

Hydrologic responses to climate change using downscaled GCM data on a watershed scale

Chao Chen, Ajay Kalra and Sajjad Ahmad

ABSTRACT

The changing climate has raised significant concerns for water resources, especially on a watershed scale. In this study, the downscaled global circulation model (GCM) products were further bias corrected and evaluated for the period of 1981–2099. Driven by the bias-corrected products, a calibrated Precipitation-Runoff Modeling System (PRMS) model was used to assess long-term hydrologic responses in the Lehman Creek watershed, eastern Nevada. The results of this study show: (1) the Parameter–elevation Regressions on Independent Slopes Model (PRISM) products offer a reliable replacement for limited observations for bias correction using quantile mapping (QM) technique; (2) average increases of 2.3 °C, 2.2 °C, and 35.1 mm in maximum temperature, minimum temperature, and precipitation by the end of century; (3) an annual streamflow increase of 7.6–11.6% with greatest increases in April and greatest decreases in June; (4) 20 days' earlier shift in annual peak flow – as indicated by the date of winter-spring center of volume – by the end of the century. For management of local water resources, this study provides a better understanding of variations in the streamflow rate and timing to a potential climate change in the study area as well as corresponding uncertainties in the estimation processes.

Key words | bias correction, climate change, CMIP5, hydrologic modeling, PRISM data

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INTRODUCTION

Global water circulation makes atmosphere and hydrology closely interact with fluxes of water and energy, which has immediate and long-term effects on water systems. Precipitation and temperature – two principal meteorological drivers of surface hydrology – significantly affect the volume and timing of streamflow (Sagarika *et al.* 2015a, 2015b). The increasing temperatures directly change the atmospheric moisture, precipitation, evapotranspiration, and subsequently the whole hydrologic system (IPCC 2007, 2014). Especially in snow-dominated areas, temperatures determine precipitation format and snow processes, the change of which would result in a snowmelt timing shift (Barnett *et al.* 2005; Stewart *et al.* 2005). Additionally, precipitation primarily determines the total water received from the atmospheric system and thus results in local

water resources volume changes as well as its spatiotemporal patterns (Nijssen *et al.* 2008). Studies have suggested that hydrologic processes are directly determined by meteorologic conditions, which are attributed as one of the major causes behind changes in hydrologic processes and their spatiotemporal features (Dawadi & Ahmad 2012; Zhang *et al.* 2014; Tamaddun *et al.* 2016, 2017a, 2017b). The consequences include an increasing frequency of extreme events, such as floods and droughts, which challenge local water resources management (Milly *et al.* 2005; Dawadi & Ahmad 2013; IPCC 2014; Carrier *et al.* 2016; Kalra *et al.* 2017).

To quantitatively evaluate past and future climate, global circulation models (GCMs) are widely used, accounting for the interactive changes driven by global atmosphere and oceans (Hagemann *et al.* 2011; Markstrom *et al.* 2011). The

data resolution is from a few degrees to hundreds of kilometers (Vidal & Wade 2008; Najafi *et al.* 2011). Due to great heterogeneities in terms of topography and hydrogeology, the meteorological conditions and corresponding hydrologic processes vary from place to place, resulting in changes in water resources (Parajuli 2011; Parajuli & Ouyang 2013). However, the resolution of GCM products cannot satisfy local studies (Raneesh 2014; Sippel *et al.* 2015). While there are downscaled Coupled Model Intercomparison Project phase 5 (CMIP5) products available with 12-km gridded meteorologic data, the resolution is still not fine enough to evaluate watershed-scale future climate conditions. Comparing to a point-scale data, these 12-km gridded data contain an integrated bias from systematic errors in climate models and the difference in spatial scales between climate model simulations and study areas (Hagemann *et al.* 2011). Therefore, further bias correction and spatial downscaling procedures are required to correct the bias from downscaled CMIP5 data for local climate change evaluation (Forsee & Ahmad 2011; Thakali *et al.* 2016; Pathak *et al.* 2017). Regarding the hydrologic changes responding to the climate change, usually, a hydrologic modeling approach is employed to translate predictions of future climate change into water-resource responses (Middelkoop *et al.* 2001). Thus, the development of a hydrologic model becomes a necessary procedure for each study area to capture the hydrologic processes and features, such as streamflow rates and timing.

Regarding the bias correction and downscaling procedure, several techniques have been developed and employed in different studies, e.g., the delta change approach (Hay *et al.* 2000), the multiple linear regression (MLR) (Themeßl *et al.* 2011; Pathak *et al.* 2017), the analog method (Ven den Dool 1994; Zorita & Von Storch 1999), and quantile mapping method (QM) (Dobler & Ahrens 2008; Themeßl *et al.* 2011; Mishra & Herath 2015). With the advantages of no specific requirement in the length of time or the number of observation stations, the QM technique has been implemented successfully in several studies (Smith *et al.* 2014; Mishra & Herath 2015), and it was found to have the best performance in reducing biases (Themeßl *et al.* 2011).

Using bias-corrected or downscaled climate data in regional or watershed scale models, various hydrologic modeling studies have been conducted, as summarized by

Chowdhury & Eslamian (2014). Depending on the study purpose and study focus, different models have been used in these studies. For example, for specific hydrologic process studies, such as soil moisture and evapotranspiration, the Sacramento soil moisture accounting model (Cooley 1990; Lettenmaier & Gan 1990; Nash & Gleick 1991) and the Penman–Monteith potential evapotranspiration model (Schaake 1990) were used, respectively. For regional water resources management, monthly rainfall–runoff (water balance) models were used (Mimikou *et al.* 1991; Arnell 1992; Xu & Singh 1998). For precipitation runoff simulation, simple empirical and regression models (Revelle & Waggoner 1983; Arnell & Reynard 1989) or physically based distributed-parameter models were used (Arnell & Reynard 1989; Thomssen 1990; Running & Nemani 1991; Markstrom *et al.* 2015).

The Lehman Creek watershed, the study area in this study, is one of the critical water sources for local irrigation and for water recharge to the basin-fill aquifer in Snake Valley. Facing increasing water demand from population, business, and tourists, the groundwater in Snake Valley is one of the potential supplies for Las Vegas Valley. Thus, in this study, a further bias correction on the downscaled CMIP5 was performed using QM method to acquire better understanding of future climate changes (i.e., precipitation and temperatures). Then, corresponding hydrologic changes were simulated by driving a calibrated hydrologic Precipitation-Runoff Modeling System (PRMS) model with bias-corrected CMIP5 results. The resulting streamflow would provide information to help evaluate the potential groundwater supply for Las Vegas and local water resources management, such as seasonal irrigation distributions, flood control management, and reservoir regulations.

STUDY AREA AND DATA

Study area

The study area was the Lehman Creek watershed, which lies in Great Basin National Park, Nevada (Figure 1). The watershed covers an area of 23.6 km², mostly evergreen forest (70%), on the south part of Snake Range, with an elevation from 2,040 m to 3,980 m. The annual precipitation estimation varies from less than 203 mm to more than 787 mm

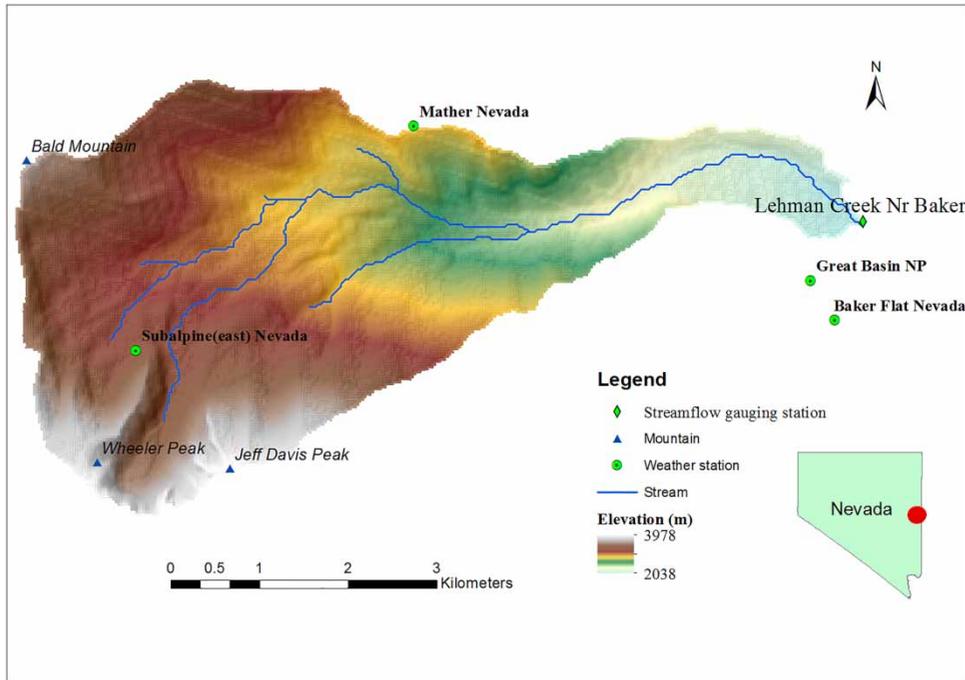


Figure 1 | The study area of Lehman Creek watershed and the nearby hydrologic and meteorological observation stations.

depending on location (PRISM Climate Group 2014; Volk 2014; Prudic et al. 2015), and most precipitation occurs as snowfall between November and April (Prudic et al. 2015). One impaired streamflow gauging station – Lehman Ck NR Baker (#10243260, 39.0117, –114.214, Elev. 2,042 m) – is located at the outlet of the watershed. Based on gauging observations of 2003–2012 (water years), this station measured $0.15 \text{ m}^3/\text{s}$ ($5.39 \text{ ft}^3/\text{s}$) of mean daily streamflow. A high variation in geography and heavy reliance on temperature make hydrologic processes in this region highly sensitive to meteorological conditions.

Meteorological observations and PRISM data

While there are five meteorological measurement stations from four different sources within or near the study area (Figure 1), some of these stations have missing data and others have short observation records. Thus, instead of using the multiple and discontinuous periods of observations, products of the Parameter-elevation Regressions on Independent Slopes Model (PRISM) were used in this study to represent observations (Brekke et al. 2013). This model contains a continuous time-series daily dataset at

high resolution (AN81D), resulting from observation networks, and showed high reliability and high proximity with observations (Di Luzio et al. 2008).

Outputs of three meteorological variables from the PRISM Climate Dataset – i.e., precipitation (P_{rcp}), maximum temperature (T_{max}), and minimum temperature (T_{min}) – were obtained from the portal of the Northwest Alliance for Computational Science and Engineering (NACSE) (30-year normals, PRISM data). The dataset was at a daily time step, gridded in 4 km, and available for the period of January 1, 1981 to December 31, 2010. Corresponding point-interpolated data were also provided, which use the climatologically aided interpolation method. For the purpose of watershed-scale hydrologic model simulation in the study area, point-scale meteorologic data were acquired at a 4-km grid enclosing the meteorologic station Great Basin NP (#263340, Elev. 2,087.88 m), which was required for the hydrologic modeling using PRMS (Chen et al. 2015).

Climate change data using down-scaled CMIP5

The products of simulations for four Representative Concentration Pathways (RCP 2.6, 4.5, 6.0, and 8.5) from global

coupled ocean-atmosphere general circulation models (coupled GCMs) were obtained from the down-scaled CMIP5 multi-model ensemble (Maurer 2007; Braconnot *et al.* 2011; Taylor *et al.* 2011). The selected data were at 12-km resolution of bias-corrected constructed analog (BCCA) products with 67 models: 16 from RCP 2.6, 19 from 4.5, 12 from 6.0, and 20 from 8.5 (Hidalgo *et al.* 2008; Gangopadhyay & Pruitt 2011). Both the historical period of 1981–2010 and the projected period of 2011–2099 were included. Full details about the climate change models and scenarios were discussed in detail by Taylor *et al.* (2011) and Thrasher *et al.* (2012). In the study, this down-scaled CMIP5 dataset was called CMIP5 dataset.

METHOD

The work was divided into two major components as follows:

1. CMIP5 data was bias corrected to a station scale. Three steps were involved: (i) validate PRISM data as an observation reference in the QM procedure, (ii) perform bias correction on the CMIP5 dataset and (iii) validate the QM bias-correction procedure.
2. The bias-corrected CMIP5 data were used to drive the developed hydrologic PRMS model in the study area of the Lehman Creek watershed. The corresponding hydrologic simulation results were evaluated.

QM bias correction

Validation of PRISM as observation reference

Before being used as the observation reference in the bias-correction procedure, the PRISM data were validated through comparisons of the climatic variables between the PRISM data and historical records. Featured statistics of mean, variance, and standard variation were compared between two datasets during the longest overlapping period of 2003–2012 (water years). While data consistency usually was expected for the temperature (Nijssen *et al.* 2008; Rahmstorf *et al.* 2012), a detailed comparison was also performed on the more uncertain variable of precipitation.

QM bias correction technique

The bias-correction technique that was applied in this study was a merged QM method (Figure 2), which combined the downscaling aspects with error correction of the model (Mejia *et al.* 2014; Wilcke *et al.* 2013). The altitude difference between the GCMs and the observation orography was included implicitly. This quantile-based approach originated from the empirical transformation of Panofsky & Brier (1968), and was successfully implemented in studies of hydrologic and biological effects under climate change (Maraun 2013; Wilcke *et al.* 2013; Sippel *et al.* 2015).

In this study, modifications were made on the basis of previous bias-correction studies (Ines & Hansen 2006). QM technique was applied to daily values to correct the biases in 12-km precipitation and temperature (T_{max} and T_{min}) relative to an individual station, and it was performed for all 67 GCM projections from four climate change scenarios archived in CMIP5 multiple-model dataset (Maurer 2007). The QM technique was based on cumulative distribution functions (CDF) that were constructed from daily modeled and observed datasets. The differences between the two quantile maps on the same referenced period were used to bias-correct the simulated projections of climate change for future periods. Especially, the drizzle effect, the probability of little precipitation in model results is greater than that in the observations (Gutowski *et al.* 2003), was resolved by a setup of ‘zero precipitation’ thresholds. Values below the probability of the thresholds were

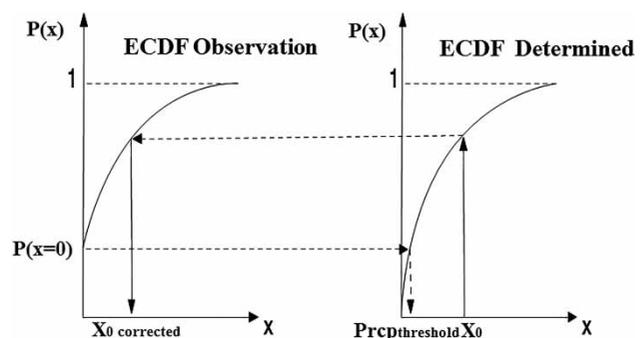


Figure 2 | Sample illustration of the quantile mapping bias correction method. Two empirical cumulative density functions (ECDFs) resulted from the observed data and the determined data on April 15. The bias-corrected value was determined by looking up the observation ECDF with the same cumulative density (e.g., 50%) as the determined value x_0 for the determined CDF.

considered as ‘no precipitation’ (Figure 2). Moreover, in order to improve the physical correlation between T_{max} and T_{min} , i.e., $T_{max} > T_{min}$. QM was applied to T_{max} and diurnal temperature range (*DTR*), with T_{min} calculated as $T_{max} - DTR$ (Thrasher *et al.* 2012).

The QM bias correction was performed on the retrospective period or baseline period of 1981–2010 and the bias-correction procedure was validated for the period of 2011–2016. Then, the CMIP5 data were bias-corrected for the projected period of 2011–2099. The differences in temperature and precipitation values between the projected period and baseline period were considered to be caused by climate change and were assessed.

Validation of QM bias correction

The QM bias-correction method was validated during the time period of January 1, 2011 to December 31, 2016, which is beyond the period of 1981–2010 used for bias-correction procedure. Bias-corrected variables of *Prcp*, T_{max} , and T_{min} were compared between bias-correction results and the observations from the PRISM data. These PRISM data were from the same source as the data used for the bias correction, which were point-interpolated values from the 4-km grid where the Great Basin NP station was located.

Hydrologic modeling

The Precipitation-Runoff Modeling System described by Markstrom *et al.* (2008) is a watershed-scale, physical-based, and distributed-parameter model designed for precipitation and snowmelt runoff. PRMS uses a modular library that contains compatible modules of a variety of process simulations (Leavesley *et al.* 2007; Markstrom *et al.* 2008; Regan *et al.* 2016), e.g., canopy interception, snowmelt, evapotranspiration, infiltration, and surface and subsurface runoff, based on physical laws or empirical rules. In both the temporal and spatial scales, the modular deterministic feature enables PRMS to evaluate various effects of combinations from both meteorological and geographical factors on each hydrologic unit. PRMS has been used in a variety of water-resource applications and climate-change studies (Battaglin *et al.* 2011; Chase *et al.* 2012).

In this study, a developed PRMS model by this research team for the Lehman Creek watershed was used (Chen *et al.* 2015). Volk (2014) has also developed a PRMS model for this study area. The model calibration and validation were performed on main hydrologic components: solar radiation, potential evapotranspiration, and streamflow, using step-wise multi-projective model calibration procedure with Luca (Hay & Umemoto 2007). Daily bias-corrected *Prcp*, T_{max} , and T_{min} from PRISM during the period of 2003–2012 (water years) were used as the driving forces for the model simulation. Comparisons were made for the main hydrologic components between observations and model simulations on mean monthly scale, and streamflow comparisons were performed on annual, mean monthly, monthly mean, and daily scales. The detailed model calibration and validation procedures can be found in Chen *et al.* (2015). While in the current study, instead of using real meteorologic observations, the PRISM data, the same dataset used for QM bias-correction procedure, were used to avoid uncertainties from different data sources when evaluating climate change influences. The model performance was better than satisfactory, evaluated by indexes of correlation coefficient (>0.6), Nash–Sutcliffe coefficient (>0.5), and percentage of bias (below $\pm 10\%$) (Moriasi *et al.* 2007, 2015). After PRMS model development, by driving the model with bias-corrected CMIP5 data, the corresponding streamflow was simulated during both the retrospective period of 1981–2010 and projected period of 2011–2099. The corresponding streamflow changes responding to future climate were evaluated as the differences in values between the projected period and retrospective period.

RESULTS

Great consistencies were found in mean monthly values of *Prcp*, T_{max} , and T_{min} , when comparing the PRISM dataset and historical records. In terms of daily mean and monthly mean values, differences between PRISM dataset and historical records were both below 5% and no pattern was found. Regarding variance and standard deviation, as expected, the PRISM dataset showed higher levels than the historical records.

Bias correction

Baseline period (1981–2010)

The performance of QM bias correction was evaluated by data comparisons among before bias correction, after bias correction, and PRISM observations, during the baseline period of 1981–2010. This procedure was applied for all RCPs, and the evaluation results from scenario RCP 6.0 are shown in Figure 3, by means of mean monthly data and daily value density distribution. Considering all climate change scenarios, bias-corrected temperatures show a 0.1 °C–3.5 °C reduction (median value) on a mean monthly scale; bias-corrected precipitation show an overall increase of 8.3 to 22.0 mm/month. Additionally, evaluated by density distribution of daily values, the bias-corrected results of both temperature and precipitation had quite similar shapes with observations. A leaning towards higher values than the observations was corrected for temperatures. Regarding

precipitation, the high density of low values (<38.1 mm/month) was flattened and shifted towards higher values, with extreme events occurring at the tail end of the distribution. Results for remaining RCPs were similar.

Validation of quantile mapping bias correction

The validation results from the period of 2011–2016 were assessed through comparisons between bias-corrected results and PRISM observations. Similar to the mean monthly results presented in the baseline period, most PRISM observations, including both precipitation and temperatures, were contained within the 5–95% distributed bias-corrected values; the majority contained within value ranging between 25% and 75%.

Specifically, the basic statistics of precipitation were calculated on both daily and mean monthly scales as shown in Table 1. Regarding the daily precipitation, mean values from the bias-corrected CMIP5 data were all 1.0 mm/d for all

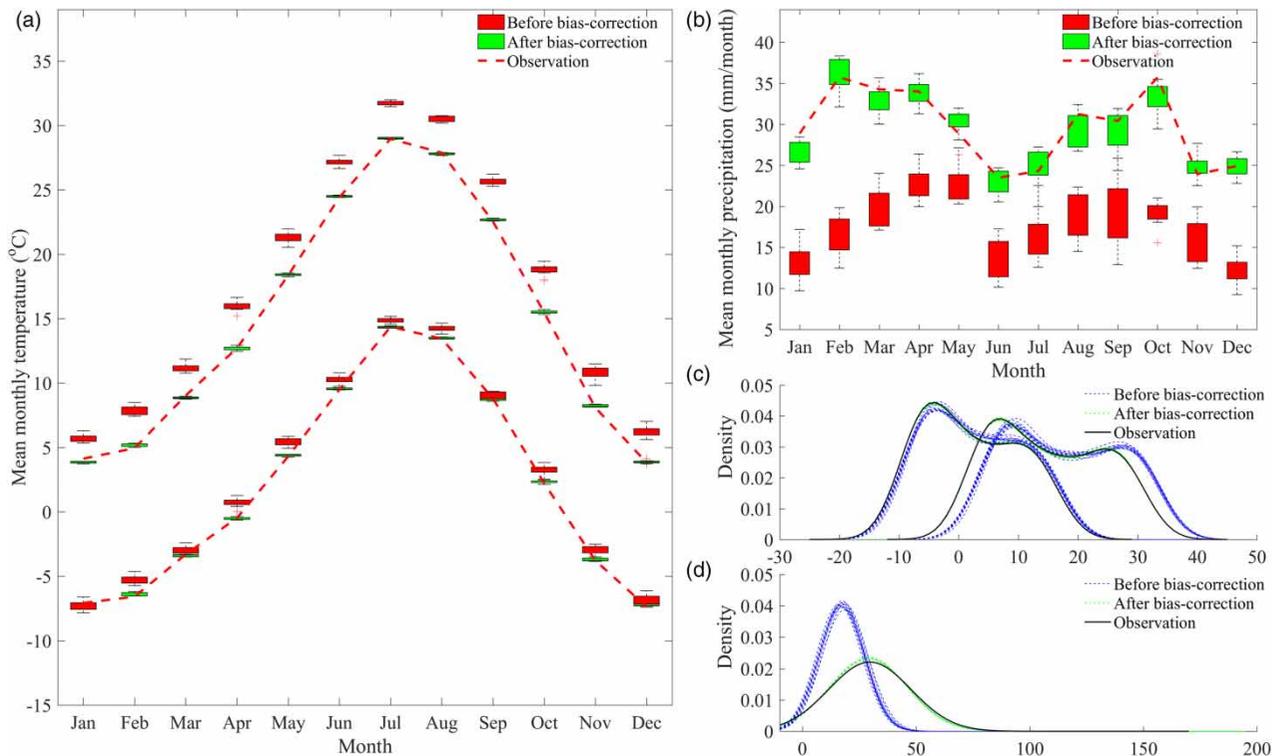


Figure 3 | Box plot comparisons of mean monthly datasets among before bias correction, after bias correction, and observations (PRISM), using multiple projected models of RCP 6.0 for the baseline period of 1981–2010: (a) maximum temperature and minimum temperature and (b) precipitation; comparison of the density distribution among the daily values for the dataset before bias correction, after bias correction and observations (PRISM), using multiple projected models of RCP 6.0 for the baseline period of 1981–2010: (c) maximum temperature and minimum temperature, and (d) precipitation.

Table 1 | Statistic comparisons of precipitation between PRISM observations and bias-corrected CMIP5 data on monthly mean scale and daily scale, at the great basin NP (#263340) during the period of 2011–2016 (unit: mm/month, mm/day)

	PRISM observation	Monthly mean				PRISM observation	Daily			
		RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5		RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Mean	28.5	31.7	31.1	29.6	30.5	0.9	1	1	1	1
Max.	40.4	85.2	88.4	77.2	74.1	32.8	58.7	55.2	59.7	66.1
Min.	8.7	7.3	5	1.9	4.3	0	0	0	0	0
SD	8.8	13.4	13.2	12.3	13.1	2.9	3.4	3.3	3.1	3.2

Max.: maximum; Min: minimum; SD: standard deviation.

climate scenarios, resulting in less than 11% difference from 0.9 mm/d in the PRISM observations. Nevertheless, comparing to 2.9 mm/d in the PRISM observations, the standard deviation reached 3.1–3.4 mm/d in the bias-corrected CMIP5 data with less than 17% of differences between them. This included the days with high precipitation reaching as high as 55.2–66.1 mm/d, while the maximum daily precipitation was 32.8 mm/d in PRISM observations.

Projected period (2011–2099) – climatic variables and bias-corrected CMIP5 data

As suggested in Maurer (2007), a comparison of results over a range of time could better support the conclusions than that of a specific month or day. In this study, the changes were summarized for the three periods: 2011–2039, 2040–2069, and 2070–2099, represented as Period 1, Period 2, and Period 3, respectively, in the 21st century. The bias-corrected climate variables of $Prcp$, T_{max} , and T_{min} were aggregated on a mean annual scale for the three periods, for the four potential climate change scenarios (Figure 4(a)–(c)). All scenarios showed general increasing trends in $Prcp$, T_{max} , and T_{min} from Period 1 to Period 3, at different levels.

On the mean annual scale, T_{max} and T_{min} shared similar patterns in long-term changes, which showed distinctive increases from low-level RCP to high-level RCP and from Period 1 to Period 3. The increase of mean annual T_{max} was at 1.1 °C–1.4 °C at the beginning of the century (Period 1), and reached 1.6 °C–5.4 °C by the end of the century (Period 3); this increase varied for different climate change scenarios. At the same time, the increase of mean

annual T_{min} changed from 1.0 °C–1.4 °C (Period 1) to 1.5 °C–5.2 °C (Period 3) for different climate change scenarios.

Although precipitation projections had an overall tendency for an increase, trends and uncertainties showed irregularities among periods and scenarios. A mild increase during the three periods was found in RCP 4.5 and RCP 6.0, while uncertain changes were found in RCP 2.6 and RCP 8.5, with an annual $Prcp$ in Period 2 either higher or lower than that in Period 3 (Figure 4(a)). Regarding the mean annual $Prcp$, the increases in all RCPs ranged from 13.1 mm to 33.2 mm (Period 1) and 39.2 mm to 60.8 mm (Period 3) (Figure 4(a)). While not shown in the study, there was no evidence of an inter-scenario pattern in mean monthly precipitation. However, increasing changes could be observed during winter seasons (i.e., October–April) and decreasing changes during summer seasons (i.e., May–September), with indistinguishable variations in the months in between. The mean monthly increase in precipitation could reach as high as 14.0 mm (RCP 2.6, Period 3, October), and the decrease could be as low as 5.6 mm (RCP 8.5, Period 3, May).

Hydrologic modeling

The streamflow simulations, driven by bias-corrected CMIP5, were analyzed using the differences in the future periods (Period 1, Period 2, and Period 3) compared to the baseline period (1981–2010), for each of the emission scenarios. The annual streamflow, mean monthly streamflow, and mean winter-spring center of volume (WSCV) were used for the comparisons.

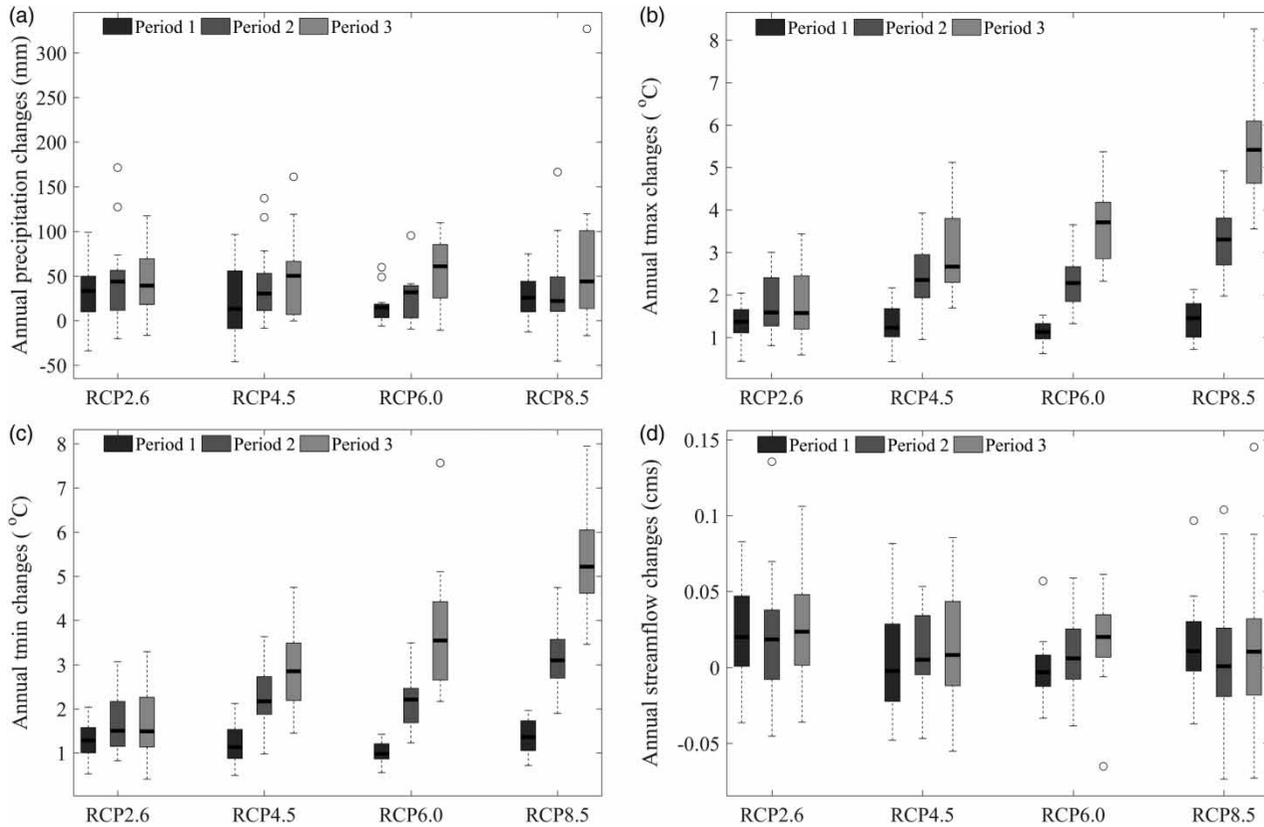


Figure 4 | Annual changes of climatic variables: (a) $Prcp$, (b) T_{max} , (c) T_{min} , and (d) streamflow in three future periods: Period 1 (2011–2039), Period 2 (2040–2069), and Period 3 (2070–2099), based on baseline period (1981–2010) for each climate change scenario (i.e., RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). Each box plot represents one climate change scenario at one period, considering all climate model data with outliers shown as circles.

Periodic variation

As shown in Figure 4(d), the changes in annual streamflow varied from -14.3% to 32.8% , depending on the emission scenarios and time and increasing trend periods. The highest range (from the first quartile to the third quartile) was found in RCP 8.5, Period 3, and the lowest range was found in RCP 6.0, Period 1. Similar patterns were found between precipitation and streamflow. A gradual increasing trend was seen along multi-decadal periods in emission scenarios RCP 4.5 and RCP 6.0. In RCP 2.6 and RCP 8.5, a decrease occurred from Period 1 to Period 2, and an increase from Period 2 to Period 3. RCP 2.6 had the highest median value of 13.3% , 12.6% , and 16.3% for the three corresponding time periods, respectively, and RCP 4.5, RCP 8.5, and RCP 6.0 had the lowest median values during these time periods.

Monthly pattern

Variations among the multiple projections were presented by means of box plots (Figure 5). Positive values indicated streamflow increases and negative values signified decreases. In a calendar year, a distinguishing time point was found between May and June that showed an increase of mean monthly streamflow during the winter (December–May) and a decrease during the summer (June–November). These increases and decreases gradually became obvious from Period 1 to Period 3. This distinguishing time point (between May and June) appeared to be shifting earlier, i.e., between April and May (Figure 5). Additionally, an increasing variation in the value of changes was found among the time periods. Generally, by comparing the results among the emission scenarios, the differentiation might not be evident during the first two periods. Nevertheless, great

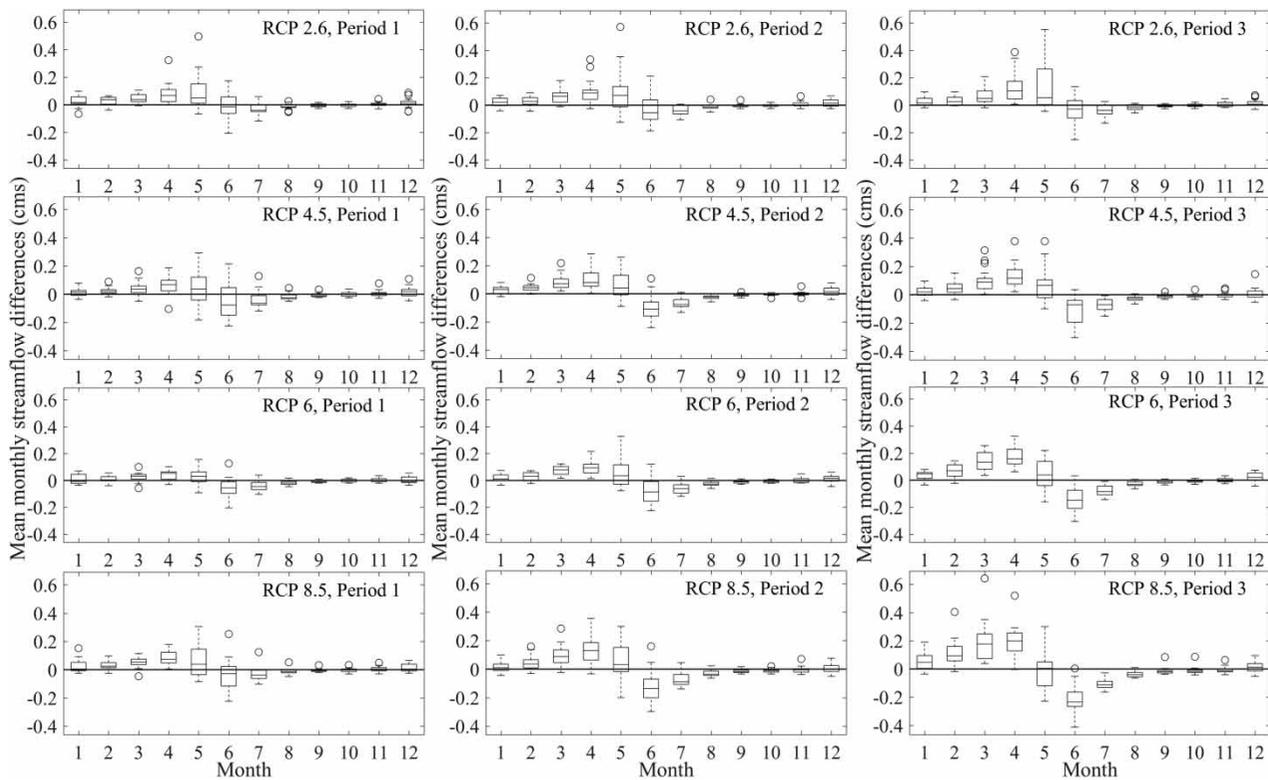


Figure 5 | Mean monthly streamflow changes on the basis of baseline period (1981–2010). Three periods were compared: Period 1 (2011–2039), Period 2 (2040–2069), and Period 3 (2070–2099), under all climate change scenarios of RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. Each box plot represents one climate change scenario at one period, considering all climate model data with outliers shown as circles.

increases in streamflow changes, especially during January to April, were observed (Figure 5).

Timing shift

The changes in WSCV dates indicate timing differences of occurrence of winter–spring streamflow (Figure 6). Positive values indicated late occurrences relative to the baseline period; negative values meant earlier occurrences. The results showed overall negative values, in the changes during all the periods and emission scenarios, which meant that the WSCV date tended to shift earlier than the baseline period. Furthermore, early shifts of the WSCV date were intensified with increased variances along the time periods. Median values for the WSCV date shifts over four climate change scenarios showed a range from -2.9 to -9.1 days for the different scenarios during Period 1, -10.1 to -16.1 days during Period 2, and -10.1 to -30 days during Period 3. Comparisons of the results from the different emission scenarios showed an increase trend in

the date shift, in the order of RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 in Period 3. No certain pattern was found during the first two periods.

DISCUSSION

Prior to applying a bias-correction method or other similar statistical transformations, it is important to understand the limitations or assumptions of the method. All statistical downscaling techniques rely on the assumption of stationarity. In this study, the differences between CMIP5 products and observations were considered stationary throughout the bias-correction period, which meant that past correlations also were retained in the future. However, it is likely that this assumption may not hold for the observed variables of interest (e.g., precipitation or temperature) especially in the case of extreme events (Gudmundsson et al. 2012). Compared to the QM statistical downscaling/bias-correction method, dynamic downscaling technique

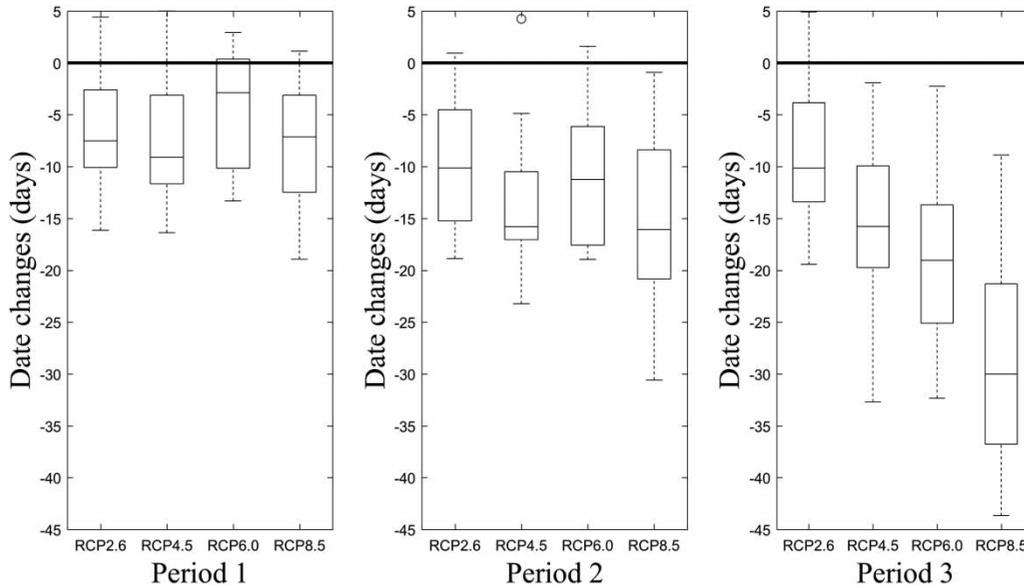


Figure 6 | Multi-projection comparisons of winter-spring center of volume (WSCV) date-shifting among four climate change scenarios: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, during three future periods: Period 1 (2011–2039), Period 2 (2040–2069), and Period 3 (2070–2099).

does not assume stationarity and is based on physical laws and conservation equations. However, it is more complicated and computationally expensive. Since the focus of this study was not extreme events, the QM results, limited by the assumptions, still provide an understanding of future trends. The bias-correction procedure of GCM products is critical in maintaining local climate features and characteristics, which are important for understanding the trends in alterations under the effects of climate change.

During the bias correction, the long-term features in the PRISM data are well maintained since there were no observation stations added or removed in surrounding areas of the study area during the PRISM data constructed period of 1981–2010. Therefore, in the study area, it was applicable to use PRISM dataset as a reference in the QM bias-correction procedure, which used long-term features with statistical basis.

By comparison, the bias-corrected CMIP5 dataset showed increases in the mean annual precipitation ranging from 13.1 mm to 33.2 mm at the beginning of this century to 39.2 mm–60.8 mm by the end of this century. At the same time, great increases occurred to the mean annual maximum and minimum temperatures, which changed from levels of 1.1 °C–1.4 °C (T_{max}) and 1.0 °C–1.4 °C (T_{min}) in Period 1 to levels of 1.6 °C–5.4 °C (T_{max}) and

1.5 °C–5.2 °C (T_{min}) in Period 3, correspondingly. Among the time periods and four emission scenarios, the increasing temperature differed with certain patterns, with the highest increase occurring in the last period with the highest emission scenario (Period 3, RCP 8.5), and the lowest increase appearing during the first period (Period 1) with a slight difference among emission scenarios. Substantial variations were found when comparing the mean monthly precipitation among periods and emission scenarios; this may be the result of the uncertainties in the QM technique, which relied significantly on the data frequencies.

The bias-corrected climate change data were forced to drive the hydrologic model, PRMS, which was calibrated using PRISM data. The changes in annual streamflow responses resulted in an increasing trend from –2.0% to 13.3% during Period 1 to 6.3% to 16.3% in Period 3 for the various emission scenarios. The variation among the emission scenarios was not consistent with the emission levels, which showed a decrease in RCP 4.5 and RCP 6.0 and an increase in RCP 2.6 and RCP 8.5 during the first study period. This pattern also could be found for precipitation, and could be a potential cause for the streamflow changes. As climate change continued during the three time periods, the signals of a warming climate were so strong that, by the end of the 21st century, they would

offset the signal differences in Period 1. The greatest streamflow decreases occurred in June (−3.9 to −58.2%), July (−18.0 to −58.1%), and August (−15.2 to −43.6%). During late winter, the greatest increase in streamflow could be greater than 100% due to an early snowmelt resulting from the increased temperature. An overall increase in precipitation was derived from the bias-corrected CMIP5 data with seasonal patterns (higher during spring and fall and lower during summer and winter). This pattern was compared with the streamflow changes. The streamflow changes had very different responses, showing a decrease from the summer until mid-winter. Because of the temporal distribution changes in streamflow volume, an earlier shift of the WSCV date could be found that ranged from 10 to 30 days by the end of this century, depending on emission levels.

A previous study indicated considerable discrepancies and varying reliabilities among different GCM products (Mohammed *et al.* 2015). In comparison to a previous study (Volk 2014), which only used one GCM product (CCSM4) for the study of warming climate influences on water resources, all GCMs were weighted equally and were used in an ensemble for this study. Apart from procedures of the bias correction method (Mejia *et al.* 2014), this could be another potential cause of the uncertainties in the GCM precipitation products. Instead of using certain specific climate models, the current study used an ensemble of all climate models, which potentially introduced additional uncertainties and averaged the results of all models. However, it is reasonable to consider the study results to be a plausible indication of future changes and to which the hydrologic processes over the next century should be capable of responding.

CONCLUSIONS

This study focused on the quantitative assessment of climate changes on a watershed-scale, the Lehman Creek watershed in Great Basin National Park, Nevada. Downscaled GCM data from the CMIP5 BCCA dataset were used, which provided the meteorological conditions under four potential climate change scenarios: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 with resolution at $1/8^\circ$ (12 km). A distributed

physically based hydrologic model, developed using the precipitation–runoff modeling system, simulated the hydrologic responses to the potentially changing climate. Instead of 10-year observation records, a 30-year PRISM dataset (1981–2010) was used for the long-term feature capture and the QM bias correction of the CMIP5 dataset in the study area. The PRMS model simulations extended over the period of 1981–2099. Evaluation of the results was performed as a relative alteration from the projected period (i.e., 2011–2099) on the basis of a baseline period (i.e., 1981–2010). Three future time periods were defined as 2011–2039, 2040–2069, and 2070–2099.

On the basis of the study results, the following conclusions were made.

1. The PRISM data preserved quite well the value scale, distribution, and long-term features in the observations at Great Basin NP station. This indicates the PRISM data can be applicable, with effective replication of observations in areas that have issues in long-time shortage of data.
2. Results of QM bias correction fitted the observations well in monthly distribution and density distribution during the same historical period and validation period. This indicates that this approach can be used to correct the combined bias from spatial resolution differences and model systems.
3. Under the influences of climate change, the average value of mean annual ensembles over the entire projected 21st century showed an increase of 2.3°C , 2.2°C , and 35.1 mm in maximum temperature, minimum temperature, and precipitation, respectively, in the study area (Great Basin NP station).
4. In the Lehman Creek watershed, the streamflow had a great correlation with precipitation. The changes responding to climate change had similar monthly patterns, in which the values tended to increase during the winter and decrease during the summer, compared to the status quo in the baseline period.
5. With the combined effects of precipitation and temperature, a distinguishing point could be identified between May and June: before May, the streamflow increased and after June, the streamflow decreased. This distinguishing point tended to move earlier towards a

point between April and May, signifying that the winter/spring high streamflow also trended earlier. This conclusion is supported by the shift to an earlier WSCV date, which showed an intensified trend during the 21st century.

6. A high amount of variance was found in both precipitation and streamflow. This variance became larger during the three time periods in the 21st century, indicating increasing uncertainties in the estimation results.

This study could contribute to increasing the understanding of water resources alterations with regard to rates and timing by responding to all potential climate change scenarios using downscaled CMIP5 products. During the study, a 30-year PRISM dataset (AN81d) was used to represent observations in order to solve the conflict between the need for observation data to downscale the climate change products and the data shortage that existed at the stations. PRISM successfully captured statistically the long-term features of local climate, and demonstrated its capability as a valid substitution for missing meteorological observations in the study area. This could provide useful insights if observations are missing, when needed, in other study areas.

The approaches employed in this study provided a solid foundation. The implementation of QM for downscaling climate change products has been recognized by other researchers as a valid method to minimize errors originating from differences in spatial resolution and modeling approach. Besides, by using a physically based parameter-distributed hydrologic model, the snow process was modeled with a two-layer and detailed simulation of energy and water balance. Consequently, the modeling results were more reliable, especially in a snow-dominant area. Finally, simulation of the streamflow responses to climate change, with regard to rates and timing, provided useful information when evaluating the water resource alterations and corresponding strategies for adaptive water management.

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