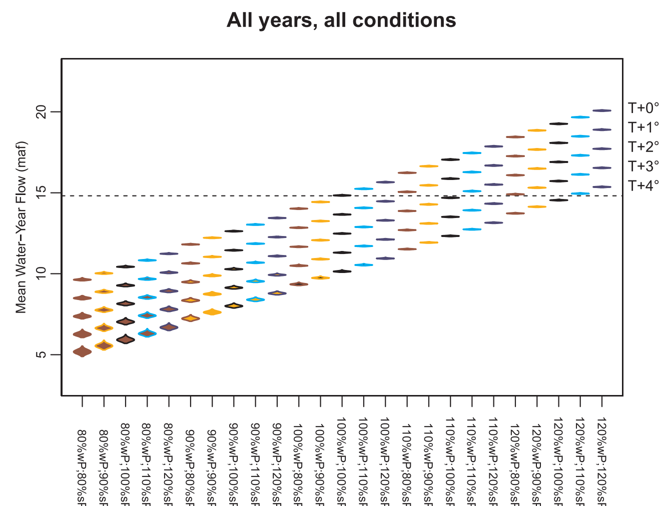

Fig. 2. Violin plots showing the range of average flows produced by each climate scenario for all initial conditions combined by climate change. The horizontal dashed line indicates the 1906–2014 average water-year flow. Each of the 25 unique precipitation change combinations is listed across the *x*-axis. The color of the interior corresponds to the winter precipitation change, and the color of the outline corresponds to the summer precipitation change (maroon = 80% of observed precipitation, gold = 90% of observed precipitation, black = no change in observed precipitation, cyan = 110% of observed precipitation, navy = 120% of observed precipitation). Flow produced by different temperature changes are labeled along the right-hand axis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Impact of climate scenarios on flow

As expected, warmer and drier conditions led to lower average flows (Fig. 2). For a given precipitation change, flows were lower with greater temperature increases. However, distinctly different changes in climate can also produce similar changes in average flow. For example, average flows similar to the 1906–2014 observed average (indicated by the dashed line in Fig. 2) are produced in scenarios with (1) no changes in temperature or precipitation; (2) a 10% increase in winP, a 20% decrease in sumP, and 1 °C warming in sumT; (3) a 10% increase in winP, no change in sumP, and 2 °C warming in sumT; (4) a 20% increase in winP, a 20% decrease in sumP, and 3 °C warming in sumT; or (5) a 20% increase in winP, a 10% increase in sumP, and 4 °C warming in sumT.

There also was variability in the average flow within climate scenarios such that identical changes in mean climate can produce average flow estimates that varied between 0.08 and 0.65 million acre feet (maf) when all initial flow values were considered, with greater variability under warmer and drier conditions (Fig. 2). The upper end of the range in values of average flow conditions is larger than the annual allotment of water from the UCRB for Nevada (SNWA, 2017).

Warmer and drier scenarios also influenced the number of LFPs (Fig. 3) and VLFPs (Fig. 4). Decreases in winP appeared to be more effective in driving increases in LFPs and VLFPs than decreases in sumP. Warming also enhanced the likelihood of significant periods with below average flow (Figs. 3 and 4). As with mean flow, the number of LFPs and VLFPs displayed substantial variability (Figs. 3 and 4) even with identical changes in mean climate. For example, with 2 °C warming and no change in sumP or winP there were between 0 and 36 LFPs (Fig. 3). In addition, similar numbers of LFPs and VLFPs can be produced under very different mean climate scenarios. For example, over 20 different sets of climate changes resulted in simulated flow series with approximately 25 VLFPs.

3.2. Impact of initial basin conditions on flow

Initial basin conditions affected streamflow primarily in the early portion of the simulations. Under all climate change scenarios, low initial flow conditions were associated with low average flow during the first 30 years of the simulations ($p < 0.05$, Fig. 5). Flow series with the same input climate data and different initial basin conditions were essentially identical by the mid-point of the 109-year simulation ($p > 0.05$, Fig. 5). However, the influence of initial conditions during the early part of the simulations was substantial enough to impact overall averages, such that dry initial basin conditions were also associated with low average flow over the full 109-year period. Initial flow conditions also influenced the number of LFPs and VLFPs under certain climate conditions. In 81 of 125 climate scenarios, repeated measures ANOVA identified a significant ($p < 0.05$) influence of initial conditions on the number of LFPs (indicated by the asterisks in Fig. 3). Initial conditions significantly impacted the number of VLFPs in 89 of 125 climate scenarios (indicated by the asterisks in Fig. 4).

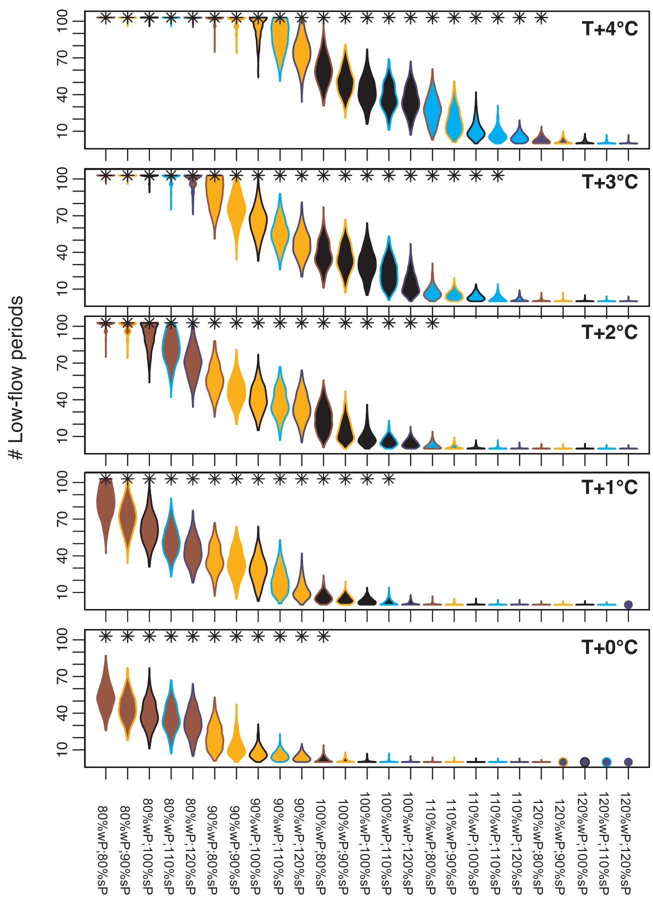

Fig. 3. Frequency of low-flow periods (LFPs) in each climate scenario with moderate initial basin conditions (50th percentile of observed 1906–2014 flow). Low-flow periods are consecutive periods, broken by no more than one year at a time when the water-year flow is less than the 1906–2014 average. All possible 7-year periods were evaluated, so each 109-year long series can contain a maximum of 103 LFPs. Each of the 25 unique precipitation change combinations is listed across the *x*-axis. The color of the interior corresponds to the winter precipitation change, and the color of the outline corresponds to the summer precipitation change (maroon = 80% of observed precipitation, gold = 90% of observed precipitation, black = no change in observed precipitation, cyan = 110% of observed precipitation, navy = 120% of observed precipitation). Filled circles indicate a zero value in all flow scenarios. Asterisks indicate climate scenarios in which repeated measures ANOVA detected a significant effect of initial conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

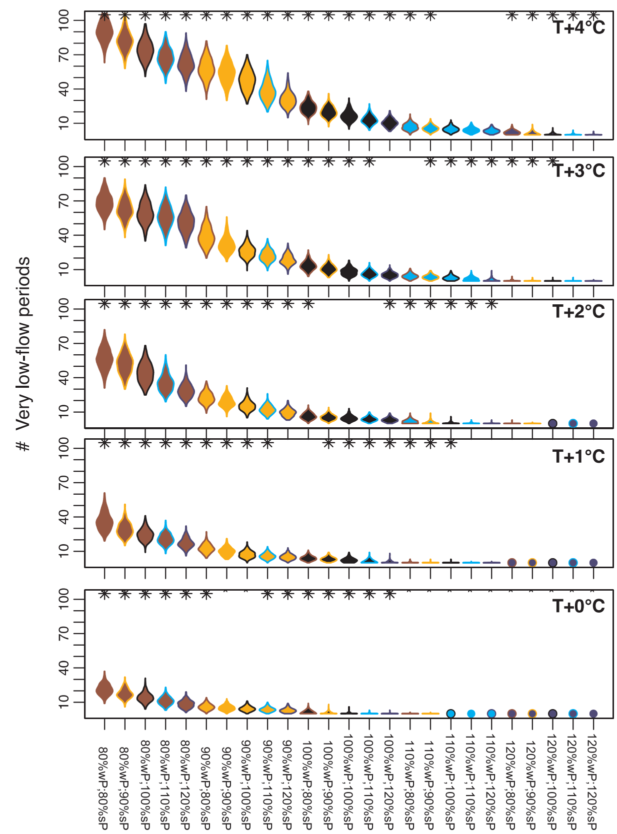

Fig. 4. Frequency of very low-flow periods (VLFPs) in each climate scenario. Very low-flow periods are consecutive periods, broken by no more than one year at a time when the water-year flow is less than 75% of the 1906–2014 average. All possible 4-year periods were evaluated, so each 109-year long series can contain a maximum of 106 VLFPs. The color of the interior corresponds to the winter precipitation change, and the color of the outline corresponds to the summer precipitation change (maroon = 80% of observed precipitation, gold = 90% of observed precipitation, black = no change in observed precipitation, cyan = 110% of observed precipitation, navy = 120% of observed precipitation). Filled circles indicate a zero value in all flow scenarios. Asterisks indicate climate scenarios in which repeated measures ANOVA detected a significant effect of initial conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

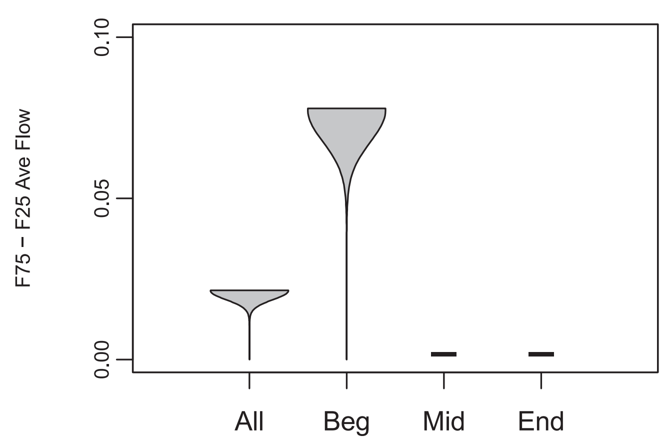

Fig. 5. Comparison of the range of average flows produced by wet (75th percentile of observed 1906–2014 flow) and dry (25th percentile) initial basin conditions. Results are shown for the full 109-year period, simulation years 1–30, 40–69, and 80–109.

3.3. Influence of the temporal characteristics of input climate data

Average climate during the first 10-years of each simulation differed strongly between the highest and lowest average flows within a climate change scenario. Table 4 shows the number of climate scenarios in which a specific climate variable differed significantly ($p < 0.05$) between best and worst case flow scenarios. We also show the number of significant tests in which the value of the climate variable was higher for worst-case series than best-case series. For example, winP and sumP were significantly higher and sumT lower during the early part of each simulation in the highest average flow scenarios than in the lower average flow scenarios (Table 4). The most likely explanation for this is that warm and dry conditions early in the time series led to lower flows in the early part of the time series. Because the model includes a lagged effect of flow, these early flow values suppress flow volumes into the middle of the series, leading to overall low average flow. Counter-intuitively, winP was greater during the last 10 years in the series with the lowest average flows. This is likely due to the fact that those series were relatively dry early on, so had to be wetter late in the series to maintain the specified average mean climate. The variability of the input climate data (indicated by the standard deviation, maximum, and minimum values) had essentially no influence on the overall average flow, with only a few scattered significant differences in the climate that produced wetter and drier average flows within a given climate

Table 4

Results from *t*-tests comparing characteristics of the input climate data that generated the wettest 95% (highest average flow, lowest number of low (LFP) or very low flow (VLFP) periods) and driest 5% (lowest average, highest number of low or very low flow periods) stream flow simulations for each climate change scenario. Analysis was limited to simulations initiated with moderate flow (50th percentile of observed 1906–2014 water-year flow). Under each flow characteristic (Average Flow, #LFP, or #VLFP), the first column shows the number of climate scenarios in which a specific climate variable differed significantly ($p < 0.05$) between best and worst case flow scenarios. Thee second column under each flow characteristic shows al the number of significant tests in which the value of the climate variable was higher for worst case series than best case series. Also indicated are the percentage of climate scenarios represented. There are 125 climate scenarios, so 125 indicates that a climate variable characteristic differed significantly between the wettest and driest simulations under all climate change scenarios.

	Mean flow		#LFP		#VLFP	
	# significant ($p < 0.05$)	# significant dry > wet	# significant ($p < 0.05$)	# significant dry > wet	# significant ($p < 0.05$)	# significant dry > wet
Average first 10 years						
winP	125 (100%)	0 (0%)	13 (10%)	13 (10%)	10 (8%)	10 (8%)
sumP	125 (100%)	0 (0%)	10 (8%)	1 (1%)	22 (18%)	2 (2%)
sumT	125 (100%)	125 (100%)	11 (9%)	6 (5%)	5 (4%)	4 (3%)
Average last 10 years						
winP	125 (100%)	125 (100%)	2 (2%)	1 (1%)	3 (2%)	3 (2%)
sumP	0 (0%)	0 (0%)	1 (1%)	1 (1%)	2 (2%)	0 (0%)
sumT	100	0 (0%)	5 (4%)	4 (3%)	7 (6%)	1 (1%)
Interannual standard deviation						
winP	0 (0%)	0 (0%)	42 (34%)	0 (0%)	52 (42%)	17 (14%)
sumP	2 (2%)	2 (2%)	47 (38%)	14 (11%)	20 (16%)	7 (6%)
sumT	0 (0%)	0 (0%)	84 (67%)	20 (16%)	84 (67%)	60
Maximum annual value						
winP	0 (0%)	0 (0%)	64 (51%)	10 (8%)	64 (51%)	7 (6%)
sumP	0 (0%)	0 (0%)	44 (35%)	6 (5%)	47 (38%)	8 (6%)
sumT	0 (0%)	0 (0%)	39 (31%)	0 (0%)	73 (58%)	46 (37%)
Minimum annual value						
winP	0 (0%)	0 (0%)	30 (24%)	24 (19%)	20 (16%)	20 (16%)
sumP	0 (0%)	0 (0%)	28 (22%)	5 (4%)	23 (18%)	20 (16%)
sumT	0 (0%)	0 (0%)	54 (43%)	49 (39%)	76 (62%)	24 (19%)

scenario.

In contrast, variability of the driving climate data differed strongly between simulations with many and few LFPs and VLFPs. The relationships were, however, sometimes complicated. For example, the standard deviation of sumT differed significantly between wet (few LFPs) and dry (more LFPs) flows for 84 different climate change scenarios. However, the sign of the response wasn't consistent. In 20 scenarios, more variable sumT was associated with a greater number of LFPs, while in 64 scenarios more variable sumT led to fewer LFPs. In general, more variable sumT was associated with increases in LFPs under scenarios with increasing precipitation. Other characteristics of the climate data that differed between flow series with particularly high and low numbers of LFPs were the minimum and maximum precipitation and temperature values. Similar, though not identical, influences were found for VLFPs (Table 4).

4. Discussion

In analyzing a large ensemble of statistically simulated streamflow projections, we found that there is substantial variability in average flow and the frequency of low-flow events within a given climate change scenario, and that similar flow conditions can be generated by a range of distinctly different climate scenarios. One of the drivers of this spread in flow is initial basin condition, which has a strong and consistent effect on water-year average flow during the early parts of simulations under essentially all climate changes, as well as on the frequency of low- or very low-flow events under many circumstances. Average climate conditions in the first ten years of the simulations also appear to influence overall average flow. Water-year flow in the UCRB displays significant persistence from one year to the next during the 1906–2014 period (AR1 = 0.25, $p < 0.05$). The simple statistical model used here includes persistence in UCRB flow in the form of a lag-1 flow term (Table 2). Thus, it is not surprising that both initial basin conditions and conditions during the first decade of a simulation influence mean flow in a model with explicit persistence.

River forecast models are regularly run using the best estimate of initial conditions, or with ranges of initial conditions to provide better seasonal projections (Harpold et al., 2016; Franz et al., 2003). Studies focused on estimating the impacts of long-term climate variability and change on flow, however, often do not account for the ways in which initial conditions influence outcomes, although Koczot et al. (2011) demonstrated that the effects of initial conditions on flow projections can be substantial. Under all climate scenarios investigated in this study, dry initial basin conditions were strongly associated with low average flows early in the simulations. While the impact of initial conditions did not persist to later years, the influence of dry early conditions was still detectable in the average flow over a full century. The simple model used here prescribes a degree of autoregressive behavior in flow that may not be constant in the real world, but the results suggest that the effects of initial hydrologic conditions on the variability of flow projections may be under-appreciated in hydrological studies that take a top-down approach. This may be particularly important for studies that are focused on the next few decades, but also is important for average flow conditions computed over as much as a century.

Internal variability is an important source of variability in climate model simulations. Over multi-decadal periods, internal variability can influence the direction of trends (Deser et al., 2012a), and at regional scales, internal variability contributes to projection uncertainty for up to a century (Hawkins and Sutton, 2009). It is often considered to be a form of "irreducible" uncertainty (Hawkins et al., 2016), i.e., a type of uncertainty that cannot reasonably be resolved. Moreover, many climate models do not skillfully simulate all of the processes that influence multi-annual to multi-decadal variability (Ault et al., 2012, 2014; Deser et al., 2012b). Thus, it is inevitable that top-down approaches will necessarily include input climate data with different temporal characteristics, as well as differing trends and changes in mean climate.

This simple study shows that the temporal characteristics of the input climate data can influence the frequency of LFPs and VLFPs, but that the impacts are not necessarily straightforward. Large interannual standard deviations in sumP are associated with more frequent LFPs under dry conditions, but less frequent LFPs when conditions are wet. Given the potential for diverse (and usually un-described) variance characteristics in the numerous downscaled climate projections used to drive hydrological models, it is worth evaluating streamflow projections in the context of the temporal characteristics of the driving data. This may be particularly important when analyzing the frequency and persistence of drought periods.

The statistical model used here may be inappropriate for some of the more detailed questions that are of interest to researchers and water managers. It is likely that there will be ecological or hydrological changes in a basin that may make the statistical model less appropriate for flow estimates far into the future. As the model is not spatially explicit, it assumes stationarity in the spatial patterns of precipitation and temperature, which we know can impact flow (e.g., Woodhouse et al., 2016; Solander et al., 2017). Finally, changes in climate could also alter relationships between seasonal climate and streamflow. Increasing temperatures could enhance evapotranspiration, reduce rain-to-snow ratios, and alter snowmelt dynamics (e.g., Barnhart et al., 2016; Solander et al., 2017). All of these types of changes could introduce non-linear streamflow responses that a linear model, like the one used here, could not begin to capture. Moreover, different formulations of the model could generate somewhat different results. For example, a model that does not include initial basin conditions will not be influenced by them. However, such models tend to be more sensitive to lagged climate variables (Table 1). Thus, flow is still impacted by initial conditions; the difference is merely in whether the initial conditions are ascribed to the basin hydro-climatic conditions or to prior-year climate.

5. Conclusions

Numerous studies have addressed the question of how changing climate will influence streamflow, yet water resource managers tasked with providing sufficient water for irrigation, power generation, and household needs, still have concerns about responding to changing climate and about the large uncertainty in climate change projections. Will a new set of climate projections associated with CMIP6 require re-evaluating streamflow projections? Could there be surprises where relatively modest changes in climate produce significant drought?

Water managers were integral in defining key elements of the research, and many provided useful and critical feedback on which results were particularly valuable and how they could be most effectively displayed. For example, managers' interest in the role of temperature drove the need to include temperature as a forcing variable. We have presented these results to managers through a webinar and project meeting and are continuing our collaboration on additional questions. For greater dissemination of the results, we plan to translate the peer-reviewed paper into a shorter publically accessible fact sheet and host a question-and-answer period with managers working in the Colorado basin and across the western U.S.

The approach we have taken here, driving a simple statistical model with synthetic climate data, provides critical context for evaluating existing streamflow projections made with more traditional "top-down" approaches. For example, such studies could be used to identify metrics that are associated with particularly modest or severe consequences relative to the projected climate change. Existing studies could be assessed in the context of those metrics. The approach taken here provides an example for exploring the concerns raised by water managers regarding future hydroclimatic conditions, and targeting particular timescales of significance to management, in a quick and economical way. Moreover, these large ensemble studies can assist managers in prioritizing which climate scenarios, initial conditions, and ecohydrological changes should be chosen for more detailed analysis, potentially reducing the costs and effort associated with climate change impacts analyses and planning.

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References

Adler, D., 2015. R Package 'vioplot'. https://cran.r-project.org/web/packages/vioplot/vioplot.pdf.
Alder, J.R., Hostetler, S.W., 2013. USGS National Climate Change Viewer. US Geological Survey https://www2.usgs.gov/climate_landuse/clu_rd/nccv.asphttp://dx.doi.org/10.5066/F7W9575T.
Ault, T.R., Cole, J.E., St., S., George, 2012. The amplitude of decadal to multidecadal variability in precipitation simulated by state-of-the-art climate models. Geophys. Res. Lett. 39, L21705. http://dx.doi.org/10.1029/2012GL053424.
Ault, T.R., Cole, J.E., Overpeck, J.T., Pederson, G.T., Meko, D.M., 2014. Assessing the risk of persistent drought using climate model simulations and paleoclimate data. J. Clim. 27, 7529–7549. http://dx.doi.org/10.1175/JCLI-D-12-00282.1.
Ayers, J., Ficklin, D.L., Stewart, I.T., Strunk, M., 2016. Comparison of CMIP3 and CMIP5 projected hydrologic conditions in the Upper Colorado River Basin. Int. J. Climatol. 36, 3807–3818. http://dx.doi.org/10.1002/joc.4594.
Barnett, T.P., Pierce, D.W., 2008. When will Lake Mead go dry? Water Resour. Res. 44, W03201. http://dx.doi.org/10.1029/2007WRR006704.
Barnhart, T.B., Molotch, N.P., Livneh, B., Harpold, A.A., Knowles, J.F., Schneider, D., 2016. Snowmelt rate dictates streamflow. Geophys. Res. Lett. 43, 8006–8016.
Bartoń, K., 2016. R Package, 'MuMin', https://cran.r-project.org/web/packages/MuMIn/MuMIn.pdf.
Bivand, R., Keitt, T., Rowlingson, B., Pebesma, E., Sumner, M., Hijmans, R., Rouault, E., 2016. R Package, 'rgdal', https://cran.r-project.org/web/packages/rgdal/rgdal.pdf.
Bosch, J.M., Hewlett, J.D., 1982. A review of catchment experiments to determine the effect of vegetation changes on water yield and evapotranspiration. J. Hydrol. 55, 3–23. http://dx.doi.org/10.1016/0022-1694(82)90117-2.
Christensen, N.S., Wood, A.W., Voisin, N., Lettenmaier, D.P., Palmer, R.N., 2004. The effects of climate change on the hydrology and water resources of the Colorado River basin. Clim. Change 62, 337–363.
Christensen, N.S., Lettenmaier, D.P., 2007. A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River basin. Hydrol. Earth Syst. Sci. 3, 1–44.
Clark, M.P., Wilby, R.L., Gutmann, E.D., Vano, J.A., Gangopadhyay, S., Wood, A.W., Fowler, H.J., Prudhomme, C., Arnold, J.R., Brekke, L.D., 2016. Characterizing uncertainty of the hydrologic impacts of climate change. Curr. Clim. Change Rep. 2, 55–64. http://dx.doi.org/10.1007/s40641-016-0034-x.
Cook, E.R., Woodhouse, C.A., Eakin, C.M., Meko, D.M., Stahle, D.W., 2004. Long-term aridity changes in the western United States. Science. 306, 1015–1018. http://dx.doi.org/10.1126/science.1102586.
Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol. 28, 2031–2064. http://dx.doi.org/10.1002/joc.1688.
Deser, C., Phillips, A., Bourdette, V., Teng, H., 2012a. Uncertainty in climate change projections: the role of internal variability. Clim. Dyn. 38, 527–546. http://dx.doi.org/10.1007/s00382-010-0977-x.
Deser, C., Phillips, A.S., Tomas, R.A., Okumura, Y.M., Alexander, M.A., Capotondi, A., Scott, J.D., Kwon, Y.O., Ohba, M., 2012b. ENSO and Pacific decadal variability in the Community Climate System Model version 4. J. Clim. 25, 2622–2651. http://dx.doi.org/10.1175/JCLI-D-11-00301.1.
Deser, C., Phillips, A.S., Alexander, M.A., Smoliak, B.V., 2014. Projecting North American climate over the next 50 years: uncertainty due to internal variability. J. Clim. 27, 2271–2296. http://dx.doi.org/10.1175/JCLI-D-13-00451.1.
Dunne, T., Zhang, W., Aubry, B.F., 1991. Effects of rainfall, vegetation, and microtopography on infiltration and runoff. Water Resour. Res. 27, 2271–2285. http://dx.doi.org/10.1029/91WR01585.
Franz, K.J., Hartmann, H.C., Sorooshian, S., Bales, R., 2003. Verification of National Weather Service ensemble streamflow predictions for water supply forecasting in the Colorado Basin. J. Hydrometeorol. 4, 1105–1117 doi: 0.1175/1525-7541(2003)004 < 1105:VONWSE > 2.0.CO;2.
Gangopadhyay, S., McCabe, G.J., Woodhouse, C.A., 2015. Beyond annual streamflow reconstructions for the Upper Colorado River Basin: a paleo-water-balance approach. Water Resour. Res. 51, 9763–9774. http://dx.doi.org/10.1002/2015WR017283.
Gao, Y., Vano, J.A., Zhu, C., Lettenmaier, D.P., 2011. Evaluating climate change over the Colorado River basin using regional climate models. J. Geophys. Res. 116, D13104. http://dx.doi.org/10.1029/2010JD015278.
Gao, Y., Leung, L.R., Salathé Jr., E.P., Dominguez, F., Nijssen, B., Lettenmaier, D.P., 2012.

Moisture flux convergence in regional and global climate models: Implications for droughts in the southwestern United States under climate change. Geophys. Res. Lett. 39, L09711. http://dx.doi.org/10.1029/2012GL051560.
Harder, P., Pomeroy, J.W., 2014. Hydrological model uncertainty due to precipitation-phase partitioning methods. Hydrol. Process. 28, 4311–4327. http://dx.doi.org/10.1002/hyp.10214.
Harding, B.L., Wood, A.W., Prairie, J.R., 2012. The implications of climate change scenario selection for future streamflow projection in the upper Colorado River basin. Hydrol. Earth Syst. Sci. Discuss. 9, 847–894. http://dx.doi.org/10.5194/hessd-9-847-2012.
Harpold, A.A., Sutcliffe, K., Clayton, J., Goodbody, A., Vazquez, S., 2016. Does including soil moisture observations improve operational streamflow forecasts in snow-dominated watersheds? J. Amer. Water Resour. Assoc. 53, 179–196. http://dx.doi.org/10.1111/1752-1688.12490.
Hawkins, E., Sutton, R., 2009. The potential to narrow uncertainty in regional climate predictions. Bull. Amer. Meteorol. Soc. 90, 1095–1107. http://dx.doi.org/10.1175/2009BAMS2607.1.
Hawkins, E., Smith, R.S., Gregory, J.M., Stainforth, D.A., 2016. Irreducible uncertainty in near-term climate projections. Clim. Dyn. 46, 3807–3819. http://dx.doi.org/10.1007/s00382-015-2806-8.
Hijmans, R.J. van Etten, J., Cheng, J., Mattiuzzi, M., Sumner, M., Greenberg, J.A., Lamigueiro, O.P., Bevan, A., Racine, E.B., Shortridge, A., 2016. R Package, 'raster', https://cran.r-project.org/web/packages/raster/raster.pdf.
Hirsch, R.M., Archfield, S.A., De Cicco, L.A., 2015. A bootstrap method for estimating uncertainty of water quality trends. Environ. Modell. Softw. 73, 148–166. http://dx.doi.org/10.1016/j.envsoft.2015.07.017.
Hoerling, M., Eischeid, J.K., 2007. Past peak water in the Southwest. Southwest Hydrol. 6, 18–19.
Hostetler, S.W., Alder, J.R., 2016. Implementation and evaluation of a monthly water balance model over the U.S. on an 800 m grid. Water Resour. Res. 52. http://dx.doi.org/10.1002/2016WR018665.
IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., Qin, D., Plattner, G.-K., Tignore, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. doi:10.1017/CB07981107415324.
Knowles, N., Dettinger, M.D., Cayan, D.R., 2006. Trends in snowfall versus rainfall in the western United States. J. Clim. 19, 4545–4559. http://dx.doi.org/10.1175/JCLI3850.1.
Koczot, K.M., Markstrom, S.L., Hay, L.E., 2011. Effects of baseline conditions on the simulated hydrologic response to projected climate change. Earth Interact. 15, 1–23 0.1175/2011EI378.1.
Lawrence, M.A., 2016. R package 'ez'. https://cran.r-project.org/web/packages/ez/index.html.
McCabe, G.J., Wolock, D.M., 2007. Warming may create substantial water supply shortages in the Colorado River basin. Geophys. Res. Lett. 34, L22708. http://dx.doi.org/10.1029/2007GL031764.
McCabe, G.J., Wolock, D.M., 2011. Independent effects of temperature and precipitation on modeled runoff in the conterminous United States. Water Resour. Res. 47, W11522. http://dx.doi.org/10.1029/2011WR010630.
McCabe, G.J., Wolock, D.M., Pederson, G.T., Woodhouse, C.A., McAfee, S.A., 2017. Evidence that recent warming is affecting upper Colorado River flows. Earth Interact. http://dx.doi.org/10.1175/EI-D-17-0007.1.
Meko, D.M., Woodhouse, C.A., Baisan, C.H., Knight, T., Lukas, J.J., Hughes, M.K., Salzer, W., 2007. Medieval drought in the upper Colorado River basin. Geophys. Res. Lett. 34, L10705. http://dx.doi.org/10.1029/2007GL029988.
Mendoza, P.A., Mizukami, N., Ikeda, K., Clark, M.P., Gutmann, E.D., Arnold, J.R., Brekke, L.D., Rajagopalan, B., 2016. Effects of different regional climate model resolution and forcing scales on projected hydrologic changes. J. Hydrol. 541, 1003–1019. http://dx.doi.org/10.1016/j.jhydrol.2016.08.010.
Milly, P.C.D., Dunne, K.A., Vecchia, A.V., 2005. Global pattern of trends in streamflow and water availability in a changing climate. Nature 438, 347–350. http://dx.doi.org/10.1038/nature04312.
Mizukami, N., Clark, M.P., Gutmann, E.D., Mendoza, P.A., Newman, A.J., Nijssen, B., Livneh, B., Hay, L.E., Arnold, J.R., Brekke, L.D., 2016. Implications of the methodological choices for hydrologic portrayals of climate change over the contiguous United States: statistically downscaled forcing data and hydrologic models. J. Hydrometeorol. 17, 73–98. http://dx.doi.org/10.1175/JHM-D-14-0187.1.
Oyler, J.W., Ballantyne, A., Jencso, K., Sweet, M., Running, S.W., 2015a. Creating a topoclimatic daily air temperature dataset for the conterminous United States using homogenized station data and remotely sensed land skin temperature. Int. J. Climatol. 35, 2258–2279. http://dx.doi.org/10.1002/joc.4127.
Oyler, J.W., Dobrowski, S.Z., Ballantyne, A.P., Klene, A.E., Running, S.W., 2015b. Artificial amplification of warming trends across the mountains of the western United States. Geophys. Res. Lett. 42, 153–161. http://dx.doi.org/10.1002/2014GL062803.
Painter, T.H., Deems, J.S., Belnap, J., Hamlet, A.F., Landry, C.C., Udall, B., 2010. Response of Colorado River runoff to dust radiative forcing in snow. Proc. Natl. Acad. Sci. USA 107, 17125–17130. http://dx.doi.org/10.1073/pnas.0913139107.
Patil, S.D., Wigington Jr., P.J., Liebowitz, S.G., Sproles, E.A., Comeleo, R.L., 2014. How does spatial variability of climate affect catchment and streamflow predictions? J. Hydrol. 517, 135–145. http://dx.doi.org/10.1016/j.jhydrol.2014.05.017.
Pebesma, E., Bivand, R., Rowlingson, B., Gomez-Rubio, V., Hijmans, R., Sumner, M., MacQueen, D., Limon, J., O'Brien, J., 2016. R Package 'sp', https://cran.r-project.org/web/packages/sp/sp.pdf.
R Core Development Team, 2008. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
Rajagopalan, B., Lall, U., 1999. A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resour. Res. 35, 3089–3101. http://dx.doi.org/10.1029/1999WR900028.
Rasmussen, R., Liu, C., Ikeda, K., Gochis, D., Yates, D., Chen, F., Tewari, M., Barlage, M., Dudhia, J., Yu, W., Miller, K., 2011. High-resolution coupled climate runoff simulations of seasonal snowfall over Colorado: a process study of current and warmer climate. J. Clim. 24, 3015–3048. http://dx.doi.org/10.1175/2010JCLI3985.1.
Seager, R., Ting, M., Held, I., Kushnir, Y., Lu, J., Vecchi, G., Huang, H.-P., Harnik, N., Leetmaa, A., Lau, N.-C., Li, C., Velez, J., Naik, N., 2007. Model projections of an imminent transition to a more arid climate in southwestern North America. Science 316, 1181–1184. http://dx.doi.org/10.1126/science.1139601.
Seager, R., Ting, M., Li, C., Naik, N., Cook, B., Nakamura, J., Liu, H., 2013. Projections of declining surface-water availability for the southwestern United States. Nat. Clim. Change 3, 482–486. http://dx.doi.org/10.1038/NCLIMATE1787.
SNWA, 2017. Southern Nevada Water Authority. Water Sources: Colorado River. [Available online at: https://www.snwa.com/ws/river.html].
Solander, K.C., Bennett, K.E., Middleton, R.S., 2017. Shifts in historical streamflow extremes in the Colorado River Basin. J. Hydrolog. 12, 363–377.
Udall, B., Overpeck, J., 2017. The 21st Century Colorado River hot drought and implications for the future. Water Resour. Res. 53, 2404–2418. http://dx.doi.org/10.1002/2016WR019638.
USBR, 2011a. U.S. Bureau of Reclamation, Colorado River basin water supply and demand study. Tech. Rep. B, U.S. Department of the Interior, Boulder City, Nevada. [Available online at: www.usbr.gov/lc/region/programs/crbstudy/finalreport/index.html].
USBR, 2011b. U.S. Bureau of Reclamation, West-wide climate risk assessments: Bias-corrected and spatially downscaled surface water projections. Tech. Memo. 86-68210-2011-01, U.S. Department of the Interior, Denver, Colorado, p. 122. [Available online at: www.usbr.gov/WaterSMART/docs/west-wide-climate-risk-assessments.pdf].
USGS Climate Change Research and Development Program. National Climate Change Viewer, 2017. < https://www2.usgs.gov/climate_landuse/clu_rd/nccv/viewer.asp > (accessed 21 July 2017).
Vano, J.A., Das, T., Lettenmaier, D.P., 2012. Hydrologic sensitivities of Colorado River runoff to changes in precipitation and temperature. J. Hydrometeorol. 13, 932–949. http://dx.doi.org/10.1175/JHM-D-11-069.1.
Vano, J.A., Udall, B., Cayan, D.R., Overpeck, J.T., Brekke, L.D., Das, T., Hartmann, H.C., Hidalgo, H.G., Hoerling, M., McCabe, G.J., Morino, K., Webb, R.S., Werner, K., Lettenmaier, D.P., 2014. Understanding uncertainties in future Colorado River streamflow. Bull. Amer. Meteorol. Soc. 95, 59–78. http://dx.doi.org/10.1175/BAMS-D-12-00228.1.
Vano, J.A., Kim, J.B., Rupp, D.E., Mote, P.W., 2015. Selecting climate change scenarios using impact-relevant sensitivities. Geophys. Res. Lett. 42, 5516–5525. http://dx.doi.org/10.1002/2015GL063208.
Wall, T.U., Meadow, A.M., Horbanic, A., 2017. Developing evaluation indicators to improve the process of coproducing usable climate science. Weather Clim. Soc. 9, 95–107. http://dx.doi.org/10.1175/WCAS-D-16-0008.1.
Wilby, R.L., Dessai, S., 2010. Robust adaptation to climate change. Weather. 65, 180–185. http://dx.doi.org/10.1002/wea.543.
Woodhouse, C.A., Gray, S.T., Meko, D.M., 2006. Updated streamflow reconstructions for the upper Colorado River basin. Water Resour. Res. 42, W05415. http://dx.doi.org/10.1029/2005WR004455.
Woodhouse, C.A., Pederson, G.T., Morino, K., McAfee, S.A., McCabe, G.J., 2016. Increasing influence of air temperature on upper Colorado River streamflow. Geophys. Res. Lett. 43, 2174–2181. http://dx.doi.org/10.1002/2015GL067613.