Assessing differences in snowmelt-dependent hydrologic projections using CMIP3 and CMIP5 climate forcing data for the western United States

Darren L. Ficklin, Sally L. Letsinger, Iris T. Stewart and Edwin P. Maurer

ABSTRACT

Most recent climate change impact studies are using Coupled Model Intercomparison Project Phase 5 (CMIP5) projections to replace older generation CMIP3 projections. Here we evaluate whether differences between projections based on comparable high emission pathways of a seven-member general circulation model CMIP3 versus CMIP5 ensemble change our understanding of the expected hydrologic impacts. This work focuses on the important snowmelt-dominated mountain runoff-generating regions of the western United States (WUS; Upper Colorado River Basin (UCRB), Columbia River Basin (CRB), and Sierra Nevada (SN) Basins). Significant declines in snowmelt, and shifts in streamflow timing owing to warmer, wetter CMIP5 projections match or exceed those based on CMIP3 throughout the WUS. CMIP3- and CMIP5-based projections, while generally in agreement about hydroclimatic changes, differ in some important aspects for key regions. The most important is the UCRB, where CMIP5-based projections suggest increases in future streamflows. Comparable hydrologic projections result from similar underlying climate signals in CMIP3 and CMIP5 output for the CRB and SN, suggesting that previous work completed in these basins based on CMIP3 projections is likely still useful. However, UCRB hydrologic projections based on CMIP5 output suggest that a re-evaluation of future impacts on water resources is warranted.

Key words | climate change, CMIP3, CMIP5, hydrology, Soil and Water Assessment Tool (SWAT), western United States

Darren L. Ficklin (corresponding author)
Department of Geography,
Indiana University,
701. E. Kirkwood Ave.,
Bloomington, IN 47405,
USA
E-mail: *dficklin@indiana.edu*

Darren L. Ficklin
Sally L. Letsinger
Center for Geospatial Data Analysis, Indiana Geological Survey,
611 N. Walnut Grove,
Bloomington, IN 47405,
USA

Iris T. Stewart
Department of Environmental Studies and Sciences,
Santa Clara University,
500 El Camino Real,
Santa Clara, CA 95053,
USA

Edwin P. Maurer
Civil Engineering Department,
Santa Clara University,
500 El Camino Real,
Santa Clara, CA 95053,
USA

INTRODUCTION

The question of whether anticipated climatic changes will lead to an increase or decrease in available water resources is particularly important in rapidly developing, economically important regions with arid or semi-arid climates. Consequently, many studies have assessed the potential impacts of climatic changes on water resources throughout the world (e.g., Barnett *et al.* 2008; Ficklin *et al.* 2013; Seager *et al.* 2013; Aich *et al.* 2014). Until recently, these studies were based on future climate information from the World Climate Research Programme's Coupled Model Intercomparison Project (CMIP) Phase 3 (CMIP3) archive. Recently, new CMIP5-based projections have become available, raising the issue of whether predictions of future climatic and hydrologic impacts should be revisited in light of our improved understanding of the climate system and greenhouse gas emission pathways. For this work, we concentrate on the arid/semi-arid western United States (WUS), where drought and water scarcity is becoming a common occurrence (Griffin & Anchukaitis 2014; Ficklin *et al.* 2015) and the sustainable management of water resources is critical.

Projected increases in air temperature and associated precipitation regime shifts (snow-dominated to rain-dominated) are widely expected to result in significant consequences for the large fraction of WUS water resources that are dependent on high-elevation snowpack (Hamlet *et al.* 2005; Mote *et al.* 2005; Karl *et al.* 2009). A large number of studies using historical data have shown that since 1950 this snowpack has declined throughout the WUS, resulting

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in reduced snowmelt, shifts toward streamflow occurring earlier in the year, longer summer drought periods, and changes from snowmelt-dominated to rainfall-dominated runoff regimes (e.g., Mote *et al.* 2005; Stewart *et al.* 2005; Knowles *et al.* 2006; Schwartz *et al.* 2006; Fritze *et al.* 2011; Klos *et al.* 2014). Indeed in 2015, measured snowpacks at Snow Telemetry (SNOTEL) stations by the National Resource Conservation Service are at record lows in the WUS (6% of normal in early April, 2015). These changes are expected to continue throughout the 21st century (Stewart *et al.* 2004; Ficklin *et al.* 2012, 2013; Harding *et al.* 2012; Klos *et al.* 2014). Furthermore, it is thought that these climatic changes will increase the frequency, duration, and intensity of extreme hydrologic events, including floods and droughts (Stewart *et al.* 2015), which carry high societal and economic costs (Dettinger *et al.* 2011; Das *et al.* 2013). Thus, an improved understanding of the future hydroclimatic patterns is critical for water resources and economic planning in such arid and semi-arid environments.

In the WUS, hydro-climatological studies have concentrated on the large runoff-producing regions of the Upper Colorado River Basin (UCRB; average annual volume of 14 billion cubic meters) (Barnett & Pierce 2009; Harding *et al.* 2012; Ficklin *et al.* 2013), Columbia River Basin (CRB; 191 billion cubic meters) (Hamlet & Lettenmaier 1999, Hamlet *et al.* 2002; Elsner *et al.* 2010; Hatcher & Jones 2013), and the Sierra Nevada (SN; 33 billion cubic meters) (Maurer *et al.* 2007a; Young *et al.* 2009; Null *et al.* 2010; Ficklin *et al.* 2012), concurring that surface air temperature increases will result in reduced snowpack, shifts in streamflow timing, and streamflow volume changes in the region. Precipitation projections vary widely across the WUS, with an average among projections tending toward slightly wetter conditions in the northwest and drier conditions in the southwest.

The CMIP3 multi-model data set (Meehl *et al.* 2007) has allowed researchers to use output from multiple general circulation models (GCMs) for regional- to global-scale climate-change impact assessments. New-generation CMIP5 (Taylor *et al.* 2011) climate model projections include a more complete representation of some physical processes and, for some models, a finer spatial resolution compared to CMIP3 (Knutti & Sedlacek 2013). For the CMIP5 projections, future atmospheric greenhouse gas concentrations are projected differently than for CMIP3, following representative concentration pathways (RCPs) rather than emission scenarios (A2, B1, etc.) (Moss *et al.* 2010).

Previous studies have examined CMIP3 and CMIP5 model climate outcomes on the global to continental scale and have found generally consistent warming patterns, trends, and uncertainty (Kharin *et al.* 2013; Knutti & Sedlacek 2013; Kumar *et al.* 2013; Markovic *et al.* 2013; Rupp *et al.* 2013). For North America, a CMIP5-based multi-model ensemble of historical simulations indicated slight improvements in representing observed climate variables compared to CMIP3 (Sheffield *et al.* 2013a, 2013b; Maloney *et al.* 2014), with significant improvement in the simulation of key Pacific climate modes and their teleconnections to North America (Polade *et al.* 2013). In the eastern USA, a comparison of differences between CMIP3 and CMIP5 projections found higher seasonal streamflow for all seasons but the spring season using comparable greenhouse gas pathways (Bastola 2013). Other recent work for the WUS and other important mountain regions using CMIP5 has suggested decreases in future soil moisture and increases in future drought conditions (Dai 2013; Cook *et al.* 2015), projected decreases in relative humidity with resultant decreases in runoff (Pierce *et al.* 2013), and imminent substantial decreases in snow accumulation and melt (Diffenbaugh *et al.* 2013), without explicitly examining the differences between the CMIP3 and CMIP5 projections. To date, no systematic comparison of how the new CMIP5 data set adjusts or confirms our expectation of CMIP3-based hydrology has been undertaken for the WUS. A regional- to continental-scale analysis of the differences could aid researchers and natural-resource managers in evaluating whether the need exists to re-evaluate results obtained in the many impact studies undertaken so far.

Our objective, then, is to assess the differences between CMIP3 and CMIP5 GCMs on hydrology at the sub-continental scale. Specifically, we examine streamflow volumes, timing, and snowmelt volumes for the runoff-generating, mountainous regions of the WUS (the UCRB, CRB, and SN; Figure 1). For comparison, we use output from seven GCMs for CMIP3 and the next-generation versions of those GCMs produced by the same modeling groups for CMIP5 (Table 1). This selection aims to include a sufficient number of GCMs to capture some level of uncertainty in the

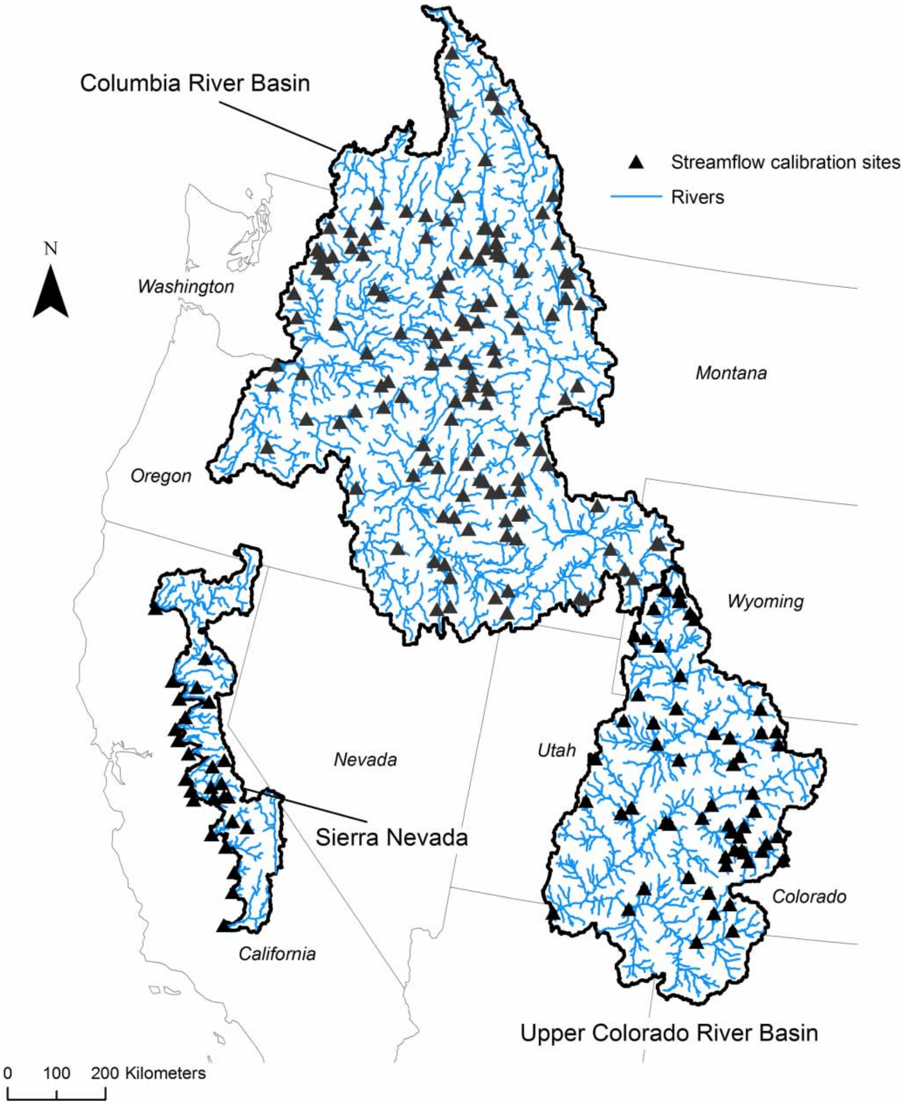

Figure 1 | Locations of the Upper Colorado River Basin, Columbia River Basin, and the Sierra Nevada mountain range in the western United States.

Table 1 | General circulation models used for the SWAT model runs

Model number	Modeling group	CMIP3 model	CMIP5 model
1	Canadian Centre for Climate Modeling and Analysis	cccma-cgcm3.1	canesm2
2	Météo-France/Centre National de Recherches Météorologiques, France	cnrm-cm3	cnrm-cm5
3	Geophysical Fluid Dynamics Laboratory, USA	gfdl-cm2.1	gfdl-cm3
4	Institut Pierre Simon Laplace, France	ipsl-cm4	ipsl-cm5a-mr
5	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan	miroc3.2_medres	miroc5
6	Max Planck Institute for Meteorology, Germany	mpi-echam5	mpi-esm-lr
7	Meteorological Research Institute, Japan	mri-cgcm2.3.2a	mri-cgcm3

ensembles, while limiting the variability between CMIP3 and CMIP5 ensembles due to structural differences among modeling groups. We compare the CMIP3 A2 emission scenario with the CMIP5 RCP 8.5, both of which constitute a higher emissions pathway, and to date are representative of 21st century observed emissions (Peters *et al.* 2013). The CMIP5 RCP 8.5 projects higher CO_2 concentrations than the A2 emission scenario at the end of the 21st century, which could result in more projected warming. GCM output was downscaled using the bias-corrected and constructed analogs (Maurer *et al.* 2010) approach and then used as input to a calibrated Soil and Water Assessment Tool (SWAT; Arnold *et al.* 1998) hydrologic model for each WUS basin. We compare the differences in hydroclimatic projections between the CMIP3 and CMIP5 models for the mid 21st century (2046–2065) and the late 21st century (2081–2099) to those of the baseline historical time period (1961–1990). The overarching goal of this work is to assess whether the new CMIP5 climate projections change our current understanding of the likely water future in the WUS. We recognize that the CMIP3 and CMIP5 ensembles used in this study differ in how the GCMs physically represent the climate (Knutti & Sedlacek 2013) and the radiative forcing differences between the A2 and RCP 8.5 emission pathways (Moss *et al.* 2010). Owing to these differences it is difficult to attribute differences in hydrology to any specific cause. To limit this, we chose GCMs from the same modeling groups, as described below. The objectives and results from this study are solely to assess how these CMIP3 and CMIP5 differences (whether it be from the physics or emission pathways) result in differences in hydrology. While this study is regional in nature, we expect the results to be of interest to researchers and water-resource managers wishing to pursue how changes in climate projections may result in changes in hydrology, especially in snowmelt-dominated regions.

STUDY AREA, MATERIALS AND METHODS

Study area

The water-generating snowmelt-dominated regions in the WUS that are considered here are the higher-elevation watersheds of the UCRB, CRB, and the SN (Figure 1). Due to their importance for agricultural, urban, and industrial development, these three regions have been studied extensively and are discussed in the literature (e.g., Null *et al.* 2010; Harding *et al.* 2012; Ficklin *et al.* 2013; Hatcher & Jones 2013). A large portion (~85%) of the streamflow in the Colorado River Basin is generated in the UCRB above Lee's Ferry, Arizona, and therefore only the UCRB is considered here. The entire CRB upstream from The Dalles, Oregon, outlet on the Columba River is included. For the Sierra Nevada, all rivers that enter reservoirs on the western SN are included, from the northern Sacramento River to the southern Kern River. For streamflow discussions, the Colorado River at Lee's Ferry, Arizona, is the outlet for the UCRB, and the Columbia River at The Dalles, Oregon, is the outlet for the CRB. All western streamflow outlets of the SN are summed and included as one streamflow value (total runoff of the western SN). These include (from north to south) the Sacramento River, Feather River, Yuba River, American River, Consumnes River, Mokelumne River, Stanislaus River, Tuolumne River, Merced River, San Joaquin River, Kings River, Kaweah River, Tule River, and the Kern River.

Downscaled general circulation models

We used the 1/8 degree (~12 km) spatial resolution daily climate data from 1949 to 2005, including precipitation, maximum and minimum temperature, and wind speed (Maurer *et al.* 2002) to drive the historical hydrological model simulations and to serve as observations for the downscaling procedure described below.

Daily downscaled output from seven GCMs (Table 1) for both the CMIP3 (A2 emission scenario) and CMIP5 (RCP 8.5) were obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive (USBR 2011; Maurer *et al.* 2014). Downscaling was achieved by using the daily bias-corrected and constructed analogs (BCCA) method (Wood *et al.* 2004; Hidalgo *et al.* 2008; Maurer *et al.* 2010). The downscaled data used here include a bias correction step that not only corrects for biases in the mean (as would simply scaling historic observations by GCM projected mean changes, sometimes referred to as the delta method) but biases in variability as well. Owing to the non-linear transformation of precipitation to streamflow, hydrologic model simulations can be sensitive to biases, and correcting GCM biases in variability while allowing variability to change in the future as projected by GCMs is desirable (Maurer *et al.* 2007b; Johnson & Sharma 2011).

BCCA downscaled precipitation projections for the study area exhibited a bias towards dry conditions for the historic period when compared to the observations. To correct this bias, a ratio-scaling factor was uniformly applied to a given projection's data over a given 1/8 degree cell location. We computed the historical bias as a period-ratio (for example, ratio of mean observed precipitation (Maurer *et al.* 2002) divided by mean historical precipitation from each downscaled GCM). Each grid-cell had a calculated ratio value, which was then multiplied by all time-series values in the BCCA projection's historical and future periods. The final results are projections that show no wet or dry precipitation bias in the mean, relative to observations for 1961–1990. This correction is similar to that applied for the new version of BCCA; BCCAv2 has corrected this dry bias and can be found on http://gdo-dcp.ucllnl.org/. No bias was found for the maximum and minimum air temperature values. All climate and hydrologic discussions hereafter are bias-corrected using these steps.

Since the hydrological model is run at a daily time step, it was desirable to use downscaled data based on daily GCM output to allow the evolution of changes in both means and extremes of daily GCM projections to be reflected in downscaled data. This is in contrast to many prior studies (Wood *et al.* 2004; Maurer *et al.* 2007b; Harding *et al.* 2012), which impose historical daily variability on monthly GCM projections, retaining considerable skill but neglecting projected changes in daily variability (Maurer *et al.* 2010).

In total for the Maurer *et al.* (2014) archive, there are nine CMIP3 and 21 CMIP5 GCMs that have been downscaled for daily data, while the total for monthly downscaled data is much greater. As in the study by Sheffield *et al.* (2013a), our aim is to focus on changes in projected impacts due to model development, not the expansion of the number of models (and modeling groups) represented in CMIP5. For this reason, we include GCMs that contributed to both CMIP3 and CMIP5, either for the same version of the model or for a newer version. While there have been many improvements in climate models between CMIP3 and CMIP5, including coupled ocean–atmosphere models evolving into earth system models, the simulated fields of temperature and precipitation of many models remain close to their predecessors (Knutti *et al.* 2013).

As shown in Figure 2, comparing the ensemble of temperature projections, averaged over the UCRB (which has shown to have increased precipitation with CMIP5 models; Rupp *et al.* 2013), between our seven-member ensemble and the larger GCM ensemble (of all GCMs, for which monthly data are available for CMIP3), the annual ensemble mean projected changes are shown to be very close for both CMIP3 (0.4 °C difference) and CMIP5 (0.1 °C difference). A two-sample t-test (accounting for unequal sample sizes) between the ensemble used in this work and the larger ensemble indicates no significant difference. This indicates that, at least for larger time and space scales, little bias in temperature-driven impacts is likely introduced by the limited ensemble size used in this study. For precipitation, our seven-member ensemble mean sets are slightly drier for CMIP3 (~2% change from historical precipitation) and slightly wetter for CMIP5 (~6%), indicating that the difference due to increased precipitation projections of CMIP5 relative to CMIP3 projections based on the smaller seven-member ensemble may be slightly exaggerated. Thus, while the seven-member ensemble is on the small side of a size desired for robust estimates of ensemble means (Pierce *et al.* 2009), the differences related to a larger ensemble, if more daily downscaled projections had been available, are not likely to be great. Furthermore, the tendency of this ensemble to slightly overestimate precipitation-driven differences between CMIP3 and CMIP5 will be somewhat offset by the conservative tendency of the statistical tests as applied here (see the section Statistical analyses).

The Soil and Water Assessment Tool hydrologic model

The Soil and Water Assessment Tool (Arnold *et al.* 1998) is a basin-scale model designed to simulate the entire hydrologic cycle. Surface runoff for all watersheds was estimated using the Soil Conservation Service curve number (SCS; US Department of Agriculture (USDA) 1954). Precipitation or snowmelt that infiltrates the soil column can be extracted via evapotranspiration, enter the groundwater system, or move laterally within the soil column. The Penman–Monteith method was

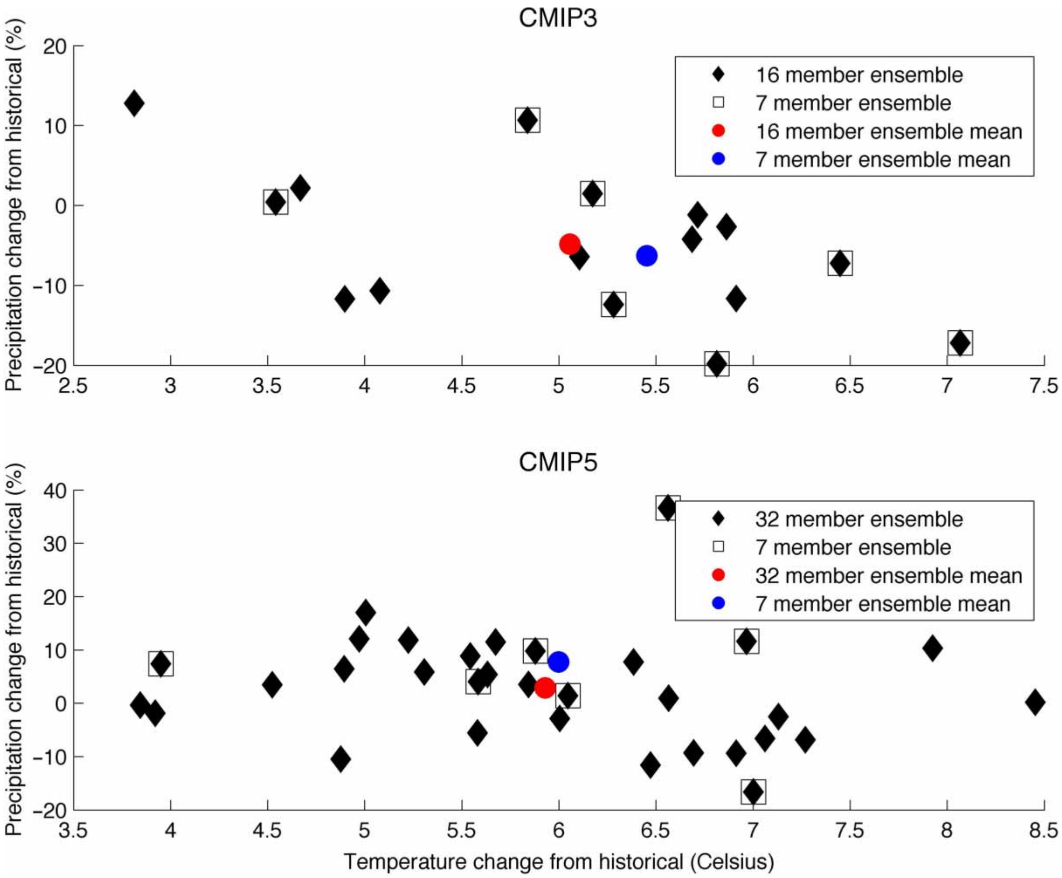

Figure 2 | Scatterplot of changes in average annual temperature and precipitation for the late 21st century compared to the historical time period for the seven-member CMIP3 and CMIP5 GCM ensemble used in this work and the entire CMIP3 and CMIP5 GCM ensemble for the Upper Colorado River Basin.

used to estimate evapotranspiration. The Penman–Monteith formulation for estimating potential evapotranspiration (PET) is internationally recommended and has been shown to provide more reliable estimates of PET than other methods (Allen *et al.* 1998; Lu *et al.* 2005; Kingston *et al.* 2009). The Penman–Monteith equation (Allen *et al.* 1998) has been applied to evaluate 20th century trends in evapotranspiration in the WUS (Hamlet *et al.* 2007) and is the method for estimating future evapotranspiration in many studies of hydrologic changes in the region (e.g., Barnett *et al.* 2008). Relative humidity and solar radiation inputs were generated based on nearby weather gauges using the built-in SWAT stochastic weather generator. In SWAT, generated relative humidity and solar radiation will change based on the air temperature and precipitation of the current day. SWAT uses a temperature index-based approach to estimate snow accumulation and snowmelt processes (Fontaine *et al.* 2002). The model was run at a daily time step for historic (1961–1990) and future climate scenarios (2046–2065; 2081–2099) and then aggregated to monthly and annual values for analysis. Detailed information regarding SWAT can be found in Neitsch *et al.* (2005).

Topography, land cover, and soils data for the SWAT model were compiled from various state and governmental agencies for all WUS watersheds. A 30-meter digital elevation model from the United States Geological Survey was used for watershed and stream delineation and estimation of stream slopes. The 2001 National Land Cover database was used to define land cover (Homer *et al.* 2004). We assume that land use remains constant for all simulations. Soil properties were established from the State Soil Geographic database (STATSGO). Estimated natural flow data for streamflow calibration were gathered from the California Data Exchange Center, United States

Bureau of Reclamation, and the University of Washington Climate Impacts Group (http://cses.washington.edu/cig/fpt/ccstreamflowtool/sftscenarios.shtml). The natural flow data are derived from climate/runoff relationships and is the streamflow that would occur if no reservoirs were present and no streamflow diversions were occurring. Additionally, unimpaired streamflow data were extracted from the Hydro-Climatic Data Network (Slack *et al.* 1993).

It is important to note that the effects of CO_2 on evapotranspiration (and therefore plant water use) are not incorporated within this study. Increases in CO_2 allow plants to decrease stomatal conductance and therefore decrease evapotranspiration. Several recent studies (Ficklin *et al.* 2009; Wu *et al.* 2012; Butcher *et al.* 2014) have examined the role that increased CO_2 may have on the hydrologic cycle using SWAT, suggesting that surface runoff may increase due to decreased evapotranspiration (and thus higher soil moisture contents). Therefore, the results from this study may be conservative, and one might expect higher streamflows than the ones presented in this study if the effects of CO_2 on plant transpiration were incorporated.

SWAT model calibration and validation procedure

An automated calibration technique using the program Sequential Uncertainty Fitting Version 2 (SUFI-2) (Abbaspour *et al.* 2007) was used to calibrate the SWAT model at 46 streamflow sites in the UCRB, 104 streamflow sites in the CRB, and 35 streamflow sites within the SN (Figure 1). These sites are considered 'natural' sites, meaning that they are not under the influence of dams, reservoirs, or a significant amount of diversion. For each watershed, sensitive parameters relating to hydrology were varied simultaneously until a best solution was found. Three criteria were used to assess model performance: (1) the coefficient of determination (R^2), (2) a modified efficiency criterion (Φ), and (3) the Nash–Sutcliffe coefficient (NS; Nash & Sutcliffe 1970). Φ is defined as the coefficient of determination, R^2, multiplied by the slope of the regression line, b (Krause *et al.* 2005). This function allows accounting for the discrepancy in the magnitude of two signals (captured by b) as well as their dynamics (captured by R^2). For NS, R^2, and Φ, a perfect simulation is represented by a value of 1.

The SWAT models (SWAT version 2009 for this work) were calibrated for the time period 1949–2005 with a spin-up time period of 1 year. A split-sample approach was used for calibration and validation. The calibration and validation years differed at each outlet depending on streamflow data availability. For the UCRB, over 56% of the gauges had observed data for the full time period (1950–2005; 79% of the gauges had observed data for 75% of the time period, and 88% of the gauges had observed data for 50% of the time period). For the CRB, over 21% of the gauges had observed data for the full time period (39% of the gauges had observed data for 75% of the time period, and 71% of the gauges had observed data for 50% of the time period). For the SN, over 54% of the gauges had observed data for the full time period (86% of the gauges had observed data for 75% of the time period, and 92% of the gauges had observed data for 50% of the time period).

Statistical analyses

The impact of potential climate change on unimpaired streamflow and hydrologic components was evaluated by comparing simulations using the GCMs in Table 1 for two future time periods: mid 21st century (2046–2065) and the late 21st century (2081–2099) to those of the baseline historical time period (1961–1990). The reference historical time period was chosen to be of sufficient length to provide a baseline for comparison, and also to exclude modern climate-change signals observed at the end of the 20th century. When describing the ensemble average (or standard deviation, σ) of a time period (i.e., mid 21st century), this value is the average (or σ) of the seven CMIP3 or CMIP5 GCMs for this time period.

The evaluations of downscaled climate components (precipitation and temperature) for the CMIP3 and CMIP5 projections were conducted in ESRI ArcGIS software using a 1/8 degree (~12 km) spatial resolution. Ensemble averages and standard deviations were calculated using local cell statistics (cell-by-cell calculation in the study domain), and values within the study basins were calculated using the basin boundaries as zone containers. Each GCM and ensemble mean for each projection and time-period scenario was compared to the historical reference period to evaluate not only deviations from observed data, but to highlight differences between the CMIP3 and CMIP5 projections. Precipitation values are presented as percent difference of the future scenarios from the historical values, whereas mean temperature is presented as the difference in degrees Celsius of the future scenarios from the historical values.

The downscaled mean annual precipitation and mean temperature for two time periods representing future conditions in the mid 21st century and the late 21st century were compared to a historical reference time period to examine differences between GCMs from the same modeling groups in the CMIP5 versus CMIP3 projections (Figures 3 and 4 show late 21st century results; mid 21st century results are included in Tables 2 and 3).

The two-sample Kolmogorov–Smirnov test was used to test for significant differences between the historical and future time periods as well as between the CMIP3 and CMIP5 data sets for annual precipitation, annual mean temperature, annual streamflow, annual snowmelt, monthly maximum streamflow timing (month of highest streamflow discharge), and monthly maximum streamflow volume (amount of water during the month of highest streamflow). The tests were applied with a statistical significance of $P = 0.05$. Although the daily downscaled GCM sample size is necessarily small, the statistical tests are much more stringent for rejection of

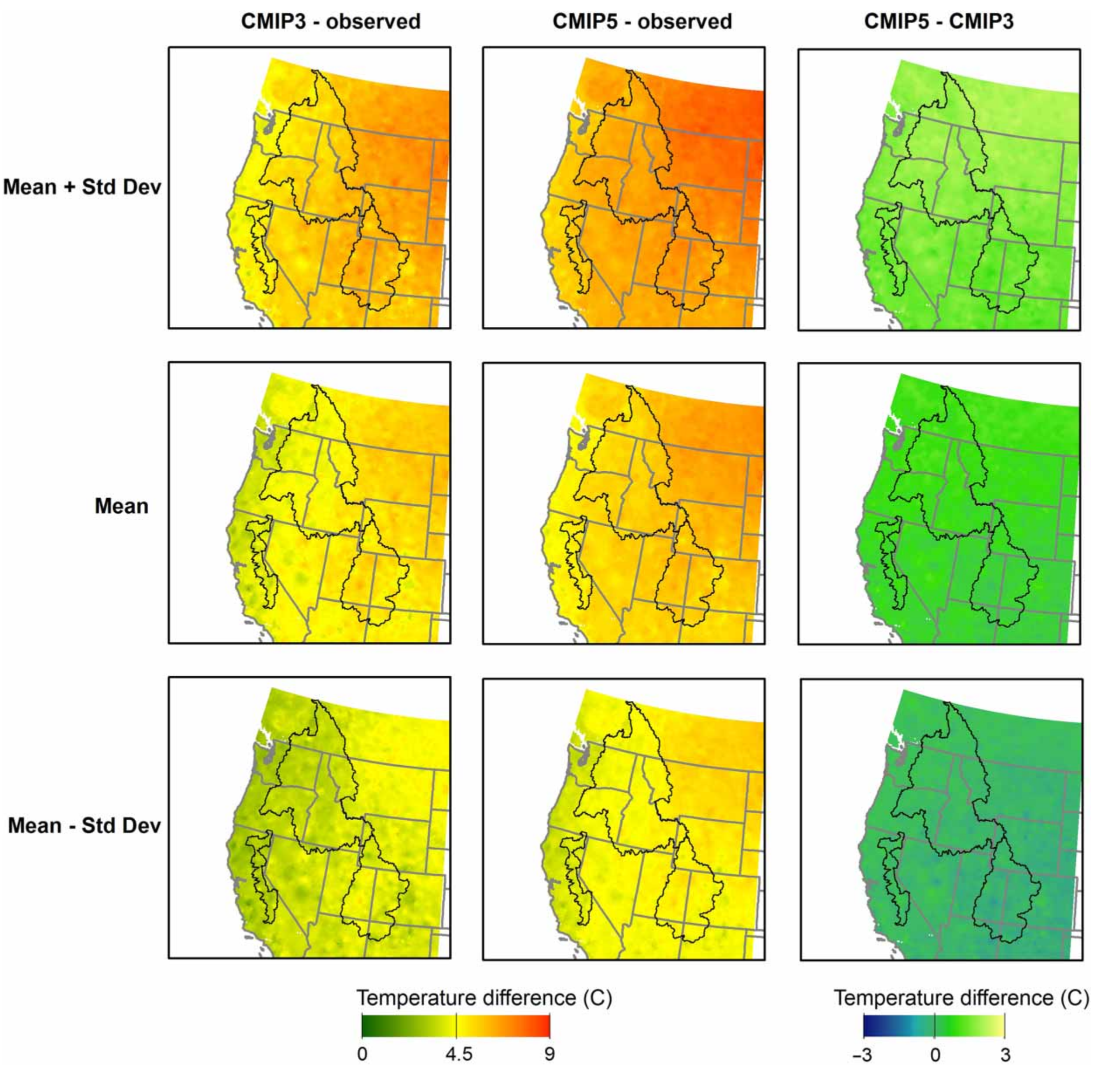

Figure 3 | Ensemble means and standard deviations for CMIP3 and CMIP5 mean temperature projections for the late 21st century. The locations of the three basins are highlighted. The first two columns compare the CMIP3 and CMIP5 ensemble mean and standard deviation against observed data. The third column compares the CMIP5 ensemble mean and standard deviation against the CMIP3 ensemble mean and standard deviation.

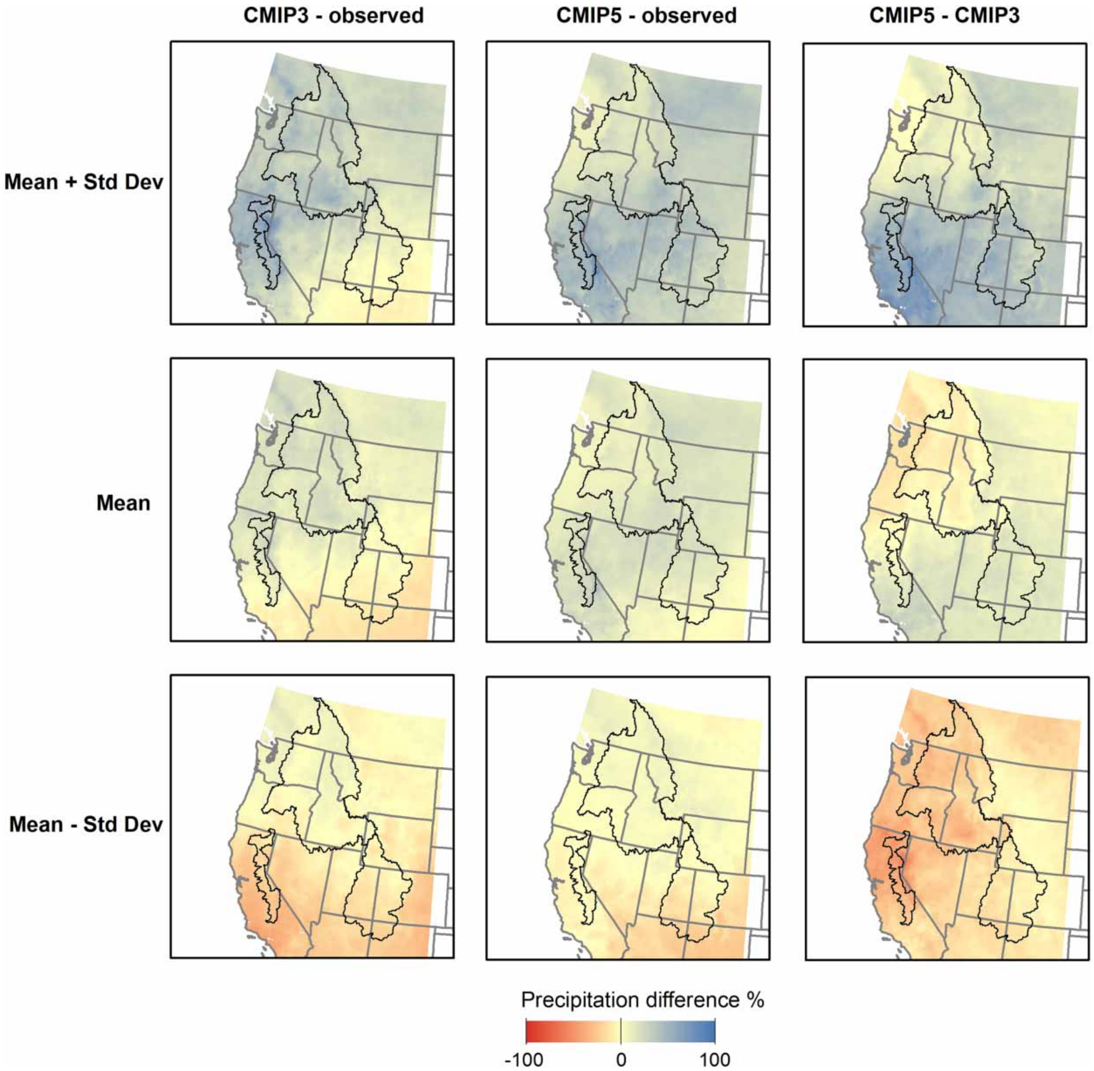

Figure 4 | Ensemble means and standard deviations for CMIP3 and CMIP5 precipitation projections for the late 21st century. The locations of the three basins are highlighted. The first two columns compare the CMIP3 and CMIP5 ensemble mean and standard deviation against observed data. The third column compares the CMIP5 ensemble mean and standard deviation against the CMIP3 ensemble mean and standard deviation.

Table 2 | Mean temperature difference (°C) and standard deviation from the historical reference period

		Upper Colorado		Columbia		Sierra Nevada		Average	
		Average	Std. dev.	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.
2050s	CMIP3	2.78*	0.4	2.44*	0.35	2.16*	0.395	2.515*	0.41
	CMIP5	3.52*	0.28	3.34*	0.28	2.96*	0.315	3.36*	0.31
	CMIP5-CMIP3	0.75^	0.18	0.89^	0.13	0.80^	0.15	0.84^	0.16
2080s	CMIP3	5.06*	0.43	4.5*	0.42	4.06*	0.44	4.62*	0.51
	CMIP5	5.68*	0.31	5.48*	0.31	4.90*	0.34	5.5*	0.36
	CMIP5-CMIP3	0.62^	0.2	0.98^	0.16	0.84^	0.16	0.87^	0.23

2050s = mid 21st century; 2080s = late 21st century.
*Statistically significant difference at $P = 0.05$ from historical.
^Statistically significant difference at $P = 0.05$ of CMIP3 compared to CMIP5 for same time period.

Table 3 | Precipitation percent difference and standard deviation from the historical reference period

		Upper Colorado		Columbia		Sierra Nevada		Average	
		Average	Std. dev.	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.
2050s	CMIP3	−4.45*	4.23	8.05*	2.32	9.73*	3.15	4.82*	6.37
	CMIP5	9.77*	3.40	11.04*	2.56	18.25*	2.87	11.20*	3.46
	CMIP5-CMIP3	14.22^	3.28	2.99^	3.25	8.52^	4.66	6.38^	5.98
2080s	CMIP3	−2.44*	5.73	17.75*	3.90	15.62*	5.25	12.20*	9.97
	CMIP5	12.63*	5.45	14.04*	4.21	21.97*	4.76	14.21*	5.11
	CMIP5-CMIP3	15.07^	3.18	−3.71^	5.51	6.34^	8.19	2.01^	9.80

2050s = mid 21st century; 2080s = late 21st century.
*Statistically significant difference at $P = 0.05$ from historical.
^Statistically significant difference at $P = 0.05$ of CMIP3 compared to CMIP5 for same time period.

the null hypothesis (H_0 = no difference) with fewer degrees of freedom ($n = 19$). This is because the tests exhibit decreased statistical power with small sample sizes, meaning there is a tendency to accept the null hypothesis of no difference between samples when in fact they differ, which makes the claim that significant differences exist more conservative (Haan 2002).

RESULTS AND DISCUSSION

Air temperature and precipitation

In concurrence with prior studies (Maloney *et al.* 2014), we find statistically significant warmer temperatures under CMIP5 RCP 8.5 than under CMIP3 A2 emission. The mean temperatures for the mid and late 21st century scenarios are projected to increase relative to the historical period for CMIP3 and CMIP5. In all but one GCM, mean temperature increases from the historic period are significantly higher under CMIP5 as compared to those of CMIP3. The temperature projections show somewhat similar, spatially uniform patterns for most of the individual GCMs as well as for the ensemble means (Figure 3). For the study basins, the ensemble mean differences between CMIP5 and CMIP3 mean temperature projections for both the mid and late 21st century are on the order of 0.6–1.0 °C (Table 2) and are statistically significant. The highest projected temperature differences between CMIP3 and CMIP5 are projected for the CRB, followed by the SN and the UCRB for both time periods.

Projected annual precipitation amounts and spatial patterns across the WUS vary greatly for each GCM under both CMIP3 and CMIP5 (Figure 4), which is not surprising, given the high uncertainty associated with the precipitation projections (Murphy *et al.* 2004; Hawkins & Sutton 2009; Sheffield *et al.* 2013a, 2013b; Maloney *et al.* 2014). Averaged over all basins, precipitation is likely to increase under both the CMIP3 and CMIP5 data sets for both time periods, with larger increases under CMIP5 (Figure 4; Table 3). The difference in CMIP3 versus CMIP5 precipitation projections was largest in the UCRB for both the mid and late 21st century scenarios and is statistically significant (Figure 4) (14.2% and 15.1%, respectively). The divergence of CMIP5 projections from CMIP3 projections was smallest for the CRB, with values of 3.0% (CMIP5 wetter; statistically significant) for the mid 21st century scenario and −3.7% (CMIP5 drier; statistically significant) for the late 21st century scenario with large standard deviations (Figure 4). For the SN, CMIP5 projections were higher than CMIP3 projections by 8.5% and 6.3%, for the mid (statistically significant) and late 21st (statistically significant) centuries, respectively, and also characterized by high standard deviations. For all basins combined, the average difference in precipitation projections between CMIP5 and CMIP3 was 6.4% for the mid 21st century and 2.0% for the late 21st century, both of which were statistically significant.

Streamflow

The interplay of projected future temperatures and precipitation results in many similarities and important spatial and temporal differences in projected streamflow between

CMIP3 and CMIP5 across the WUS. After calibration and validation (Tables 4 and 5), the hydrologic models were driven with the downscaled and bias-corrected CMIP3 and CMIP5 daily output, and aggregated to monthly values for analysis. Model results showed that the greatest differences in streamflow within the WUS are expected for the important UCRB region, where ensemble-averaged streamflow based on CMIP3 indicate decreases of 3% for the mid 21st century and 8% for the late 21st century as compared to historical averages (Table 6). By contrast, the CMIP5-based average annual streamflow results suggest statistically significant increases of 12% for the mid 21st century and 9% for the late 21st century. The CMIP3 and CMIP5 ensemble average streamflow projections were found to be statistically different from each other for the UCRB. Under CMIP5, only three out of the seven GCMs for both the mid 21st century and two out of seven GCMs for the late 21st century indicate decreases in average annual streamflow for the region, leading to an ensemble average increase in streamflow as compared to the historical time period and CMIP3. Thus, in the UCRB the average of the CMIP5 models project not only a wetter, warmer climate (Figures 3 and 4) under CMIP5 as compared to CMIP3, but also a significant increase in average annual streamflow (Table 6).

Differences in annual streamflow under CMIP5 and CMIP3 were less substantial for the CRB and the SN. In the CRB, increases in streamflow compared to the historical time period were found under both CMIP3 and CMIP5. Although, for individual GCMs average annual streamflow increases of 16–28% for mid and late 21st century under both CMIP3 and CMIP5 were all statistically different from the historical baseline averages (Table 6), and the differences in CMIP3 and CMIP5 ensemble averages were not statistically different from each other. For the SN (as well as the UCRB), we found much GCM-to-GCM variation in precipitation and streamflow projections with no agreement on wetter or drier conditions (Table 6 and Figure 5). Overall, the ensemble average projects an annual streamflow increase compared to the historical average for all time periods for the CMIP3 and CMIP5 data sets. In the SN, the difference between the CMIP3 and CMIP5 ensemble average annual streamflow projections for both time periods was not statistically significant.

Table 4 | Streamflow calibration statistics for the three western United States regions

	Upper Colorado		Columbia		Sierra Nevada	
	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.
Calibration						
NS	0.71	0.12	0.69	0.13	0.75	0.09
R^2	0.79	0.08	0.75	0.10	0.8	0.07
Φ	0.67	0.12	0.62	0.15	0.65	0.11
Validation						
NS	0.72	0.11	0.64	0.13	0.78	0.08
R^2	0.79	0.08	0.75	0.08	0.82	0.07
Φ	0.69	0.11	0.65	0.13	0.65	0.11

NS, Nash–Sutcliffe coefficient; R^2, coefficient of determination; Φ, coefficient of determination multiplied by slope of regression line, *b*.

Snowmelt

Snowmelt is the largest contributor to streamflow for each of these regions and is sensitive to both temperature and precipitation changes. For each region in the WUS, a large portion of the GCM output for both time periods and ensembles projected statistically significant decreases of 20–60% in average annual snowmelt as compared to the historical time period (Table 6). For each region, the CMIP5 GCMs projected larger snowmelt volume decreases than the CMIP3 GCMs, which can be tied to warmer surface air temperatures projected under CMIP5.

For the UCRB, the CMIP3 and CMIP5 ensemble snowmelt declines were nearly identical (Table 6). Likely, the greater increase in projected precipitation (as compared to the CRB and SN basins) compensates for the higher air temperatures in the CMIP5 scenarios. We suggest that under CMIP5, increased air temperature and increased precipitation at higher elevations may drive a conversion of much of the precipitation to rain rather than snow, leading to more streamflow, but still accumulating similar snow volumes as projected by the CMIP3 GCMs. This snow-to-rain conversion has been documented in the historical streamflow record (Stewart *et al.* 2005; Fritze *et al.* 2011). Snowmelt projections for the SN and CRB varied from GCM-to-GCM (Table 6), but overall there were larger decreases in snowmelt under CMIP5 than CMIP3 with statistically significant differences. The partitioning of precipitation into rain and snow in important

Table 5 | Mean and standard deviation of SWAT calibrated parameters for each basin. Calibrated parameters varied depending on location within the basin

	Upper Colorado River Basin		Columbia River Basin		Sierra Nevada	
Parameters	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
ALPHA_BF.gw (-)	0.48	0.27	0.57	0.25	0.01	0.16
GW_DELAY.gw (days)	84.92	67.04	64.89	63.58	97.64	48.83
GW_REVAP.gw (-)	0.10	0.06	0.09	0.05	0.10	0.05
GWQMN.gw (mm)	526.06	334.39	1,069.53	1,083.59	2,209.21	1,327.32
LAT_TTIME.hru (days)	25.62	16.12	34.56	24.19	36.81	38.39
REVAPMN.gw (mm)	247.72	142.22	247.42	147.20	221.39	143.08
CN2.mgt (% from original value)	−9.12	13.85	3.96	14.10	1.38	16.27
SOL_AWC.sol (% from original value)	−1.35	17.04	−1.92	13.75	3.86	16.66
SOL_K.sol (% from original value)	0.75	17.07	1.07	16.58	−2.16	18.85
SOL_BD.sol (% from original value)	−0.07	16.68	−2.42	12.47	2.09	18.12
CH_N2.rte (-)	0.20	0.12	0.22	0.13	0.16	0.08
CH_K2.rte (mm/hr)	80.01	38.31	66.36	41.71	87.12	38.81
EPCO.hru (-)	0.51	0.29	0.51	0.29	0.57	0.34
ESCO.hru (-)	0.49	0.25	0.48	0.31	0.57	0.32
RCHRG_DP.gw (%)	0.44	0.27	0.53	0.32	0.59	0.25
TLAPS.sub (°C/km)	−5.61	2.54	−4.62	2.76	−4.93	2.50
PLAPS.sub (mm H_2O/km)	516.19	285.67	421.10	312.18	525.50	255.82
SFTMP.bsn (°C)	−0.34	–	−4.03	–	1.42	–
SMFMN.bsn (°C)	0.64	–	4.03	–	3.96	–
SMFMX.bsn (°C)	2.89	–	7.83	–	4.64	–
SMTMP.bsn (°C)	2.91	–	3.03	–	1.40	–
TIMP (-)	0.03		0.02		0.76	
SNO50COV.bsn (-)	0.23	–	0.36	–	0.65	–
SNOCOVMX.bsn (mm H_2O)	384.43	–	461.67	–	402.66	–
SURLAG.bsn (days)	2.47	–	17.02	–	5.31	–

See Neitsch *et al.* (2005) for detailed information about parameters.
*The parameter name extension refers to the location of the input file.

water-producing regions highlights the importance of understanding the timing of precipitation receipt as well as streamflow runoff.

Streamflow projections based on both CMIP3 and CMIP5 output showed statistically significant changes in average maximum monthly streamflow timing from the historical time period, with a near concurrence of a shift of approximately 1 month earlier in the year for the UCRB and CRB and a shift of 2–3 months for the SN (Figure 5) in the same direction. For both time periods for the UCRB, the CMIP3 and CMIP5 ensemble averages of maximum streamflow timing (month with the maximum streamflow) were not statistically different from each other, but were different from historic reference values. Additionally, the uncertainty (or standard deviation) band in Figure 5 indicates that all CMIP3 and CMIP5 simulations were in agreement with a shift towards earlier streamflow timing. This suggests that for the UCRB with the new CMIP5 projections, the timing is not expected to differ from the CMIP3 projections (Figure 5).

For the CRB, the CMIP3 and CMIP5 ensemble averages showed statistically similar maximum streamflow timing

Table 6 | Annual streamflow and snowmelt summaries for the Upper Colorado River Basin, Columbia River Basin, and the Sierra Nevada Basins

		Streamflow				Snowmelt			
		Mid 21st century		Late 21st century		Mid 21st century		Late 21st century	
	Model #	CMIP3	CMIP5	CMIP3	CMIP5	CMIP3	CMIP5	CMIP3	CMIP5
Upper Colorado	1	447 (−1)^	653 (45)*	426 (−6)^	739 (64)*	81 (−23)*	95 (−10)	71 (−33)*	77 (−26)
	2	341 (−24)^	505 (12)	385 (−15)^	524 (16)	83 (−21)	87 (−17)	71 (−32)*^	69 (−34)
	3	477 (6)	551 (22)	373 (−17)^	532 (18)*	91 (−13)	81 (−23)*	72 (−31)*	68 (−36)*
	4	526 (17)^	360 (−20)	461 (2)^	292 (−35)*	83 (−21)^	63 (−40)*	58 (−44)*	49 (−53)*
	5	366 (−18)^	418 (−7)	318 (−29)*	378 (−16)	74 (−29)*	72 (−31)*	56 (−47)*	55 (−48)*
	6	405 (−10)	446 (−1)	485 (7)	453 (1)	88 (−16)	80 (−24)	78 (−26)*	73 (−30)*
	7	484 (7)	599 (32)*	444 (−1)^	531 (18)*	101 (−4)	111 (6)	89 (−14)	88 (−16)
	Ensemble mean	435 (−3)^	504 (12)*	413 (−8)^	493 (9)*	86 (−18)	84 (−20)*	71 (−33)*	69 (−35)*
Columbia	1	7,806 (29)*	7,918 (31)*	9,292 (53)*^	7,968 (32)*	220 (−30)*	179 (−43)*	149 (−52)*^	104 (−67)*
	2	6,854 (13)*	7,408 (22)*	8,015 (32)*	7,525 (24)*	326 (4)^	214 (−31)*	301 (−4)^	121 (−61)*
	3	6,123 (1)^	8,338 (38)*	6,610 (9)^	8,208 (35)*	208 (−33)*	209 (−33)*	158 (−49)*	154 (−50)*
	4	7,831 (29)*^	6,633 (10)*	9,234 (52)*^	6,466 (7)	240 (−23)*^	174 (−44)*	147 (−53)*^	110 (−65)*
	5	7,015 (16)	7,506 (24)*	7,878 (30)*^	6,710 (11)*	259 (−17)	259 (−17)	193 (−38)*	159 (−49)*
	6	7,154 (18)*	7,035 (16)*	6,852 (13)*	7,601 (26)*	244 (−22)*^	202 (−35)*	142 (−55)*	141 (−55)*
	7	6,308 (4)	6,716 (11)	6,529 (8)	6,890 (14)*	228 (−27)*	239 (−24)*	180 (−43)*	194 (−38)*
	Ensemble mean	7,013 (16)*	7,365 (22)*	7,773 (28)*	7,338 (21)*	225 (−28)*^	189 (−40)*	169 (−46)*^	133 (−57)*
Sierra Nevada	1	1,059 (0)	1,079 (2)	1,142 (8)	1,202 (14)	103 (−30)*	91 (−38)*	75 (−49)*	74 (−50)*
	2	874 (−17)	1,119 (6)	1,015 (−4)	1,233 (17)	114 (−23)*	112 (−24)*	102 (−31)*	85 (−42)*
	3	1,130 (7)	1,173 (11)	810 (−23)*^	1,091 (3)	110 (−26)*	89 (−40)*	67 (−54)*	63 (−57)*
	4	1,665 (58)*^	1,048 (−1)	2,181 (107)*^	1,077 (2)	131 (−11)^	87 (−41)*	104 (−29)*^	59 (−60)*
	5	906 (−14)	949 (−10)	873 (−17)	970 (−8)	99 (−33)*	96 (−35)*	71 (−52)*	74 (−50)*
	6	1,034 (−2)	1,064 (1)	1,112 (5)	1,189 (13)	111 (−24)	96 (−35)*	86 (−42)*	80 (−46)*
	7	1,420 (35)*	1,573 (49)*	1,318 (25)*	1,310 (24)*	153 (4)	149 (1)	118 (−20)	111 (−24)*
	Ensemble mean	1,156 (10)	1,144 (8)	1,207 (14)	1,153 (9)	117 (−20)*	103 (−30)*	89 (−40)*^	78 (−47)*

Percent change values from the historical time period are shown in parentheses. See Table 1 for model names. All values are in m^3/s for streamflow and meters for snowmelt. Dark gray indicates a decrease from the historical period and light gray indicates an increase from the historical period. Upper Colorado River Basin historical mean: 450 m^3/s for streamflow and 105 m for snowmelt. Columbia River Basin historical mean: 6,056 m^3/s for streamflow and 312 m for snowmelt. Sierra Nevada Basins historical mean: 1,054 m^3/s for streamflow and 147 m for snowmelt.

*Statistically significant difference at $P = 0.05$ from historical.

^Statistically significant difference at $P = 0.05$ of CMIP3 compared to CMIP5 for same time period.

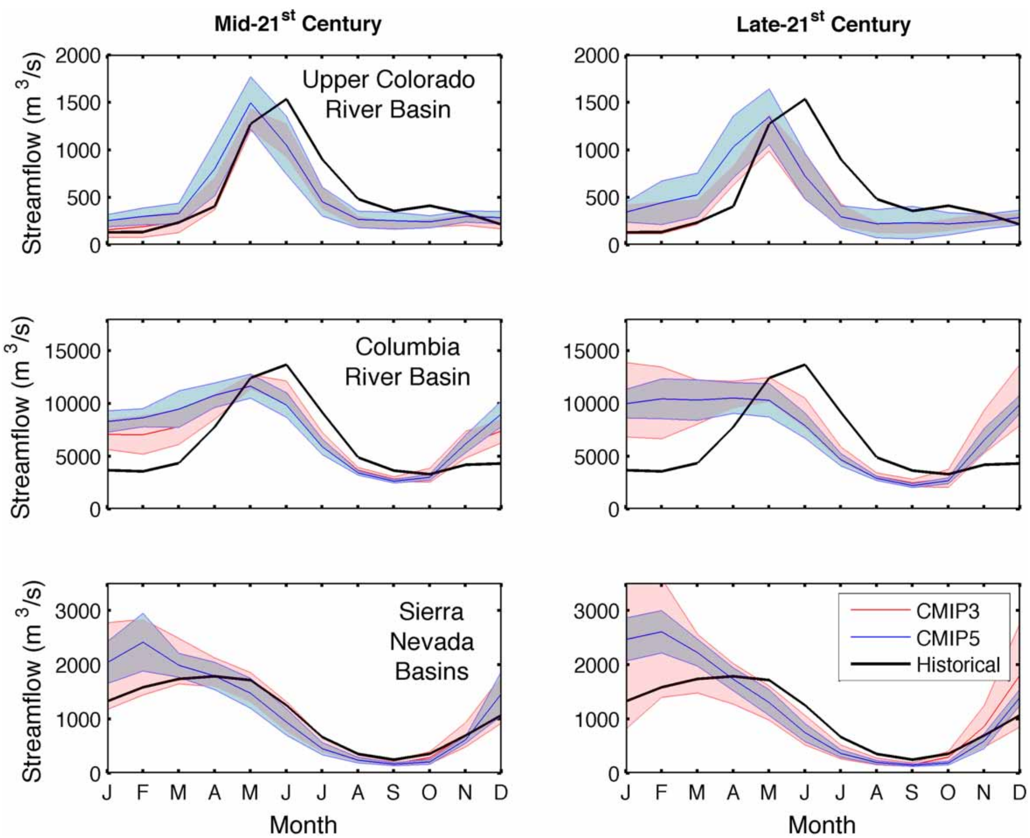

Figure 5 | Ensemble mean and standard deviation for streamflow at the outlets for the Upper Colorado River Basin, Columbia River Basin, and Sierra Nevada mountain range. The CMIP3 ensemble mean and standard deviation are represented by the solid red (pale gray) line and cloud, respectively, while the CMIP5 ensemble mean and standard deviation are represented by the solid blue (dark gray) line and cloud. The solid black line shows the 1961–1990 historical average. Please refer to the online version of this paper to see this figure in color.

projections for the mid 21st and late 21st century. Interestingly, based on the uncertainty bands in Figure 5, there were occurrences where GCM projections could shift peak streamflow into January and February under CMIP5.

The SN showed the largest difference in streamflow timing from the historical conditions. This is largely the result of lumping the entire SN runoff into one value (adding up the streamflows of all SN outlets, rather than assessing each individual outlet), where different runoff environments are included that produce different streamflow maximum timing values at different times. It is interesting to note that for the SN, the uncertainty around the mean was much smaller for the CMIP5 projections than the CMIP3 projections, suggesting a convergence of the hydrologic futures projected by the individual GCMs (Figure 5).

It should be noted that for each of the three regions considered, there were large variations between individual GCMs regarding the overall maximum monthly streamflow amount based on the standard deviation bands in Figure 5, which is to be expected from the variability in precipitation projections. While there were GCM-to-GCM differences in maximum monthly streamflow, the CMIP5 projections led to an average higher maximum monthly streamflow than the CMIP3 projections. This is illustrated in Figure 4, where the CMIP5 ensemble projects higher precipitation for the UCRB. The ensemble means of maximum monthly streamflow (maximum streamflow for a particular year) for the CMIP3 and CMIP5 projections for both time periods were significantly different from each other. Based on an inspection of the monthly extreme values, the CMIP5 streamflow projections suggest more extreme monthly values than the CMIP3 streamflow projections for the UCRB (Figure 5). Again, this is largely a consequence of higher precipitation and temperature projections from the CMIP5 simulations.

For the CRB and SN, the CMIP3 and CMIP5 ensemble averages of maximum monthly streamflow showed no statistical difference from each other for both time periods. This indicates that CMIP3 maximum monthly streamflow volumes are projected to remain nearly equivalent for the CMIP5 projections. However, it is important to note that there was some GCM-to-GCM variation around the maximum streamflow means, and much more uncertainty for the SN CMIP3 ensemble (Figure 5).

CONCLUSIONS

In summary, taken over comparable GCM ensemble means for the WUS mountainous regions, CMIP5 projections are warmer and wetter than CMIP3 projections. While all GCMs from both CMIP5 and CMIP3 agree on annual temperature increases, with minor variations in magnitude, there is much greater variability among projections for future precipitation for both CMIP3 and CMIP5. Based on the ensemble of GCMs used here, the decreases in precipitation projected for CMIP3 for some regions of the WUS are generally not evident in the newer CMIP5 output. The warmer and wetter conditions under CMIP5 lead to statistically significant larger annual streamflows for the UCRB, while streamflows for the CRB and SN remain statistically similar under CMIP3 projections.

Warmer temperatures and increased precipitation act together to shift the center of mass of streamflow earlier in the year (more winter precipitation, more precipitation arriving as rain, and earlier melt), and work in opposite directions with regard to water and snowmelt runoff (warmer temperatures leading to greater evapotranspiration and less snow deposition, compensated for by precipitation). Although, for the most part, the resulting streamflow, snowmelt volumes, and runoff timing between the CMIP5 and CMIP3 models are not sufficiently different to warrant a re-evaluation of our understanding of future water availability in all basins of the WUS, some key regional discrepancies between CMIP5- and CMIP3-based assessments have emerged. For example, annual streamflow volumes may not be, as previously thought, decreasing, but increasing for some important regions. Increases in expected annual flows, which exceed those of historical observations, are especially relevant for the UCRB. This is a water-generating region for millions of people and with important agricultural demands, for which mostly decreases had been previously projected to date. Based on our results, those expectations should be revised in the context of current and future assessments.

In addition to annual volumes, the seasonal distribution of water is an important metric for water supplies. Both the CMIP3 and CMIP5 predictions are in agreement about an earlier snowmelt pulse and substantially decreased snowmelt runoff volumes across the region, both of which can greatly impact water-management options. As the focus of this paper was on monthly and annual means over several decades using a multi-model ensemble, changes in the frequency of extreme hydrologic events (usually evaluated on a daily time scale), which have high societal and ecological importance, could not be examined.

Many of our findings with respect to projections of temperature, precipitation, and streamflow timing are similar across the entire WUS, which emphasizes the robustness of the underlying climatic signals in both CMIP3 and CMIP5 ensembles, despite some structural and greenhouse gas emission differences. However, our findings for the UCRB illustrate the need to evaluate differences in hydrologic consequences between CMIP3 and CMIP5 models on the sub-continental to local scale because the integrated effects of individual basin characteristics are not always predictable. There is a motivation for those investigating climate change impacts to use data derived from the CMIP5 models, with their overall finer spatial resolution, improved representation of processes, and skill that is generally equal to or better than the related CMIP3 versions. Our findings support this, suggesting that even for an ensemble of the same size composed of related GCMs, projections based on CMIP5 output can result in significantly different outcomes. Others have found differences in CMIP5 simulations to be related to improved spatial resolution in CMIP5 models (e.g., Polade *et al.* 2013; Sheffield *et al.* 2013a).

We anticipate that the basin-specific results from this work could be useful to WUS water-resources managers for making informed decisions about future water infrastructure planning and management based on studies using both CMIP3 and CMIP5 climate projections. We also suggest that the insights gained about the differences in impacts, as projected by CMIP3 and CMIP5, can be applied to other settings globally, especially arid and semi-arid mid-latitude mountainous regions.

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