Case Study

Bias Correction Methods for Hydrologic Impact Studies over India's Western Ghat Basins

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Abstract: The regional climate models (RCMs) used in the analysis of the impact of climate variables on the hydrology of river basins needs appropriate preprocessing (bias correction) to represent and reproduce future climate with a fair degree of accuracy. The performance of bias corrections methods was assessed in this investigation on the basis of their ability to minimize error on climate variables and streamflow. This work compares the performance of five bias correction methods applied for precipitation and four methods for temperature in modeling the hydrology of the river catchments of the Western Ghats of India. The Western Ghats are a mountainous forest range along the entire west coast of India that plays a major role in the distribution of Indian monsoon rains. Simulations were used to evaluate the performance of the bias correction methods. Using raw RCM, bias corrected precipitation and temperature time series, streamflows were estimated by the soil and water assessment tool (SWAT) hydrological model. The results indicated that the raw RCM-simulated precipitation was biased by 42% and the temperature was biased by 12% across the catchments investigated. Subsequently, a bias of 65% was found in the streamflow. The performance of the delta change correction method was consistently better for precipitation (with Nash-Sutcliffe efficiency, NSE > 0.75 for 5 catchments) and temperature (NSE = 1) compared with other methods. Good performance was observed between the observed and bias corrected streamflow (daily time scale) for the catchments Purna (NSE = 0.97), Ulhas (NSE = 0.64), Aghanashini (NSE = 0.82), Netravathi (NSE = 0.89), and Chaliyar (NSE = 0.90); low performance with an NSE of 0.3 was observed for the catchments Kajvi and Vamanapuram. The methods failed for Malaprabha and Tunga catchments. The results indicate that the delta change correction method performed best in analyzing the hydrological impact of climate variables on the windward side of Western Ghats of India.
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Introduction

The impacts of climate change on the hydrology of river catchments play an integral role in the field of water resources and hydropower (Bates et al. 2008). The assessment of hydrological impacts of climate change involves combining hydrological models with the outputs of general circulation models (GCMs) (Graham et al. 2007; Pechlivanidis et al. 2011). The GCMs incorporate the major complexities of the global system and exhibit substantial skill at the hemispheric and continental scales, but inherently are unable to represent features at the catchment scale (Fowler et al. 2007). The hydrologic modeling of montane catchments requires climate information on a fine scale and the GCMs do not represent the altitude dependence of climatic variables (Seager and Vecchi 2010). The GCMs are not capable of providing reliable climate information on scales <200 km (Maraun et al. 2010) and, therefore, GCM output is not combined directly with hydrological models for impact assessment of climate change on river hydrology (Chen et al. 2011b; Feddersen and Andersen 2005; Hansen et al. 2006; Sharma et al. 2007).

The GCM information is transferred to finer scales by dynamic downscaling, which uses a high-resolution regional climate model (RCM) with the boundary conditions adopted from a driving GCM (Dickinson et al. 1989; Giorgi 1990; Yang et al. 2010). The topographical effects on precipitation and the mesoscale patterns of local precipitation are represented more reliably in the RCMs (Buonomo et al. 2007; Frei et al. 2003, 2006; IPCC 2007). The World Climate Research Programme (WCRP) initiated the Coordinated Regional Climate Downscaling Experiment (CORDEX) to increase confidence in hydrological long-term predictions and to improve the robustness of regional hydro-climatic variables. The CORDEX generates ensembles of regional climate projections at fine scale for the continents (called domains). The CORDEX (CORDEX-SA/WAS-44) (CORDEX 2014) domain translates regionally downscaled climate information into the monsoon of South Asia (Chaturvedi et al. 2012; Giorgi et al. 2009).

The RCMs transfer large-scale GCM information to the watershed/catchment/basin scale (spatial resolution of 10–50 km). However, comparison of RCM outputs with reference period at similar scale exhibits bias in the spatial distribution and magnitude of precipitation and temperature (Foley 2010). The biases in RCMs often are attributed to the imperfect parameterization of climate processes in the model and by inappropriate boundary conditions of GCM or reanalysis data (i.e., climate data produced by combining models and observations) used to run the RCM (Ehret et al. 2012; Teutschbein and Seibert 2012). The convective rainfall is predominant in the tropical regions and owing to the subdaily rainfall, the RCMs do not perform well in tropical climatic conditions (Lenderink and van Meijgaard 2008). Studies show the lesser

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accuracy of the RCMs in representing convective and summer precipitation than the winter precipitation (Maraun et al. 2010). The heavy precipitation is generally underestimated, whereas the light precipitation events and precipitation frequencies are overestimated (Fowler et al. 2007; Murphy 1999). The accuracy of RCMs in representing climate, therefore, is regionally and seasonally dependent (Kotlarski et al. 2005; Maraun et al. 2010). The present study is an effort to evaluate the performance of the CORDEX-SA domain over the western mountainous regions (Western Ghats) of India.

In light of the bias, preprocessing RCM outputs is a prerequisite step before forcing the data on hydrological models to assess the hydrological impacts of climate change. The bias correction methods are model output statistics that reproduce RCM misrepresentation into historical observed statistics with a certain degree of acceptance (Teutschbein and Seibert 2012). Different approaches of bias correction were developed, ranging from sophisticated distribution mapping to simpler methods, such as linear scaling (Chen et al. 2011a, 2013b; Iizumi et al. 2011; Lafon et al. 2013; Mpelasoka and Chiew 2009; Piani et al. 2010; Ryu et al. 2009; Salvi et al. 2011; Sharma et al. 2007; Teutschbein and Seibert 2012). The simpler methods involve shifting seasonal and/or long-term annual mean to match with observations, and the sophisticated methods involve adjusting the frequency distribution. Although these methods preserve the variability of climate data generated by RCM projections, the performance of the RCMs depends on the governing atmospheric circulation of the region. The evaluation of bias correction methods for a specific region is essential for comparing the performance of an impact study.

Several studies explore the performance and evaluate the different bias correction methods across the world, and report the ability of the methods to minimize the RCM output errors (Bennett et al. 2011; Terink et al. 2009; Themeßl et al. 2011). Although the standard deviation and the mean of precipitation datasets are corrected robustly in most cases, the kurtosis and skewness corrections are sensitive to the selection of the calibration period and the bias correction methods (Lafon et al. 2013).

The runoff projections for Australian catchments (Mpelasoka and Chiew 2009) show the superiority of daily translation and daily scaling methods over constant scaling in extreme runoff representation because these two methods take extreme daily rainfall into consideration. The quantile mapping method improves the spatial correlation between RCM and observed output (Bennett et al. 2011). The comparison of raw RCM results with a set of seven statistical downscaling and error correction methods shows a very good performance of the local intensity (LI) and the quantile mapping method for daily precipitation over the Alps region. The best performance in downscaling precipitation extremes is by the quantile mapping method (Themeßl et al. 2011). A great deal of uncertainty always creeps into the simulation of streamflow under changed climate conditions because of empirical downscaling methods (Chen et al. 2013b). The study was incomplete owing to the fact that it was carried out on only two basins of North America. The complete study (Chen et al. 2013a) calibrated the hydrological models with direct RCM output and also evaluated the performance of six bias correction methods over 10 North American river basins. The comparison showed better performance of distribution-based methods than mean-based methods.

The selection of bias correction method plays a major role in the response of extreme hydrological events. Nonlinear methods are quite effective in reducing errors, whereas the gamma-based quantile mapping gives very good results when the precipitation datasets (observed and modeled) follow a gamma distribution (Lafon et al. 2013). The distribution mapping was established on the gamma distribution and has performed well, even for heavy precipitation and drought index apart from daily precipitation over Europe (Piani et al. 2010). The most widely used distribution for fitting daily precipitation is the gamma distribution (Block et al. 2009; Ines and Hansen 2006; Katz 1999; Watterson and Dix 2003). The limitation of the gamma distribution is that it cannot adequately represent the extreme tail of precipitation's distribution at a daily time step. To overcome such limitations, Vrac and Naveau (2007) used a mixed distribution involving Pareto distribution and gamma distribution. The distribution mapping and the delta change methods did not differ in projecting hydrological statistics for a catchment located on the west coast of Denmark (van Roosmalen et al. 2011).

The performance of the methods also depends on the size of the catchments owing to the spatial average of RCM outputs (large-scale, mesoscale, and small-scale). One of the most comprehensive studies in terms of bias correction methods for hydrological impacts of climate change was carried out on five catchments in Sweden (Teutschbein and Seibert 2012). The study assessed three methods of bias correction for temperature and four methods of bias correction for precipitation. The distribution mapping method was found to perform the best for hydrological impact quantification and climate projections. Although the study was thorough in terms of method and climatic conditions, the size of the catchments was small and ranged from 147 to 293 km^2.

The Western Ghats of India are listed as a UNESCO World Heritage Site and are classified as one of the eight hottest hotspots of biological diversity in the world (UNESCO 2013). Several studies are being carried out to assess the hydrologic impact of climate change in the region by using the outputs of RCM forced on hydrologic models. Precipitation is an integral part of the hydrological studies, and the simulation of precipitation by RCM is more difficult than temperature. The reliability of the studies, therefore, is critically dependent on the ability of the RCM to represent the southwestern monsoon precipitation and regional dependency in the performance of the bias correction methods. It is essential to study the regional variability of various bias correction methods in quantifying hydrologic impacts. This work evaluated the performance of five methods of bias correction for precipitation and four methods of bias correction for temperature along the Western Ghats of India with regard to hydrological modeling. The spatial variability of the performance was assessed on nine river catchments spread across the topographic conditions and climate zones of the Western Ghats of India.

Study Area

Nine river catchments originating in the Western Ghats of India were selected for this study (Fig. 1), covering five climate zones on the basis of the revised Thornthwaite-type global climate classification (Feddema 2005): per-humid (A), humid (B3 and B4), dry subhumid (C1), and moist subhumid (C2). The Western Ghats of India are a mountainous, tropical forest range extending approximately 2,300 km parallel to the entire west coast of India (Fig. 1). It is a stable land mass of Archaean and Precambrian rock formations with an elevation exceeding 2,500 m above mean sea level (MSL) at some places. The study area extends from 8° 30′ N to 21° 0′ N latitude and 73° 0′ E to 77° 30′ E longitude, and covers districts in four states of India: Gujarat, Maharashtra, Karnataka, and Kerala.

The Indian monsoon rains approach the Indian subcontinent simultaneously from the Arabian Sea through the Western Ghats, and from the Bay of Bengal through Gangetic West Bengal by the end of May or beginning of June, and cover the entire country by the

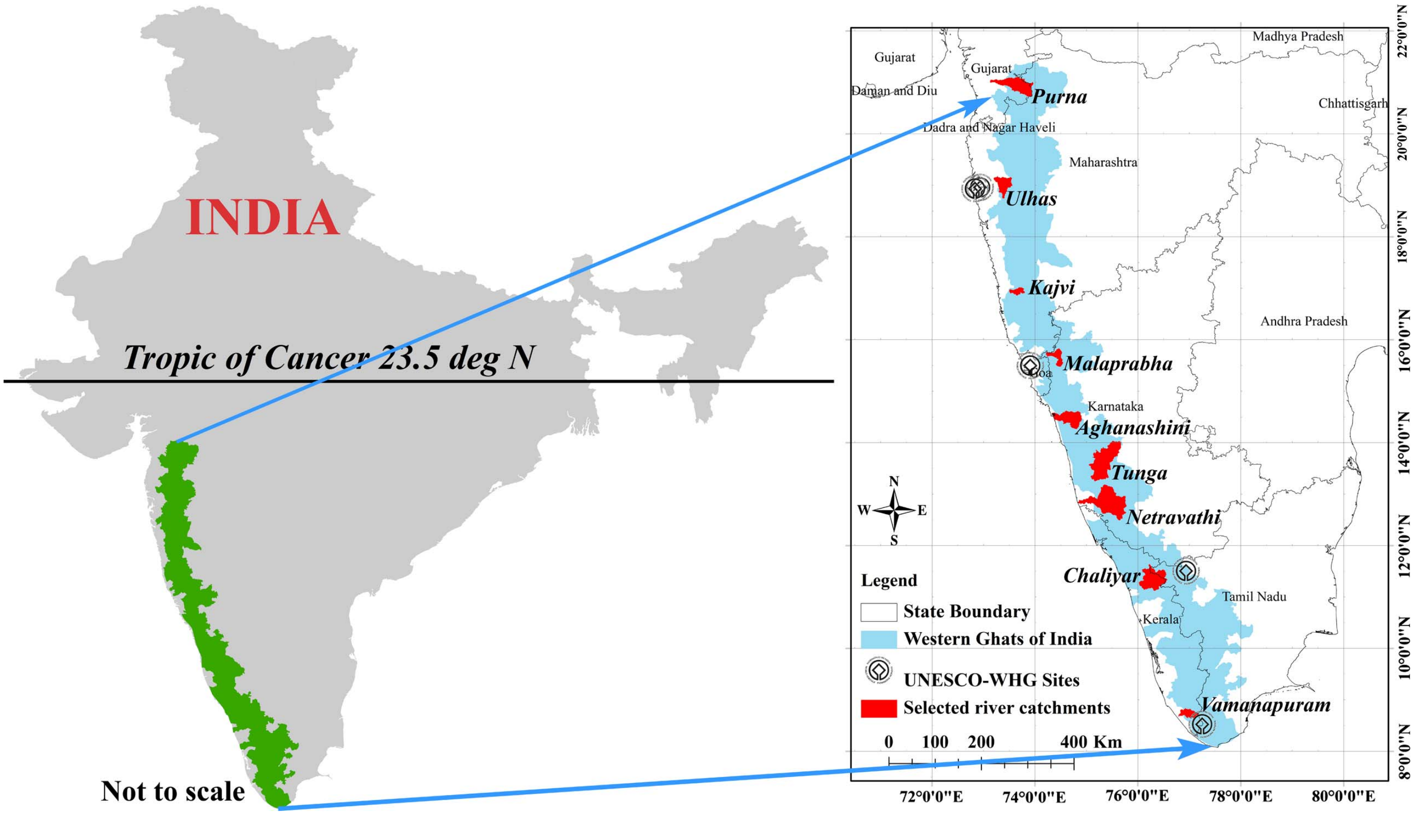

Fig. 1. Location map of the nine river catchments

end of July. The strip of land between the Western Ghats and the sea coast (windward side) has a width ranging from 100 to 200 km. The region receives an annual average rainfall of approximately 3,000 mm near the sea coast to approximately 6,000 mm near the Ghats. The maximum rainfall over the Western Ghats is approximately 7,000 mm. The eastern part of the Western Ghats is a plateau region with a gentle slope toward the Bay of Bengal and an annual average rainfall of approximately 1,500 mm, which decreases toward the east. The variation of topography and precipitation in the Western Ghats spawns a wide variety of vegetation varying from evergreen forests (west side) and dry deciduous (higher altitudes), to shrub vegetation on the east side. In the present study, the river catchments were selected to represent the entire range of topography of the Western Ghats of India, such as westerly mountain area to flatter terrains. The basic information of the nine river catchments is presented in Table 1. The catchment areas range between 287 and 3,351 km^2, representing small to mesoscale catchments across the Western Ghats. The average annual maximum and minimum temperatures range from 35 to 41.5°C, and 6 to 12°C, respectively.

Data Used

The gridded data on precipitation (0.25° × 0.25°) and temperature (1° × 1°) were procured from the India Meteorological Department (IMD). The processing of the gridded data may be found elsewhere (Pai et al. 2014). The discharge data were obtained from the India Water Resources Information System and from the Water Resources Development Organization (WRDO), Government of Karnataka, India. The RCM-simulated precipitation and temperature were obtained from CORDEX. The South Asian domain (WAS-44) (CORDEX 2014) of the CORDEX experiment has 11 suites that constitute a combination of various RCMs, driven by the initial and boundary conditions of different GCMs. Although four suites provide bias corrected data, they employ distribution-based correction methods.

Table 1. Basic Information on the River Catchments

State	Catchment name	Climate zone	Area (km^2)	Average annual rainfall (mm)	Flow data availability
Gujarat	Purna	Dry subhumid (C1)	1,655	1,600	1971–2000
Maharashtra	Ulhas	Humid (B4)	886	3,800	1982–2011
	Kajvi	Humid (B4)	287	3,600	1992–2010
Karnataka	Malaprabha	Moist subhumid (C2)	428	2,800	1977–1996
	Aghanashini	Per humid (A)	1,295	3,700	1989–2002
	Tunga	Per humid (A)	2,922	4,700	1973–2000
	Netravathi	Per humid (A)	3,351	3,700	1980–1995
Kerala	Chaliyar	Dry subhumid (C1)	1,953	2,700	1981–2000
	Vamanapuram	Humid (B3)	541	1,800	1990–2011

The Rossby Centre Regional Climate Model, RCA4, developed at the Rossby Centre, Norrköping, Sweden, and downscaled to a subset of GCM simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012) was used in this study. The data was available at a horizontal spatial resolution of 0.44° × 0.44° (~50 km) and daily temporal resolution. Of the 11 experiment suites of CORDEX, the RCA4 simulations were selected for the present study because it demonstrated good performance (close proximity to observed data) in the complex mountainous topography of India (Ghimire et al. 2015). For catchments smaller than one RCM grid box, precipitations were basin averaged. The averaging of grid points is a requisite for watersheds of smaller size and also helps in elimination of the grid-point numerical effect of computational schemes in climate models. The averaging concept also was used in studies carried out elsewhere (Teutschbein and Seibert 2012).

Methodology

Bias Correction

The bias correction methods adopted and compared in this study are the linear scaling (LS), delta change correction (DC), local intensity (LI) scaling, power transform (PT), variance scaling (VS), and the distribution mapping (DM). These six methods may be classified into five bias correction methods applied for precipitation (LS, DC, LI, PT, and DM) and four methods for temperature (LS, DC, VS, and DM). The bias corrections were carried out daily. A brief description of the methods is presented in Table 2. The complete details of the bias correction methods can be found in Teutschbein and Seibert (2012) and Chen et al. (2013a).

The bias correction methods were evaluated by the split-sampling and cross-validation approaches (Bennett et al. 2011). The calibration was carried out using four steps: (1) separation of the observed and RCM-simulated meteorological variables (precipitation and temperature) into 40-year (1951–1990) and 15-year (1991–2005) periods; (2) calibration using 40 years of data and validation using 15 years of data; and (3) in an opposite sense, 15 years (1951–1965) were used to calibrate and 40 years (1966–2005) were used to validate. The split-sampling and cross-validation approaches are a common practice in hydrological studies. It helps in reducing the risk of over fitting the model to a period and the effects of interannual variation of the climate system. The bias corrected precipitation and temperature were compared with the observed values.

Table 2. Brief Description of the Bias Correction Methods

Serial number	Bias correction method	Pros	Cons	References
1.	Linear scaling (LS)	A mean monthly correction factor is used for the daily precipitation. It is the simplest bias correction method.	The daily precipitation sequence is the same as that of the RCM-simulated data (usually, too many wet days are simulated). The frequency distribution of the precipitation is not accounted. The temporal structure of the precipitation is not adjusted.	Lenderink and van Meijgaard (2008) and Teutschbein and Seibert (2012)
2.	Delta change correction (DC)	The RCM-simulated anomalies are superimposed over the observed time series. It is a stable method because it uses observed data as the basis and produces future time series with dynamics similar to current conditions.	It does not account for potential future changes in climate dynamics. Major events (e.g., heavy precipitation or hot days) will change by the same amount as all other events.	Teutschbein and Seibert (2012)
3.	Local intensity scaling (LI)	The frequency of wet days is corrected and a monthly correction is applied to the precipitation dataset.	The changes in the frequency distribution of precipitation are not accounted. No adjustment is made to the temporal structure of daily precipitation occurrence.	Schmidli et al. (2006)
4.	Power transform (PT)	The mean and variance of data are adjusted, i.e., corrects percentiles and the coefficient of variation to some extent.	The probability of dry days and precipitation intensity is not corrected. The nonlinear transformation does not perform well when the bias in the frequency of wet days is large. Limited to precipitation because of power function.	Leander and Buishand, (2007) and Leander et al. (2008)
5.	Variance scaling (VS)	The mean and the variance of temperature time series are corrected. The correction factors are assumed to remain the same for future conditions, but allow for changes in response to control and scenario run.	The nonlinear transformation does not perform well when the bias in the frequency of wet days is large.	Chen et al. (2011a, b)
6.	Distribution mapping (DM)	The RCM-simulated precipitation is corrected on the basis of a gamma distribution. The frequency of precipitation occurrence is corrected using the LI method. It corrects most of the statistical characteristics and has the narrowest variability ranges, combined with the best fit of the ensemble mean.	The stationarity assumption that the same correction algorithm applies to both current and future climate conditions. The performance depends on whether the observed and RCM-simulated precipitation follows the gamma distribution (or not).	Ines and Hansen (2006), Piani et al. (2010), and Teutschbein and Seibert (2012)

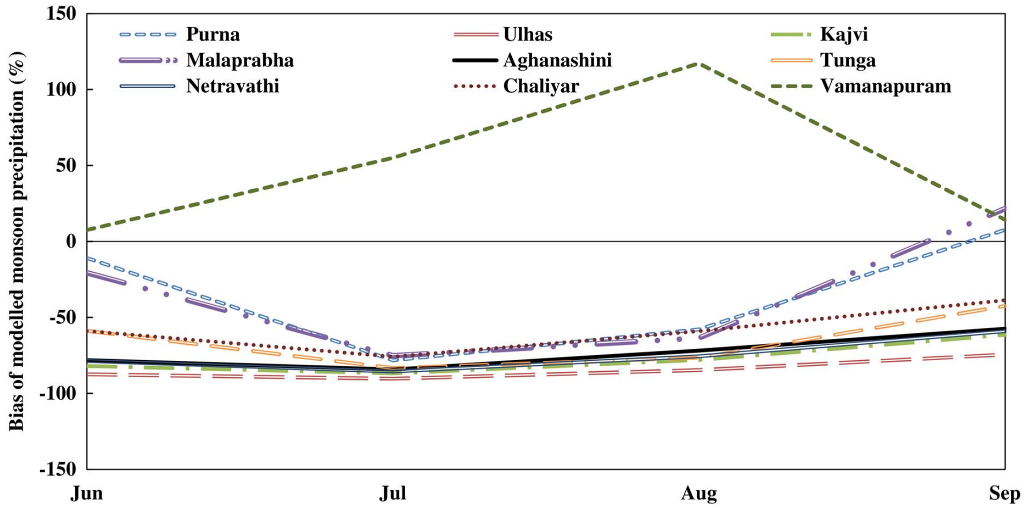

Fig. 2. Bias of raw-RCM precipitation during monsoon season

Hydrological Simulation

After correcting for bias, the precipitation and temperature data were used to drive the soil and water assessment tool (SWAT) model and simulate daily streamflow for 55 years (1951–2005). The precipitation and temperature output of the raw RCM (without bias correction) was used to run the hydrological model. The streamflow, simulated using bias corrected variables and raw RCM, was compared with the reference streamflow.

The Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model Version 2 (ASTER GDEM 2) (Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California) was used to delineate the watershed and to analyze the drainage patterns of the land surface terrain. The Soil Conservation Service curve number procedure (USDA 1986) was used in this study to estimate the streamflow in the SWAT model. The potential evapotranspiration was estimated by the Hargreaves method (Hargreaves and Samani 1985). The Hargreaves method is a temperature-based method and has demonstrated the ability to give accurate results compared with standard methods (Allen et al. 1998).

The SWAT hydrological model was calibrated and validated using the discharge data. The models were calibrated on a daily time step to achieve robust calibration and to avoid averaging of data errors over monthly calibration. The split-sampling approach was adopted with the available data. The guidelines on optimal Nash-Sutcliffe efficiency (NSE) and coefficient of determination (R^2) and their ranges for the hydrologic modeling were given by Moriasi et al. (2007). The sequential uncertainty fitness version 2 (SUFI-2) algorithm was employed and the SWAT model was subjected to uncertainty analysis. The R-factor (Abbaspour 2013) was used to ascertain the degree of uncertainty and strength of calibration. The SUFI-2 algorithm was selected specifically for the present study because parameter uncertainty would account for all sources of uncertainties, including uncertainty in conceptual model, measured data, driving variables (e.g., rainfall), and parameters (Abbaspour 2013).

Results and Discussion

Climate Simulation

The rainfall effects on the overall hydrology of the catchment and successful simulation of wet and dry days was very important in the impact studies. The factors affecting the performance possibly could be the location, topography, and catchment area of the rivers. The elevation of Western Ghats of India varies and is approximately 2,695 m above MSL; the Ghats are close to the sea coast at certain locations. The bias in the RCM precipitation was calculated for all the months, and the results of monsoon months (June–September) are presented in Fig. 2. The results obtained across the river catchments indicated the inability of the raw RCM in the representation of Indian southwest monsoon. The raw RCM tended to underestimate the heavy rainfall events leading to negative values. The overestimation in the Vamanapuram River may be because it is one of the southernmost rivers of India and is influenced by both the southwest and northeast monsoons. It may be, therefore, that the hydrology of a catchment is very sensitive to precipitation and a small bias could lead to large deviation in the hydrological components.

The absolute relative error (ARE) for precipitation is defined as $|(P_{\mathrm{sim}} - P_{\mathrm{obs}}) \times 100/P_{\mathrm{obs}})|$ of mean wet-day precipitation (precipitation intensity >2.5 mm/day), where P_{sim} and P_{obs} represent simulated precipitation and observed precipitation, respectively. Fig. 3(a) presents the boxplot of the ARE for mean wet-day precipitation (annual precipitation). The results clearly show the bias of raw-RCM precipitation when compared with the observed precipitation. The LS, LI, PT, and DM methods did not improve the statistic of mean wet-day precipitation. The LS and LI methods applied corrections to monthly mean precipitation and tended to overestimate the wet days. The DC method corrected the frequency of wet days because the anomalies between the scenario runs were superimposed over the observed time series. The DC method improved the mean precipitation of wet days significantly. The ARE for the LS, LI, PT, and DM methods were 24.78, 24.81, 28.30, and 28.74%, respectively. The DC method tended to perform better than other methods consistently.

The aim of the bias correction methods was not to correct the variance of precipitation (on a daily basis). However, the variance was affected when mean precipitation was corrected. The ARE for the standard deviation of daily precipitation was calculated and is presented in Fig. 3(b). The standard deviation of the raw RCM was biased similar to the mean precipitation. The bias correction methods corrected the standard deviation of precipitation to a certain degree. The LS, LI, PT, and DM methods performed equally in the correction of standard deviation. The DC method performed the best in improving the ARE of standard deviation. The performance evaluation metrics for observed and bias corrected daily precipitation time series are presented in Table 3. The DC method performed well with NSE > 0.75 for the Purna, Ulhas, Kajvi,

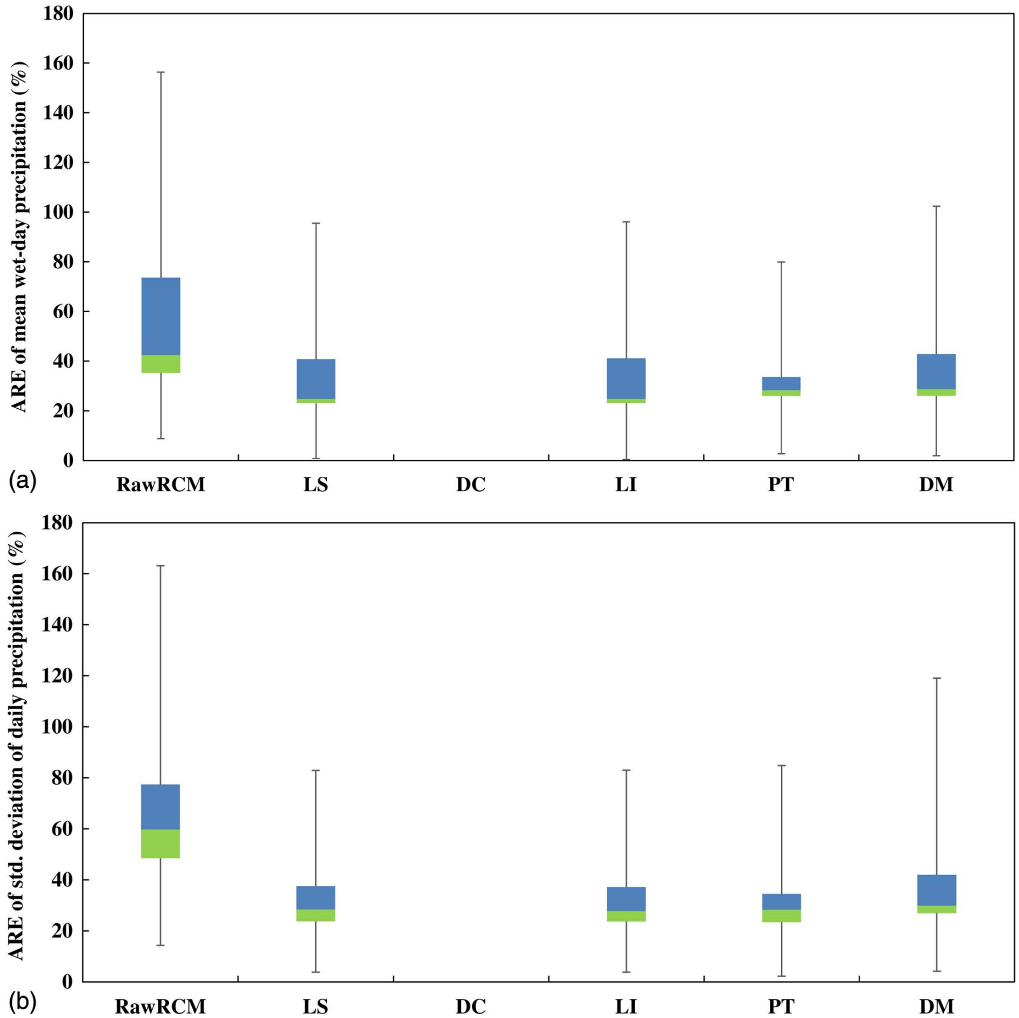

Fig. 3. Boxplot of the absolute relative error (ARE) for (a) mean wet-day precipitation (annual precipitation); (b) standard deviation of daily precipitation

Table 3. Performance of Bias Correction Methods in Correcting Daily Precipitation Time Series

	Raw RCM		LS		DC		LI		PT		DM	
Catchment	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2
Purna	−0.09	0.01	−0.79	0.04	**0.96**	**0.98**	−0.81	0.04	−0.92	0.03	−1.03	0.02
Ulhas	0.00	0.05	−0.14	0.14	**0.95**	**0.96**	−0.15	0.13	−0.59	0.08	−0.44	0.08
Kajvi	0.01	0.08	−0.48	0.16	**0.75**	**0.92**	−0.48	0.16	−0.87	0.12	−0.56	0.13
Malaprabha	−0.27	0.02	−0.47	0.15	0.43	**0.86**	−0.52	0.14	−1.61	0.07	−2.08	0.06
Aghanashini	0.01	0.06	−0.19	0.17	**0.76**	**0.82**	−0.21	0.17	−0.51	0.13	−0.56	0.10
Tunga	−0.15	0.01	−0.64	0.16	0.44	**0.83**	−0.67	0.16	—	—	−1.75	0.09
Netravathi	−0.04	0.03	−0.07	0.21	**0.92**	**0.94**	−0.10	0.20	−0.48	0.14	−0.72	0.11
Chaliyar	−0.41	0.01	−0.27	0.13	**0.73**	**0.91**	−0.33	0.13	−1.14	0.07	−1.64	0.06
Vamanapuram	−0.96	0.00	−0.38	0.01	0.41	0.54	−0.50	0.01	−1.15	0.00	−1.67	0.00

Note: Bold indicates good performance.

Aghanashini, Netravathi, and Chaliyar catchments. The performance of the methods was poor for the remaining three catchments, with NSE < 0.50. This indicated that the bias correction methods that use raw-RCM anomalies for correcting the observed data performed better in the correction of standard deviation rather than the direct use of RCM simulations for future conditions. The extremes in daily precipitation were not considered specifically in the LS and LI methods. The precipitation during the monsoon (accounted for approximately 80% of annual precipitation) and post-monsoon (10–15% of annual precipitation) were corrected with the same factors calculated for winter and summer (light precipitation). It was observed, therefore, that heavy precipitation was not satisfactorily corrected for bias.

The PT method uses the power function and the degree of correction depends on the scaling parameter, which is a function of the exponent. The exponent was estimated to be large for most of the months in this study, indicating underestimation of the coefficient of variation (CV) of observed precipitation on a daily time step.

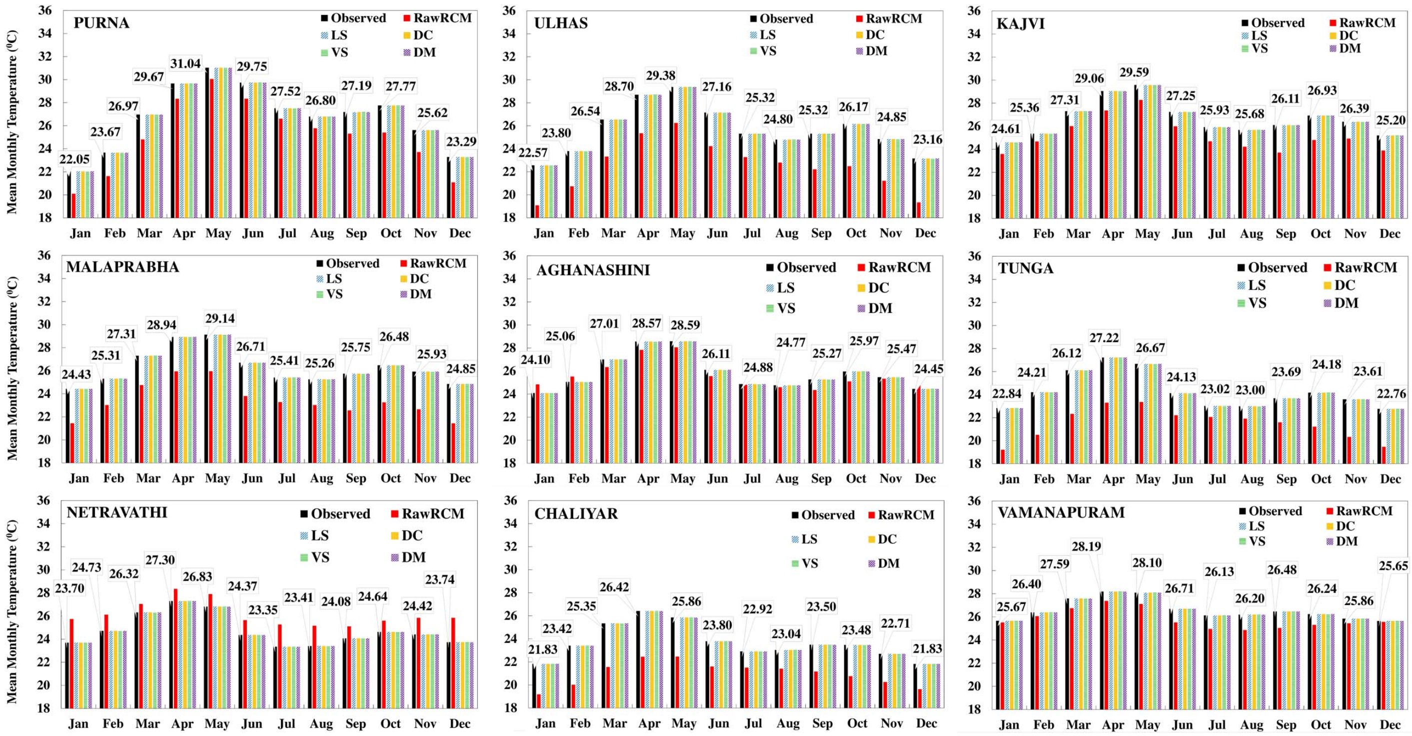

Fig. 4. Mean monthly temperature for the river catchments

The DC method performed better, although the bias in heavy precipitation was dependent on RCM. The DC method reduced the bias to a good degree and indicated the robust performance in correcting the bias of daily precipitation along the Western Ghats of India.

Effort was made to figure out the reason behind the satisfactory and poor performance of bias correction methods. The precipitation in the plateau region on the leeward side was more difficult to model than the precipitation on the windward side of the mountain. The rivers, such as the Purna (1,387 m above MSL to 9 m above MSL), the Ulhas (1,083 m above MSL to 4 m above MSL), the Aghanashini (797 m above MSL to 0 m above MSL), the Netravathi (1,700 m above MSL to 0 m above MSL), and the Chaliyar (2,600 m above MSL to 1 m above MSL), which flow across larger elevation difference on the windward side of the Western Ghats, showed good performance (NSE > 0.64; $R^2 > 0.84$). Also, the catchment areas of these rivers are greater than 850 km^2. The Malaprabha and Tunga rivers originate on the leeward side of the Western Ghats and flow in the eastern direction to join the Krishna River. Although, the sizes of the Malaprabha and Tunga are 428 and 2,922 km^2, respectively, the performance of the bias correction method was not satisfactory for these catchments. This may be because the RCMs were forced to work from a lower elevation to a higher elevation. Hence, the model was more appropriate to simulate orographic precipitation than the precipitation in the plateau regions (leeward side of Western Ghats).

The temperature simulated by the raw RCM was biased compared with the observed temperature. The extent of overestimation varied from 1 to 12% across the catchments investigated. In the Netravathi catchment, the RCM underestimated the temperature by 6%. The LS, DC, VS, and DM methods were used to correct the bias in the temperature datasets. The mean monthly variation of temperature and the performance of the bias correction methods across the nine catchments is presented in Fig. 4. All the bias correction methods performed well in correcting the temporal agreement of temperature on a monthly time step. The daily temperature was evaluated and the DC method was found to be very accurate (NSE $= 1$) across all the nine catchments (Table 4). The VS and

Table 4. Performance of Bias Correction Methods in Correcting Daily Temperature Time Series

Catchment	Raw RCM NSE	Raw RCM R^2	LS NSE	LS R^2	DC NSE	DC R^2	VS NSE	VS R^2	DM NSE	DM R^2
Purna	0.03	0.56	0.38	0.53	**1.00**	**1.00**	**0.62**	**0.65**	**0.62**	**0.66**
Ulhas	−1.53	0.47	0.31	0.48	**1.00**	**1.00**	0.57	**0.61**	0.57	**0.61**
Kajvi	−0.60	0.33	0.09	0.37	**1.00**	**1.00**	0.41	0.49	0.42	0.49
Malaprabha	−2.41	0.36	0.16	0.39	**1.00**	**1.00**	0.44	0.51	0.44	0.51
Aghanashini	0.16	0.33	0.27	0.44	**1.00**	**1.00**	0.44	0.51	0.44	0.51
Tunga	−2.58	0.24	0.29	0.46	**1.00**	**1.00**	0.54	0.58	0.54	0.58
Netravathi	−0.56	0.35	0.31	0.46	**1.00**	**1.00**	0.42	0.51	0.42	0.50
Chaliyar	−2.40	0.26	0.32	0.48	**1.00**	**1.00**	0.57	**0.60**	0.56	**0.60**
Vamanapuram	−0.59	0.22	0.03	0.31	**1.00**	**1.00**	0.22	0.36	0.21	0.36

Note: Bold indicates good performance.

Table 5. Performance of SWAT Hydrological Model during Calibration and Validation (Daily Streamflow)

State	Catchment name	Calibration period	NSE (calibration)	Validation period	NSE (validation)	*R*-factor
Gujarat	Purna	1971–1990	0.79	1991–2000	0.70	0.36
Maharashtra	Ulhas	1982–2000	0.73	2001–2011	0.67	0.17
	Kajvi	1992–2001	0.74	2002–2010	0.78	0.10
Karnataka	Malaprabha	1977–1990	0.87	1991–1996	0.77	0.05
	Aghanashini	1989–1996	0.84	1997–2002	0.85	0.04
	Tunga	1973–1992	0.87	1993–2000	0.87	0.07
	Netravathi	1980–1995	0.85	1991–1995	0.87	0.37
Kerala	Chaliyar	1981–1995	0.78	1996–2000	0.79	0.18
	Vamanapuram	1990–2005	0.71	2006–2011	0.83	0.05

DM method performed satisfactorily for the Purna catchment, whereas the remaining methods did not perform well. The mean monthly time series tended to conceal the bias and, hence, the performance of the bias correction methods on the monthly time step was good. The evaluation of a daily time series provided a clear picture.

Flow Simulation

The details of calibration and validation of the SWAT hydrological model are presented in Table 5. The calibration and validation were carried out using daily average flow. Fig. 5 compares the annual cycle of streamflow for the observed (Qobs) and simulated (Qsim) during the validation period. The minor deviations observed in the hydrographs might be introduced by the hydrological model. The NSE values across the nine basins ranged between 0.71 and 0.87 for the calibration period, and between 0.67 and 0.87 for the validation period (Table 5). The NSE values indicated a good fit of the model because the calibration was done on a daily scale and represented the good quality of meteorological inputs. The R-factor for the nine catchments ranged from 0.05 to 0.37, indicating a good strength of calibration.

Efficacy of Bias Correction Methods in Representing Streamflow

The annual hydrographs for the river catchments under investigation are presented in Fig. 6. The streamflow simulated using the raw RCM did not match accurately with the reference streamflow of the river catchments of the Western Ghats of India. Chen et al. (2013a) also reported that the streamflow generation by raw RCM was generally better in snow-dominated basins than in basins that have no snowfall. Particularly, the RCM could not represent the southwestern monsoon (June to September) in this study. Because the southwestern monsoon contributes to approximately 80% of the total rainfall over the Western Ghats of India, it plays an important role in the hydrological impact studies. The peak discharge was underestimated significantly in all the catchments, except for Chaliyar and Vamanapuram. The temporal agreement of streamflow was improved by all the bias correction methods across the

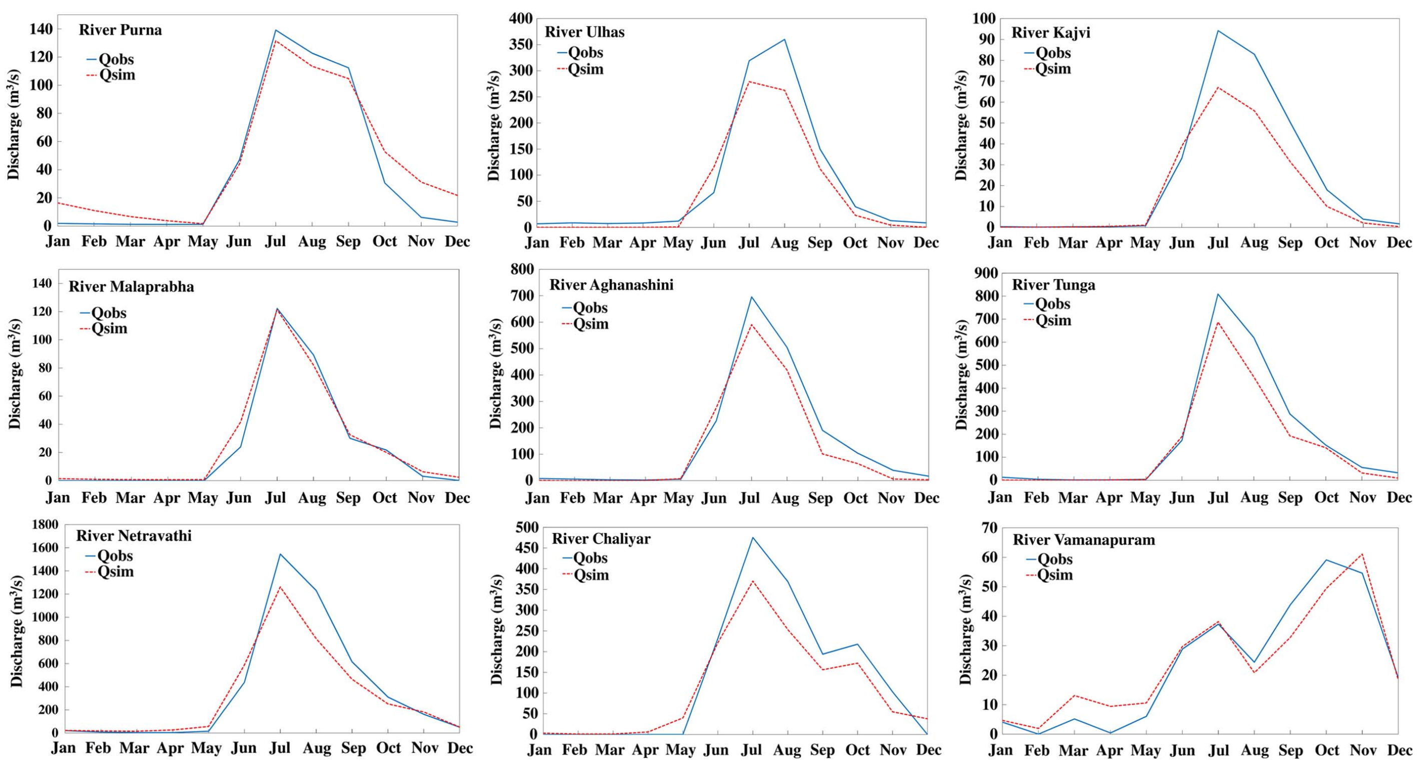

Fig. 5. Performance of SWAT model during validation period

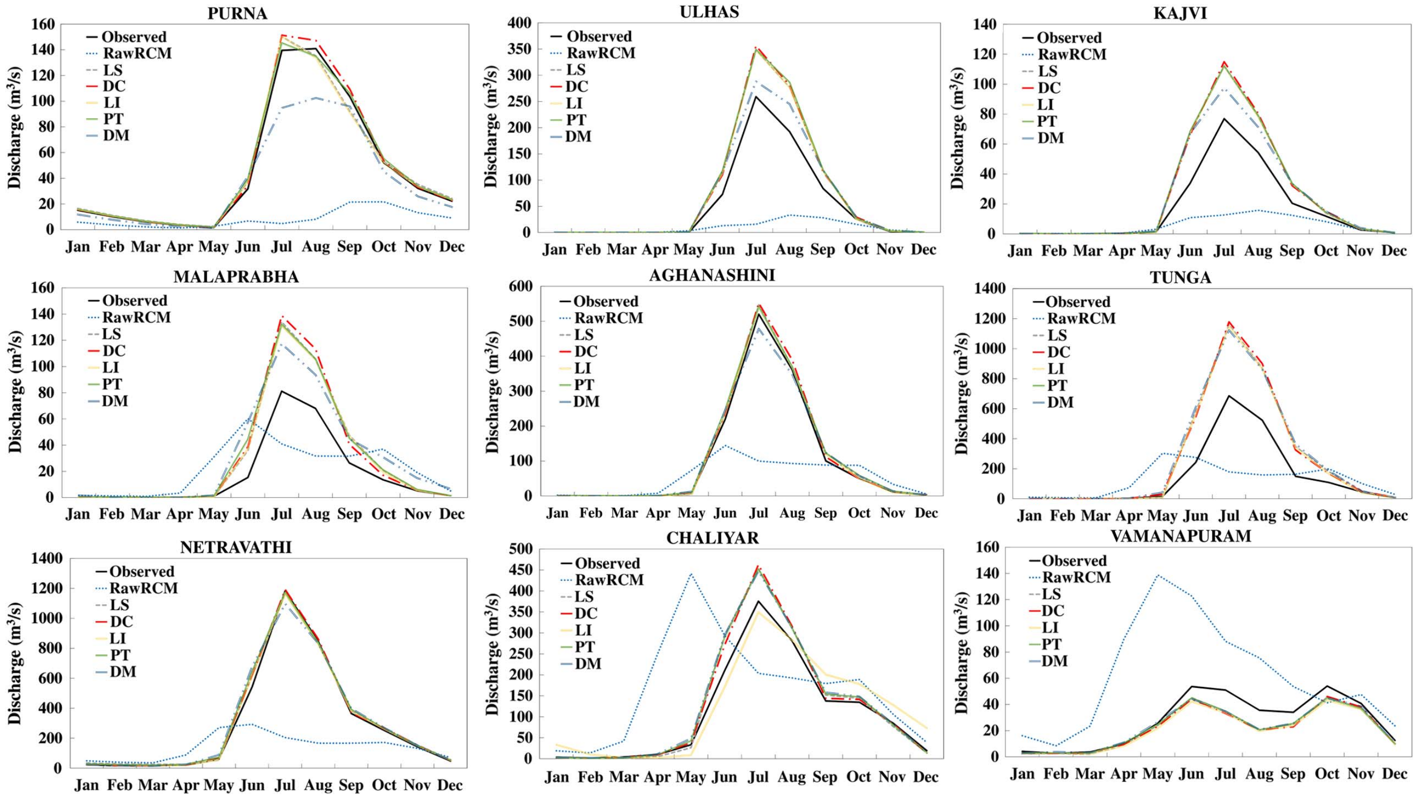

Fig. 6. Annual hydrographs for the river catchments

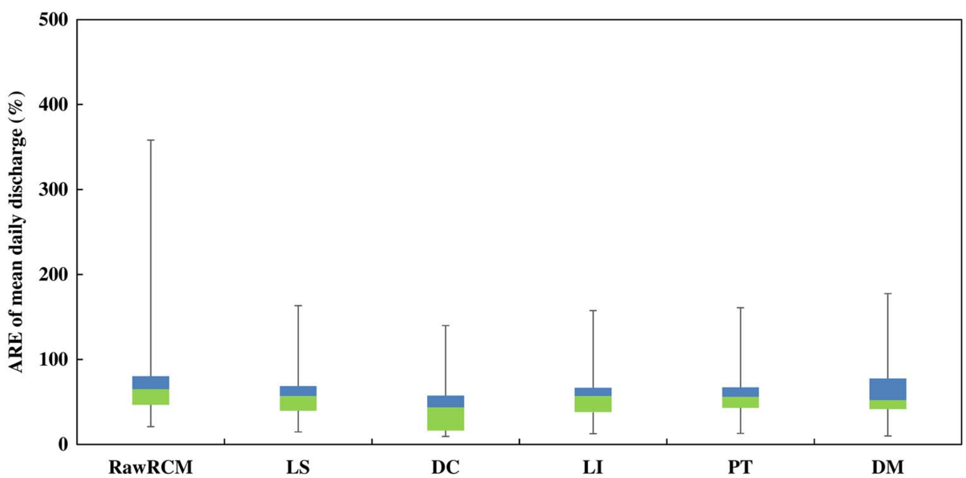

Fig. 7. Boxplot of the ARE of the mean daily discharge

Western Ghats. A reasonably good match with the reference streamflow was seen with the use of bias corrected climate variables. The evaluation metrics and hydrological statistics served as better tools in assessing the differences and are described in subsequent sections.

The AREs for the mean daily discharge were calculated for the simulations with and without correction of bias and are shown in Fig. 7. As expected, the mean discharge without bias correction (raw RCM) was very biased, with ARE of 65%. The mean discharge was improved to a small degree by all the methods. The ARE for LS and LI method was 57%, 52% for PT method, and 52% for DM method. The DC method with an ARE of 44% performed better than the remaining methods. Although all the methods of bias correction differed in the way they dealt with data, there was no obvious difference in the bias correction of the LS, LI, PT, and DM methods. There was a presence of outliers (especially in the DC method), and their mere presence indicated that the method may not have performed well on at least one basin.

The AREs for high-flow and low-flow seasons are presented in Fig. 8. During the high-flow seasons (monsoon and post-monsoon), the ARE was very high for the raw RCM. The ARE was calculated to be 71 and 91% during high-flow season [Fig. 8(a)]. The ARE during the monsoon season for the LS and LI methods was 68%, and that for the PT and DM methods was 61%. The DC method

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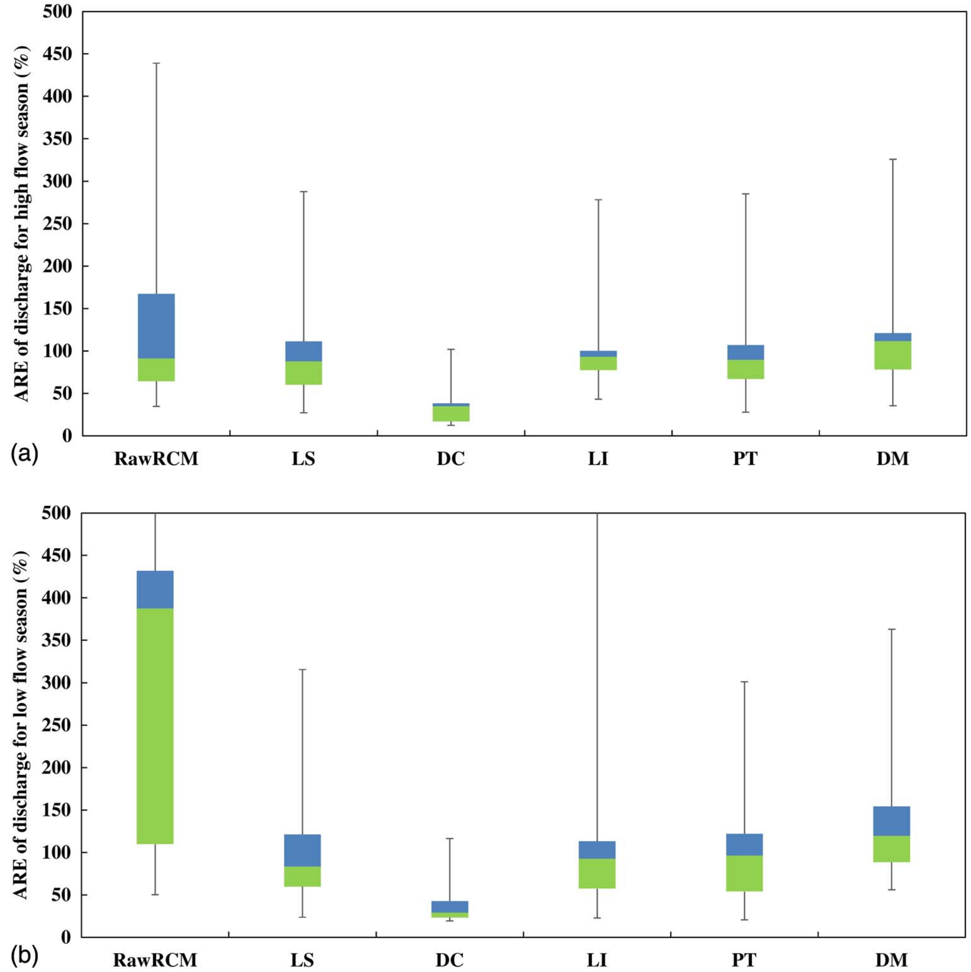

Fig. 8. Boxplots of the ARE of discharge for (a) high-flow season; (b) low-flow season

significantly improved the ARE during monsoon (45%) and post-monsoon (35%). The DC method was unable to perform better during monsoon and post-monsoon seasons because of the inherent property of RCMs to underestimate Indian southwest monsoon rainfall. Fig. 8(b) presents the ARE during low flow (lean-season flow), i.e., winter and summer. The ARE during the lean season was very large and the bias correction methods marginally reduced the error. The ARE for DC method was 29 and 17% during winter and summer, respectively. The variability across river catchments was small and indicated that all the bias correction methods improved the representation of low flows. Although all the methods performed equally well, the DC method was the best compared with the others.

The performance evaluation metrics for a daily streamflow time series across the nine river catchments is presented in Table 6. The NSE and R^2 between streamflow simulated by the raw RCM and reference streamflow was not good. The study by Chen et al. (2013a) attempted to eliminate the bias of raw RCM by calibrating the hydrological model with direct use of raw RCM. Minor improvement in the simulation of streamflow was reported from the investigation. The direct use of raw RCM in the SWAT hydrological model did not improve the simulation of streamflow in this

Table 6. Performance of Bias Correction Methods in Correcting Daily Streamflow Time Series

	Raw RCM		LS		DC		LI		PT		DM	
Catchment	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2
Purna	−0.09	0.00	−1.02	0.01	**0.97**	**0.97**	−1.02	0.01	−0.96	0.02	−1.15	0.00
Ulhas	−0.04	0.06	−0.47	0.16	**0.64**	**0.86**	−0.47	0.16	−2.32	0.07	−0.74	0.10
Kajvi	0.03	0.14	−0.63	0.24	0.37	**0.82**	−0.63	0.24	−1.39	0.17	−0.85	0.17
Malaprabha	−0.06	0.08	−0.53	0.30	−0.19	**0.80**	−0.53	0.29	−2.06	0.16	−3.79	0.08
Aghanashini	0.05	0.09	0.13	0.26	**0.82**	**0.84**	0.12	0.26	−0.28	0.17	−0.36	0.13
Tunga	−0.02	0.03	−0.67	0.26	−0.18	**0.72**	−0.66	0.26	—	—	−2.29	0.13
Netravathi	−0.01	0.07	0.13	0.27	**0.89**	**0.90**	0.12	0.26	−0.30	0.17	−0.53	0.13
Chaliyar	−0.57	0.02	0.06	0.25	**0.90**	**0.96**	0.10	0.14	−0.54	0.14	−0.84	0.11
Vamanapuram	−1.32	0.01	−0.05	0.03	0.34	0.35	−0.08	0.03	−0.37	0.01	−0.47	0.01

Note: Bold indicates good performance.

study. Therefore, the calibration of the SWAT model using raw-RCM simulated streamflow was not attempted. The LS, LI, PT, and DM methods failed to accurately represent the streamflow of the catchments in the Western Ghats.

The DC method performed well in correcting the bias of climatic variables (precipitation and temperature) and, subsequently, the streamflow simulated using the DC method data performed well. Table 6 shows that the streamflow using the DC method data yielded good results for five catchments. The NSE for Purna, Ulhas, Aghanashini, Netravathi, and Chaliyar were found to be 0.97, 0.64, 0.82, 0.89, and 0.90, respectively. The performance of the DC method was poor in the Kajvi and Vamanapuram catchments with NSE of 0.37 and 0.34, respectively. The DC method failed to perform in the Malaprabha and Tunga catchments. The R^2 was very good (>0.70) in most of the catchments, even when NSE was poor. This was because the statistical goodness-of-fit was good, but the bias correction methods were not capable of correcting the residual variance (noise) of the climatic variables (especially precipitation). The NSE determined the magnitude of the residual variance compared with the measured data variance. Hence, the inability of the bias correction methods in correcting the variance was highlighted in four of the catchments investigated, i.e., Kajvi, Vamanapuram, Malaprabha, and Tunga.

The bias correction methods did not work when the grid points were away from the basin/catchment. The continental circulation could be accurately modeled, whereas, the local storm paths could completely miss a watershed because the storms may occur north or south of grid points. To establish the basis of the bias correction methods, it is required to have a consistent temporal structure of the precipitation and the bias must remain constant to a certain degree. Most of the bias correction methods assume a constant bias and very few studies consider the temporal structure. The performance of bias correction methods was studied in the past by using the boundary conditions given by reanalysis data (Chen et al. 2013a; Teutschbein and Seibert 2012). When an RCM is driven by a GCM, the RCM bias is superimposed on the GCM bias at the boundary conditions. Also, the RCMs driven by GCMs tend to conceal the bias in the temporal structure. Therefore, when the rest of the bias correction methods failed to perform for the Western Ghats of India, the delta change method of bias correction performed very well.

Conclusions

This work attempted to evaluate the appropriate bias correction methods for the catchments spread over the temperate zone along the west coast of India. Because the Indian economy is dependent primarily on the monsoon rains, the hydrological impact of climate variables play a crucial role. The Western Ghats are the tropical forest ranges covering the entire west coast of India. Many rivers originate in these mountain ranges and flow west or eastward to join the Arabian Sea and the Bay of Bengal, respectively. The bias correction methods investigated in this work included simple methods, such as LS to complex distribution mapping method. The performance of the correction methods was assessed on the basis of the precipitation and temperature simulated by an RCM, driven by GCM. The following conclusions may be drawn from this study.

The climatic variables (precipitation and temperature) simulated by the RCM are always biased and cannot be directly forced on hydrological models. The importance of correcting the frequency of wet days plays a major role in the projection of climate and in the selection of appropriate bias correction methods. The distribution-based methods may not always be superior to the mean-based methods in hydrological simulations and projecting climate. The bias correction methods may not hold well when the temporal structure of climatic variables is inaccurately reproduced by the climate models. This is particularly true when the bias correction is on a daily time step.

The raw-RCM precipitation was very biased compared with the observed precipitation. No improvement was observed in the statistic of mean wet-day precipitation using the LS, LI, PT, and DM methods; the DC method was the exception. The DC method corrected the frequency of wet days because the anomalies between the simulated results were superimposed over the observed time series, improving the mean wet-day precipitation significantly. The NSE for Purna, Ulhas, Kajvi, Aghanashini, Netravathi, and Chaliyar were 0.96, 0.95, 0.75, 0.76, 0.92, and 0.73, respectively. Comparing the season-wise performance, the raw RCM tended to underestimate the heavy rainfall events leading to negative values. The DC method significantly improved the ARE during monsoon (45%) and post-monsoon (35%) compared with other methods. However, the method was unable to perform exceptionally well during monsoon and post-monsoon seasons because of the inherent property of RCMs to underestimate southwest Indian monsoon rainfall. The temperature was simulated better than precipitation in the climate models. The DC method was capable of representing the mean daily temperature accurately.

The streamflow estimated using the DC method yielded good results for five catchments. The NSE for Purna, Ulhas, Aghanashini, Netravathi, and Chaliyar were 0.97, 0.64, 0.82, 0.89, and 0.90, respectively. Hence, the performance of the RCM was better for the catchments on the windward side of the Western Ghats that flow across larger elevation differences. The performance of the DC method was poor in the Kajvi and Vamanapuram catchments, with NSE of 0.37 and 0.34, respectively. The DC method failed to perform in the Malaprabha and Tunga catchments, which are on the leeward side of the Western Ghats. When the RCM was applied away from computational boundaries, i.e., in the case of plateau regions, the problem was more pronounced. Hence, the RCM was more appropriate to simulate orographic precipitation than the precipitation in the plateau regions (leeward side of Western Ghats).

The overestimation in the Vamanapuram River may be because it is one of the southernmost rivers of India and is influenced by both the southwest and the northeast monsoons. The hydrology of a catchment is very sensitive to precipitation and a small bias could lead to large deviation in the hydrological components. This work concluded that the delta-correction method is the most appropriate method of bias correction for the impact analysis of climate variables for the catchments of the Western Ghats. Hence, there is a need for validation of preprocessing methods prior to studying the impacts of climate variables specific to the region, depending on its climate pattern.

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