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Performance assessment of six bias correction methods using observed and RCM data at upper Awash basin, Oromia, Ethiopia

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ABSTRACT

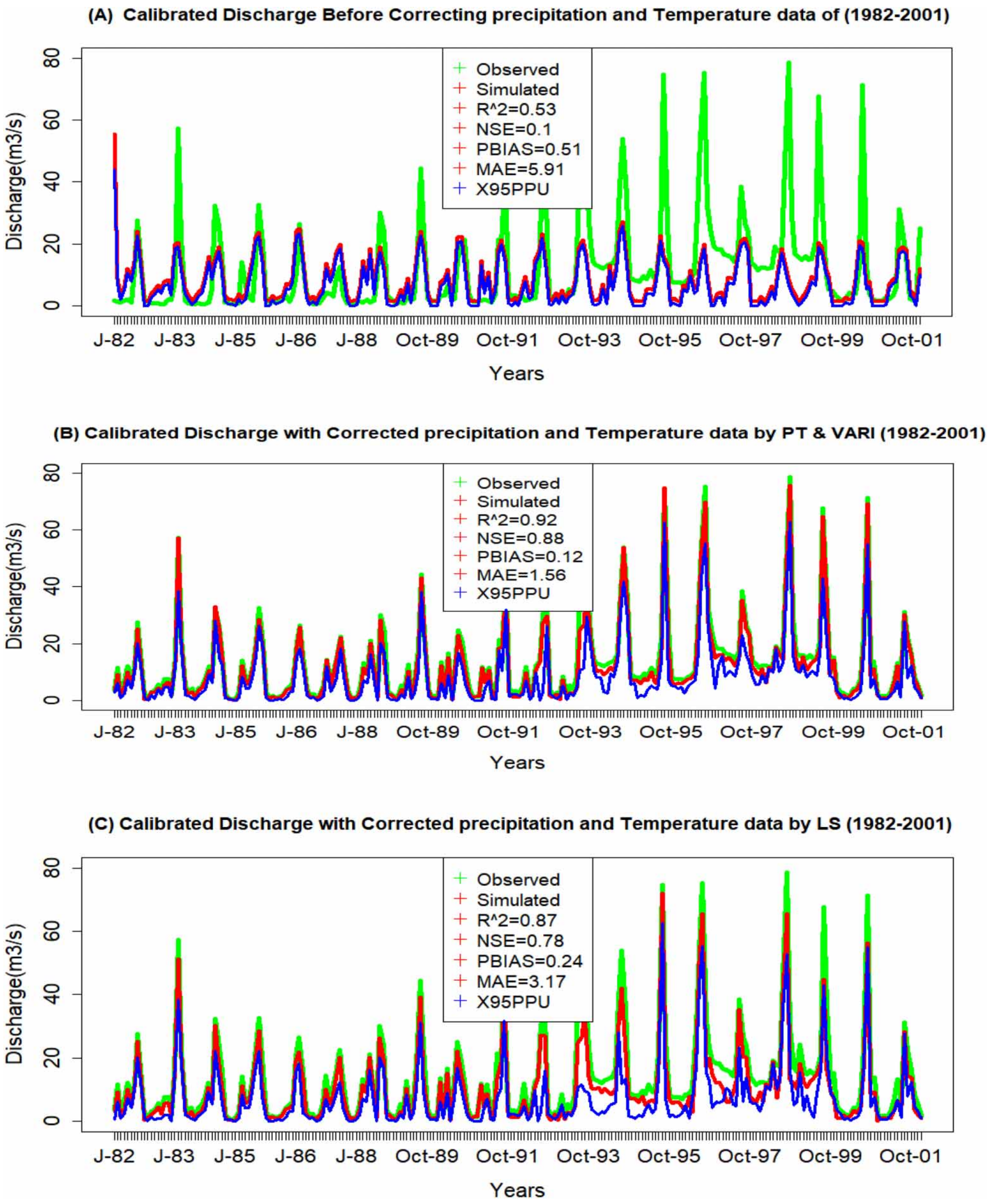
Selecting a suitable bias correction method is important to provide reliable inputs for evaluation of climate change impact. Their influence was studied by comparing three discharge outputs from the SWAT model. The result after calibration with original RCM indicates that the raw RCM are heavily biased, and lead to streamflow simulation with large biases (NSE = 0.1, R^2 = 0.53, MAE = 5.91 mm/°C, and PBIAS = 0.51). Power transformation and linear scaling methods performed best in correcting the frequency-based indices, while the LS method performed best in terms of the time series-based indices (NSE = 0.87, R^2 = 0.78, MAE = 3.14 mm/°C, PBIAS = 0.24) during calibration. Meanwhile, daily translation was underestimating simulated streamflow compared with observed and was considered as the least performing method. The precipitation correction method has higher visual influence than temperature, and its performance in streamflow simulations was consistent and considerable. Power transformation and variance scaling showed highly qualified performance compared to others with indicated time series values (NSE = 0.92, R^2 = 0.88, MAE = 1.58 mm/°C and PBIAS = 0.12) during calibration and validation of streamflow. Hence, PT and VARI were the dominant methods to remove bias from RCM models at Akaki River basin.

Key words: Akaki River, bias correction methods, climate change, performance assessment

HIGHLIGHTS

- This paper clearly identifies that bias correction methods' performances are watershed-dependent.
- Bias correction methods should be separately applied to each watershed.
- Also SWAT Model clearly identifies that bias correction methods have not been adjusted for all uncertainty related to the models.
- Bias of RCM should be removed with caution.
- Power Transformation and Variance scaling methods performed best.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water is the most crucial and significant resource from which life is sustained over the Earth's surface, and saving and protecting this resource is not something that has been easily considered and recognized. In the recent era, particularly the 21st century, in which the world is growing in terms of technology and industrial civilizations, emissions from industry have brought climate change and the resulting variability has exposed water resource depletion. Currently, climate change is recognized in most parts of the globe and modeling it will lead to reducing the crises relating to food security, drought, and loss of energy sectors in the future by developing mitigation policies. Awash basin is the most irrigable area in Ethiopia and many farmers rely on this basin as a guarantee of their food security. However, climate change has become one of the causes for depletion of agricultural products in this region and impacts many farmers and their economic productivity and self-sufficiency (Taye 2018). For climate changes and variability assessments, general circulation models (GCMs) are the most appropriate and advanced tools, evaluating the impacts of climate change by removing its biasness (Haile 2017).

GCM and regional climate models (RCMs) are crucial models to predict, simulate, and project the future climate changes of the Earth globally and regionally (IPCC 2014). Since the 1950s, GCMs have been gradually developing and there have been many changes and improvements to model Earth systems' phenomena through climate change impact modeling (Smith *et al.* 2014). In the Coupled Model Intercomparison Project – Phase 5 (CMIP5), enormous GCMs have been developed into Earth systems' models including biogeochemical and hydrological cycles with predetermined verifications (Dale *et al.* 2017). In many studies related to climate change assessments, changes in precipitation and temperature, which have a direct involvement in global and regional hydrological processes, are the main factors that influence climate change outcomes (Endris *et al.* 2013). On the other hand, the development of new RCMs leads to another opportunity for scientists to analyze the effects of climate change as they inclusively consider higher spatial resolution and further reliable outcomes on a regional scale compared to GCMs (Kang *et al.* 2020). As a result, the GCM predicts the global scale mean surface temperature and periodical circulation of sea-ice extent of the oceans (Fang *et al.* 2015a). The Intergovernmental Panel on Climate Change (IPCC) investigations have been revealed and suggest that climate variables, specifically precipitation and temperature, are more closely related to global warming and are mostly impacting regional- or catchment-scale hydrological processes (Rakhimova *et al.* 2020).

Therefore, pre-processing of RCM outputs such as removing uncertainty (bias) should be the first step of most climate change impact studies to further estimate and predict the climate change consequences and suggest anticipation mechanisms throughout the global community (Chen *et al.* 2013). Generally, GCM or RCM modeled data are not directly used because of their bias as natural phenomena cannot be predicted accurately. Furthermore, this uncertainty and bias were developed during the advancement of circulation models by scientists due to a lack of an absolute and concrete idea about the nature of atmospheric circulation (Tan *et al.* 2020). All these facts suggest that GCM models may not estimate climate variables in the necessary way to reduce the differences, and there is always a deviation between observed and simulated climate variables even if the difference is insignificant. Therefore, it is very important to count on bias correction methods to remove bias from GCM/RCM outputs for predicting climate change impacts over the world's climate regions (Luo *et al.* 2018; Tan *et al.* 2020). The application of appropriate and suitable bias correction methods to the climate model enables researchers to be more confident of the hydrological models' outcome as large errors are expected to be removed. Several studies in this regard, such as that by Ezéchiel *et al.* (2016), have been developed and successfully applied in different climate regions in the world. Moreover, several methods, ranked from simple to more sophisticated approaches, were developed by different researchers depending on the characteristics of catchments up to basin scale for global climate change analysis of regions (Teutschbein 2013). In fact, the selection and application of appropriate bias correction methods to semi-arid climate regions is the most challenging issue due to the behavior of rainfall in such regions being very scarce, erratic, and infrequent in nature according to Mendez *et al.* (2020).

Furthermore, on average, several both simulated and corrected multi-model packages have much better performance in comparison to separate GCM/RCM and provide a reliable approach to the development of climate change scenarios (Olsson *et al.* 2015). In climate change impact analysis, it is more advantageous to select appropriate and suitable bias correction methods to realize the input data are free of bias to some extent. Regarding this concern, Teutschbein & Seibert (2013) have applied six bias corrections to correct precipitation and temperature data relying on statistical metrics with 11 RCM outputs in five typical catchments in Sweden and selected crucial methods that remove bias from RCM models. The main objective of selecting bias correction climate models prior to using them as input for hydrological related models is to suit the simulation of discharge or groundwater recharge by taking into account the accuracy of models' simulations with observed hydrological variables. This is aimed at reducing misleading results from simulation of hydrological processes in unrealistic magnitude, and even though bias correction methods are a relevant mechanism of reducing bias from climate models they are also susceptible to developing another source of uncertainty in the model chain (van Griensven *et al.* 2006).

Most of the time hydrological modeling is based on meteorological and hydrological data that are very sensitive to bias, and it is essential to find out its uncertainty which discourages a realistic result when conducting research (Xiang Soo *et al.* 2020). Since the performance of bias correction methods is watershed, catchment and sub-basin scale dependent, selecting appropriate bias correction methods is necessary to provide reliable inputs for global climate impact analysis (Fang *et al.* 2015b). In reality, there are different bias correction methods that are adapted to different regions and climate conditions and this issue is fundamentally the target of this research. Accordingly, the aim of this study is to clearly evaluate and investigate that the performance of bias correction methods is watershed dependent; and also to clearly identify that the power transformation (PT), linear scaling (LS), and variance scaling methods perform well in removing bias from RCM models.

2. MATERIALS AND METHODS

2.1. Description of the study area

The study was conducted on upper Awash catchment which is located in central Ethiopia along the western margin of the Main Ethiopian Rift (Figure 1). Awash basin is a large river basin which covers a huge area of farmland in the country. This basin is crucial for the farmers whose agricultural productivity serves them as the source of their daily life. It covers a total land area of 110,000 km^2 and is home to 10.5 million inhabitants (Getahun & Gebre 2015). The watershed is geographically bounded between 8°42′ to 9°10′N latitude and 38°24′ to 39°06′E longitude, covering an area of about 9,526 km^2. The entire Akaki sub-basin is surrounded by the valley in the north direction and by the Addis Ababa to Ambo road in the west.

2.2. Climate condition

Great Awash River watershed has a subtropical highland climate. Geographically, the study area is found near to the equator and due to this the temperature is remarkably constant from month to month. It is challenging to find climate data specific to the site, but Addis Ababa is found nearby the catchment. Based on monthly averages for 30 years (1981–2010), the mean monthly minimum and maximum temperatures vary from 7 °C to 11 °C and 21 °C to 28 °C, respectively. The lowest temperature of the study area was 7 °C, which was registered in November and December, and the maximum temperature was 28 °C, registered in March and May. The main rainy season for Akaki watershed is late June to early September. It is characterized by a dry winter, which is the dry season of the area. Generally, the project area has an average annual precipitation of 1,965 mm/year.

2.3. Meteorological data

Meteorological data gained from four stations in the catchment and simulated data from models were applied for the future to evaluate the bias correction method performance in removing bias. Depending on these fundamental aims, climate and hydrological models need meteorological data which are used as raw input for both bias correction and hydrological modeling processes to simulate climate phenomena. These meteorological and hydrological data were gathered from the Ethiopian National Meteorological Agency and Ministry of Water, Energy and Electricity office found in Addis Ababa. Four meteorological stations with relatively long periods of records within the catchment were used for this study and all stations contain every variable for each of them (Table 1).

2.4. Hydrological data

Akaki River flow was required for calibrating and validating the SWAT model. The main gauging stations were along the river basin inside the Akaki catchment and had continuous records at the outlet for 25 years (1982–2007) which were collected from the Ministry of Water, Energy and Electricity of Ethiopia. The purpose of the selected reference climate data set was to provide a reliable database for the study of all aspects of climate. These aspects range from global- to local-scale studies of fluctuations, trends, changes in variability and changes in the numbers of extreme events. Understanding and informing past changes and variations in climate are vitally important to improve the ability to predict, project, and prepare for future events to happen through climate change impacts.

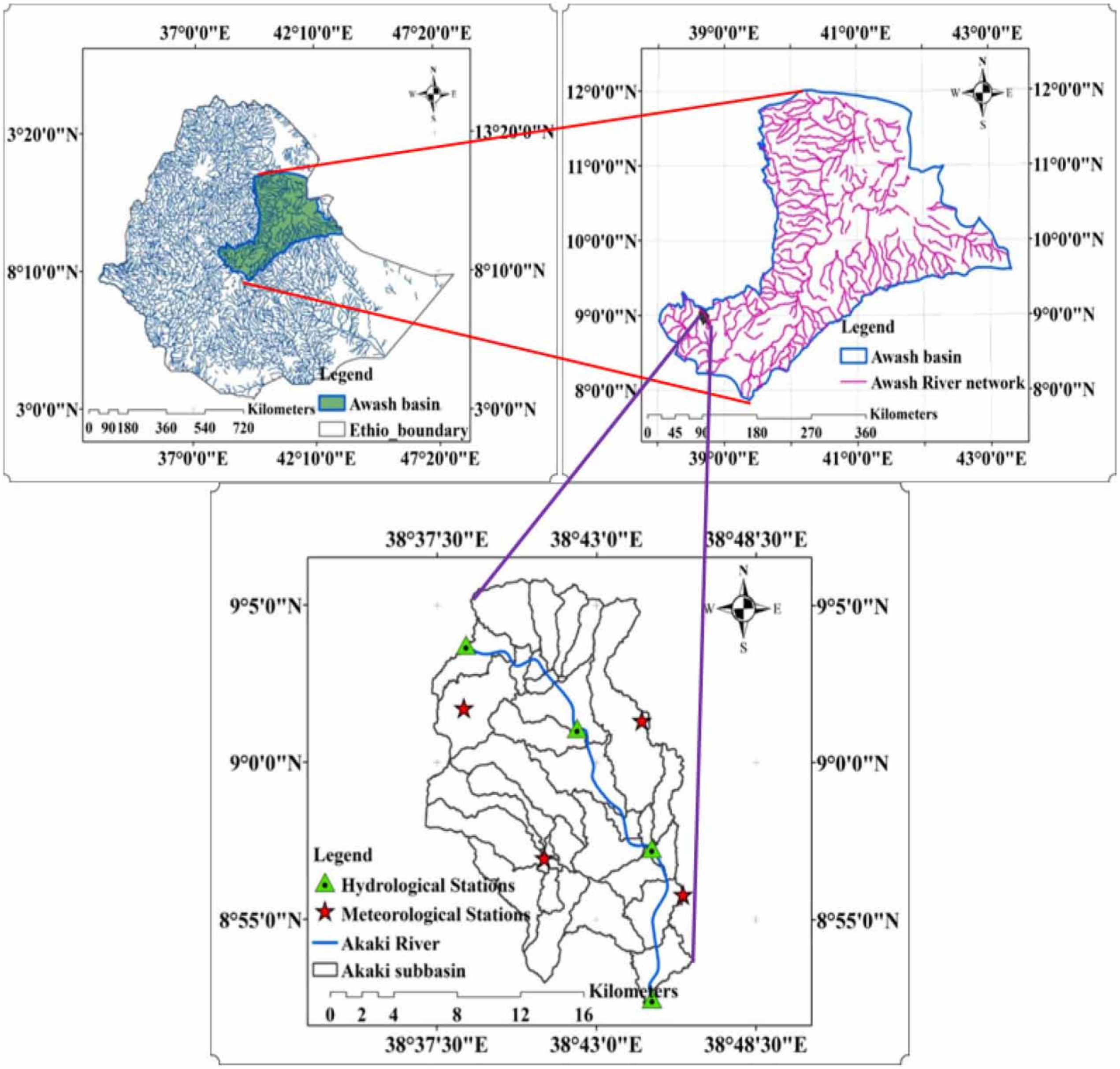


Figure 1 | Map of the study area and Akaki River basin's gauging stations.

Table 1 | The used input data, sources of data, and lengths of records based on the selected stations

Data types	Stations	Length of records	Source of data
Meteorological	Addis Ababa	1981–2010	National Meteorological Agency
and	Boneya		
Simulated data	Bulbula		CORDEX-(CanSEM2) and (RCA4)
	Sebeta		
Streamflow data		1982–2007	Ministry of Water, Energy and Electricity
LULC and soil data		2013	Ministry of Water, Energy and Electricity

2.5. Digital elevation model

Nowadays, the traditional method has been replaced by automatic extraction from a digital elevation model (DEM) due to the release of different types of high-resolution satellites in space at different times and the production of high-quality data. DEM data are used to describe topographic characteristics such as contour, slope, elevation difference, aspect, hill shade, and others. For this study, DEM is the main data set used for development of the sub-basin model components and geometrical data in the SWAT models as well as development of the physical model. The DEM data (Figure 2) used in this study were extracted from http://vertex.daac.asf.alaska.edu, with 12.5 × 12.5 m resolution.

2.6. Land use land cover and soil classification

Soil texture and land use land cover information are the primary input data for SWAT models in hydrological simulation (Figure 3). These parameters have been considered as the factors affecting the characteristics of watershed including hydrological impacts (the amount of runoff and peak discharge rates, and base flow are altered), physical impacts (streamflow morphology and temperature are changed), water quality impacts (nutrient and pollutant loads increase), and biological impacts (stream biodiversity decreases) (Du *et al.* 2020). The general land use/cover pattern of Akaki river basin was broadly classified into: annual and perennial crop, bare soil, grassland, shrubland, dense and sparse forest, residential, salt pan, water body, wetland, and woodland. On the other hand, the soil development in the study area was mostly due to the physical disintegration and chemical decomposition of volcanic rocks composed of different soil classes such as Calcic Xerosols, Chromic Luvisols, Chromic Vertisols, Eutric Nitisols, Orthic Solonchaks, Pellic Vertisols, and Vertic Cambisols.

2.7. CORDEX climate model

Different climate models have been developed containing different sets of components which, as a result, describe climate systems differently, and are expected to produce different results from their simulation packages. This development of climate models has considered the global climate phenomena throughout the world, but may not free models of uncertainty since nature by itself is unpredictable (Worku *et al.* 2020). On the other hand, while selecting hydrological models for evaluating hydrological simulation, the climate models selected should take into account the simplicity, availability, and familiarity of climate models with the objectives to be considered (Matiu *et al.* 2020). The Canadian Center for Climate Modeling and Analysis (GCM-CCCma) with a high resolution of 3.75° × 3.75° and SMHI as the deriving model, was used for this study as it was preferred for the high resolution which can incorporate other GCM models (Mekonnen *et al.* 2011).

The Second Generation Canadian Earth System (CanSEM2) model and Rossby Centre Regional atmospheric (RCA4) model and with 0.44°/0.11° resolution were used as the raw RCM in this study for its preference to clearly consider an atmosphere-ocean general circulation model, a land-vegetation model, and terrestrial as well as oceanic interactive carbon cycle

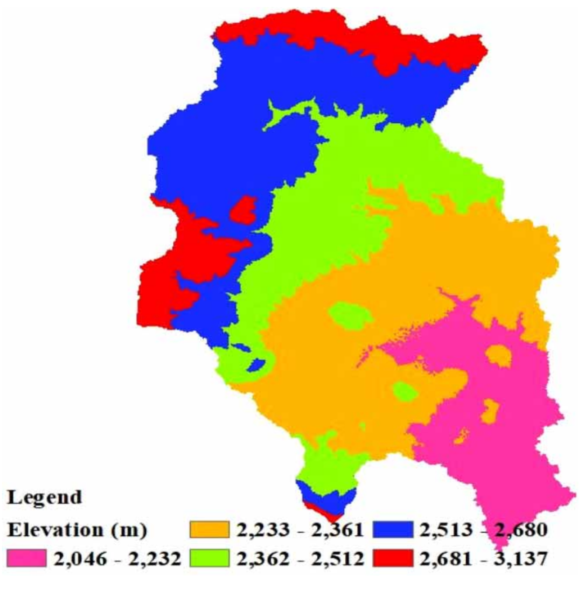


Figure 2 | Digital elevation model of the study area.

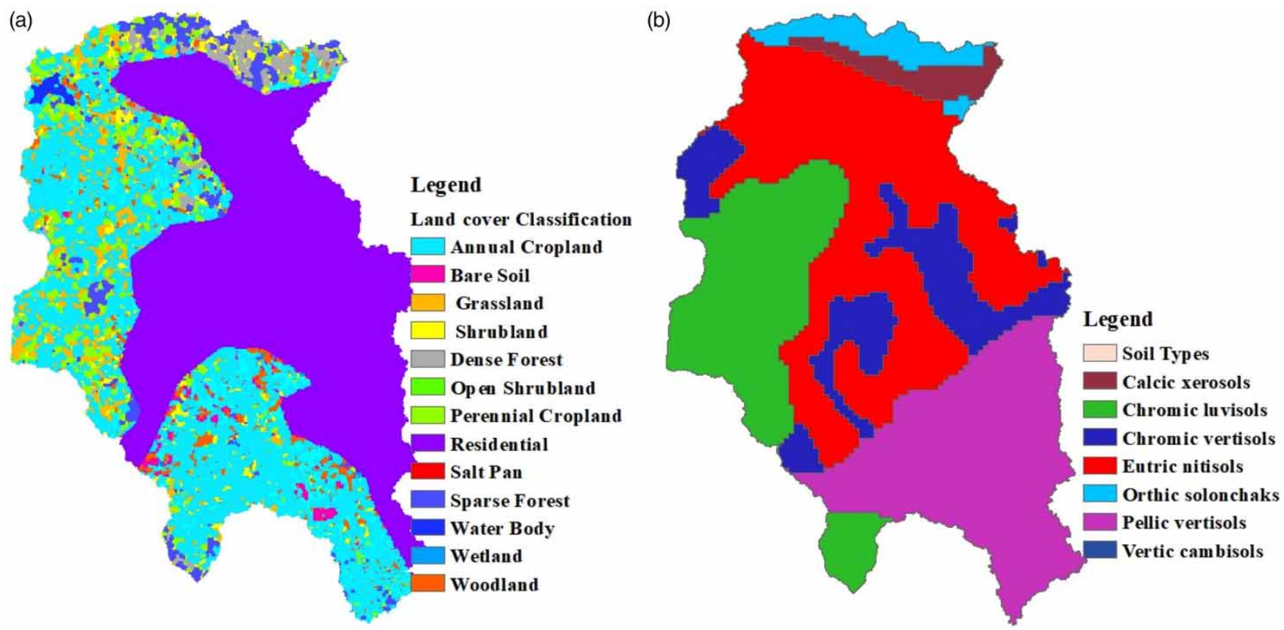


Figure 3 | (a) Land use land cover map and (b) soil map of Akaki River basin.

which basically cause climate variability (Chylek *et al.* 2011). Related to the RCA4 model, the data set is unique, not only as it is large but also as it takes lateral boundary conditions from a very large number of different GCMs with different resolutions. The spatial resolution of observed data was $0.28° \times 02.8°$, which was already included in the selected GCM models with stated resolution. Therefore, the types of hydrological models used (SWAT in this case), bulkiness of the data, and six bias correction methods being applied with this study, and high resolution with inclusiveness of boundary condition from many other GCMs by this model in consideration was used for the selection of those GCM and RCM models.

2.8. SWAT model and uncertainty

The impacts of corrected precipitation and temperature by bias correction methods in hydrological processes were evaluated by the SWAT hydrological model. This model is a semi-distributed, physically based, and time-continuous hydrological model that uses spatial information such as land use, soil texture, meteorological and topographic data to develop hydrological processes, particularly on climate change assessments. It divides a basin into sub-basins that include topographic information. The sub-basin information was further divided into a minimum of 78 hydrologic response units (HRUs) that uniquely combine land use, slope, and soil type (Zhang *et al.* 2016). This study uses 25 years (1982–2007) of daily streamflow data of Akaki River which was used for model calibration (1982–2001) and validation (2002–2007). This model is encrypted with ARGIS as its extension and performs different hydrological process functions in prediction of Earth system phenomena which is highly necessary to address. However, there are some uncertainties involved with SWAT model projection such as parameter uncertainty, model prediction uncertainty, and simulation effects which are fundamentally overcome by uncertainty analysis methods like 95% prediction uncertainty, SUFI-2, and GLUE during simulation, particularly in calibrating streamflow (Zhang 2019). In general, uncertainty of hydrologic models (SWAT) may emerge from discharge simulation, GCM emission scenario models, and hydrologic model parameterization as well as the hydrologic process in projecting future streamflow (Feng & Beighley 2020).

2.9. Description of bias correction methods

Based on their performance in removing bias from RCMs, there are a number of bias correction methods which are ranked according to their tendency to adjust mean, variance, coefficient of variation, and standard deviation climate variables. For instance, linear scaling is best at adjusting mean of climate variables, whereas power transformation corrects both mean and frequency of climate variables (Smitha *et al.* 2018). These statistical tools play an important role in estimating the differences between recorded and simulated data during climate change impact analysis. The main objective of this study was to verify and identify the best bias correction methods, from six selected methods, upon precipitation and temperature in removing and adjusting bias from RCM models for upper Awash River basin. These bias correction methods consist of linear scaling for both precipitation and temperature, power transformation for precipitation and variance scaling method for temperature, and daily translation (DT) for precipitation and temperature (Table 2). They are classified as major types of existing bias correction methods which enable researchers to remove unnecessary uncertainty from RCMs. All of them were conducted on a daily basis for SWAT models and monthly basis of meteorological data to analyze the result for each calendar month during the period 1981–2010. All bias correction methods were applied to daily values for all methods except daily translation methods which rely on a monthly basis, as described by Ezéchiel *et al.* (2016). Therefore, strong bias correction methods are to be identified before using bias-corrected methods to be applied on climate models' output for future climate change impact assessment. Thus, it is critical to develop strong climate change information that can be used for hydrological modeling in climate change impact assessment and to build optimal adaptation decisions in the water resource sector of the sub-basin. This study was planned to evaluate the performance of six different bias correction methods in adjusting the RCM rainfall and temperature with observed precipitation and temperatures at four gauging stations in Akaki River basin (Figure 4).

2.10. Performance evaluation by time series and frequency-based metrics

During the assessment and evaluation of the performance of each bias correction method, it is critical to consider the capacity of each method in generating discharge, precipitation, and temperature by identifying the daily average, maximum and minimum temperature based on frequency- and time-based indices (Worku *et al.* 2020). These time series metrics like R^2, NSE, PBIAS, and MAE were used in the explanations about the goodness of fit for bias correction methods' performance in correcting the bias from RCM models in comparison with observed meteorological and hydrological series. Meanwhile, frequency-based metrics were used to analyze the mean, coefficient of variation and standard deviation for both precipitation and temperature to estimate the difference between observed and simulated series to indicate further correction if necessary (Luo *et al.* 2018).

$$\mathrm{R}^2 = \left\{\sum_{i=1}^{N}(P_{si} - \bar{P}_s)(P_{oi} - \bar{P}_O)\right\} \Big/ \sqrt{\left\{\sum_{i=1}^{N}(P_{Si} - \bar{P}_S)^2 \sum_{i=1}^{N}(P_{Oi} - \bar{P}_O)^2\right\}}, 0 \leq R^2 \leq 1 \quad (1)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}(P_{Oi} - P_{Si})^2}{\sum_{i=1}^{N}(P_{Oi} - \bar{P}_O)^2}, \quad -\infty \leq NSE \leq 1 \quad (2)$$

$$\mathrm{PBIA} = \frac{\sum_{i=1}^{N}(P_{Oi} - P_{Si})}{\sum_{i=1}^{N}P_{Oi}} \quad (3)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N}|P_{Oi} - P_{Si}|}{n} \quad (4)$$

where P_{si} and P_{oi} represent the RCM models' precipitation and observed series at time step i, and P_s and P_o are the corresponding average values for RCM and observed variables, respectively.

Table 2 | Selected bias correction methods to be evaluated for precipitation and temperature series

Bias correction methods for precipitation	Bias correction methods for temperature
Power transformation function	Variance scaling
Linear scaling	Linear scaling
Daily translation	Daily translation

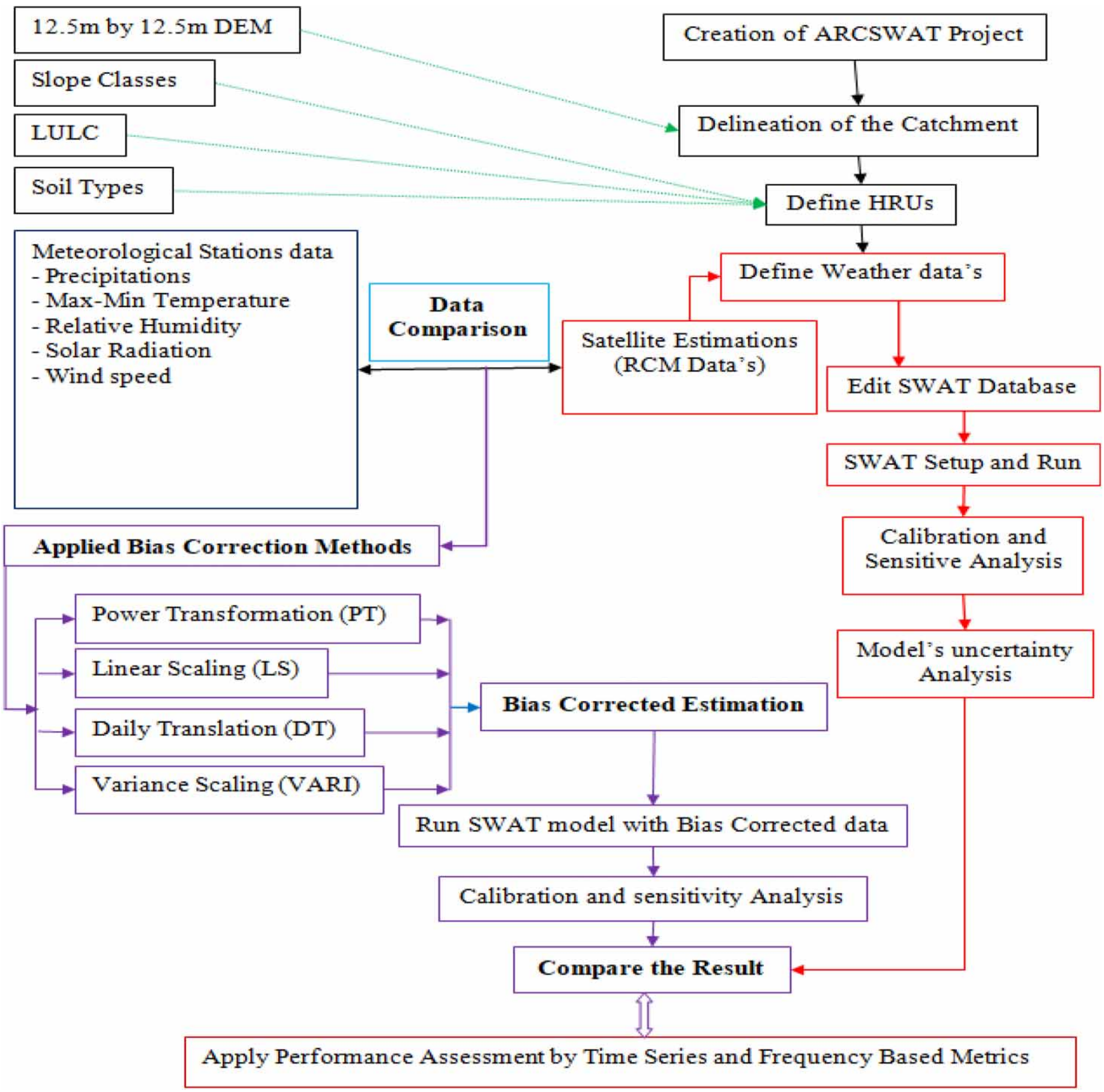


Figure 4 | Flow chart of the methodology.

3. RESULTS AND DISCUSSION

3.1. Performance of RCM models' outputs in reproducing discharges

Most of the time, climate variables modeled from different RCMs do not match with the recorded one because of significant bias during simulation of precipitation or temperature. In this case, evaluation of original RCM data in simulating discharge from precipitation and temperature data series was directly applied to the SWAT model and clearly shows great deviation from June to December when compared to observed discharge, as indicated in Figure 5. In a different study with a similar concept, it was stated that if biased RCM output in modeling discharge is considered small enough to be adjusted through calibration, it is not necessary to apply bias correction (Velasquez *et al.* 2020). However, since the deviation between RCM output and observed discharge had significant bias, the application of bias correction was necessary but intolerable as it aimed to mislead the result. Therefore, the next step to improve the bias of RCM models was to consider the reference,

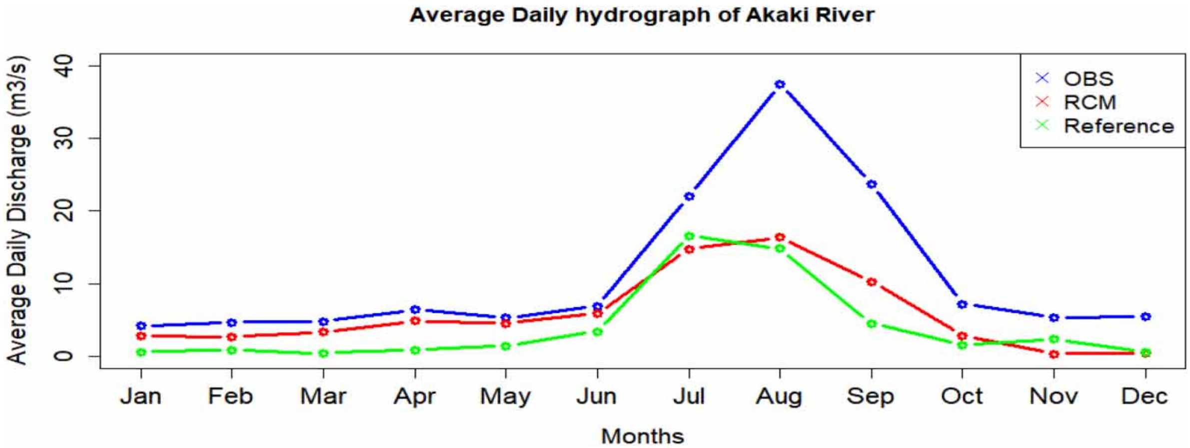


Figure 5 | Daily hydrograph of Akaki River comparing observed, simulated and refence discharge.

simulated and observed discharge with necessary and appropriate bias correction methods depending on their capacity for removing bias. As seen from the developed daily hydrograph in Figure 5, the simulated discharge along with the observed precipitation and temperature was highly biased and underestimated by RCM models' output.

3.2. Validation of original precipitation and temperature of RCM

Assessment mainly focused on the performance of original precipitation and temperature in simulating average discharge from simulated model output which proved that the original RCM output is not advisable to use directly by hydrological models. The study conducted related to precipitation bias correction in Britain also concluded that using original simulated RCM model output directly in modeling discharge was not advisable as it misled the final result from hydrological models' output (Lafon *et al.* 2013). This study also reveals that different bias correction methods correct originally simulated RCM output at different levels of certainty in different climate regions. Accordingly, as seen from Figure 6(a) on the basis of exceedance probability, original RCM output underestimated precipitation compared to others. At the same time, the corrected average precipitation by daily translation method was overestimated with a maximum probability of 0.3 in January to May and underestimated with a probability range between 0.32 and 0.9 during the summer season (June, July, and August). In addition, power transformation function and linear scaling methods overestimated the average precipitation in the summer season (June, July, and August) and almost corrected exactly in the other months in comparison to the observed precipitation. Hence, linear scaling and power transformation function were best performed in bias correction of precipitation at Addis Ababa station.

The simulated precipitations by RCM at Sebeta meteorological station indicate that the model simulates precipitation below the observed and bias corrected in all aspects. This simply indicates that the simulated precipitation by the RCM model used in this study was highly biased and is not advisable to be directly used by hydrological models. Meanwhile, power transformation, daily translation, and linear scaling methods overestimated corrected precipitation with maximum probability of 0.35 from April to May and underestimated it at the beginning of January but discontinued and began new underestimation from May to June. This variation of underestimation or overestimation according to season fundamentally happened from the model capacity during simulation and was corrected by bias correction methods to the required level of removing bias. Hence, power transformation and linear scaling methods were recognized as the best performing methods. The RCM – model outputs for temperature obtained at the Boneya and Bulbula stations were more accurate than other stations as RCM – was overestimated at the two stations compared to others in almost all months except July and November. The probability distribution of maximum temperature of RCM models at Addis Ababa and Sebeta stations was overestimated as seen from Figure 6(e) when compared to observed temperature.

However, linear scaling and daily translation methods corrected the bias of simulated temperature very well, and variance scaling methods also adjusted the bias even though underestimation and overestimation was seen along the observed data. The RCM model overestimated the maximum temperature with probabilities above 0.92. At the same time, underestimation with average exceedance probability of 0.2 by variance scaling method was also verified. However, the exceedance

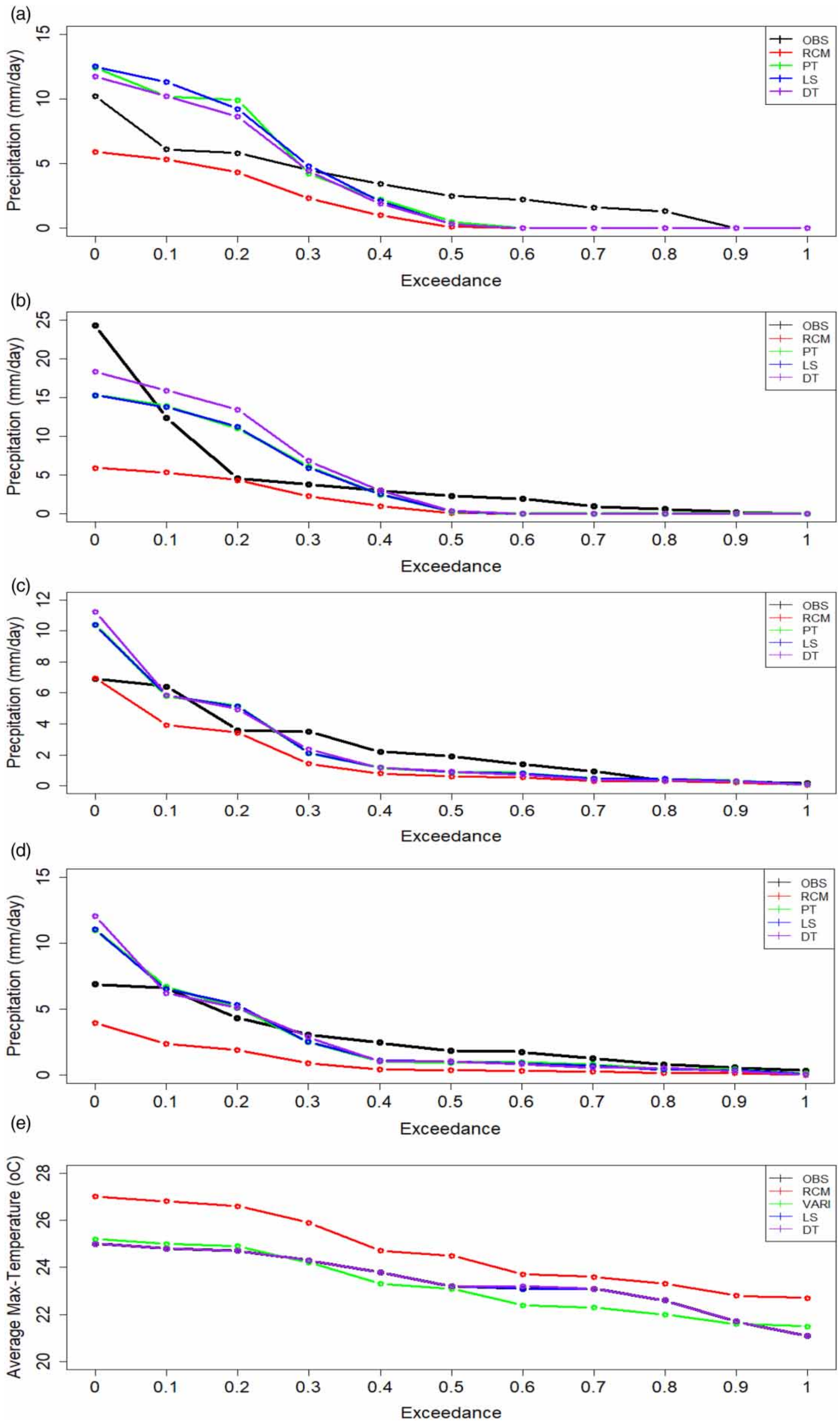


Figure 6 | Exceedance probabilities for (a) Addis Ababa, (b) Boneya, (c) Bulbula, (d) Sebeta stations with the observed, RCM, and bias-corrected precipitation and (e) for temperature at Akaki River basin.

probability of maximum temperature in overestimation or underestimation by linear scaling and daily translation methods was very rare and corrected to the maximum level of its requirement. Hence, daily translation and linear scaling performed very well in correcting bias of the RCM models.

3.3. Validation of corrected precipitation with frequency and time series-based metrics

The clear importance of bias correction methods should be to compare and evaluate to achieve the reliability of input data for hydrological models based on time series and frequency-based metrics. These two statistical methods that were used to verify the capability of bias correction methods used the final SWAT model output to analyze their performance in removing bias from the RCM models. Accordingly, all bias correction methods used in this study performed highly in adjusting mean values and coefficient of variation of climate variables on the daily basis. However, linear scaling methods cannot analyze extreme events due to their unique scaling character in heavy rainfall seasons as a result of their underestimations compared to the observed data. A similar result was arrived at by Piani *et al.* 2010. As seen from Table 3, monthly mean and standard deviation were corrected relative to observed climate variables by all methods, while coefficient of variation was adjusted relative to the RCM (simulated) climate variables. However, power transformation and linear scaling methods were adjusted exactly on the monthly average of precipitation at all stations. This clearly indicates that power transformation and linear scaling methods performed very well in terms of frequency-based metrics (mean) but only slightly in adjusting standard deviation as they overestimated at Addis Ababa station. While evaluating these bias correction methods for precipitation in terms of coefficient of variation, all methods were adjusted to RCM. Hence, when comparing the corrected precipitation adjusted by those methods based on frequency-based metrics, all bias correction methods performed best by adjusting daily precipitation than monthly. These facts demonstrate that bias correction methods were watershed- and season-dependent as they were directly involved with regional watershed characteristics and hydrological processes. Therefore, power transformation function performed best according to the result obtained from the analysis using frequency-based metrics. Generally, this result shows that daily translation and linear scaling methods performed less well in adjusting STD and CV of monthly values than daily at all stations. However, the power transformation method consistently and uniquely adjusted mean and standard deviation correctly in comparison with observed precipitation data at all stations. Hence, this method was very suitable for removing bias from GCM/RCM at this sub-basin.

On the other hand, time series-based metrics are the most imperative statistical method for the evaluation of bias correction methods. Depending on these statistical metrics, different bias correction corrects or adjusts the bias of RCM along with the observed one to different levels of capability. As stated in Table 4, the performance of RCM in simulating precipitation was very poor and needed to be adjusted to use as raw input data for hydrological models' simulation. According to these time series-based metrics, MAE of 2.82 mm, NSE of -1.12, PBIAS of 26.4%, and R^2 of 0.51 at Addis Ababa station shows the simulated precipitation by RCM model is very biased. The daily translation method still underestimates the corrected precipitation

Table 3 | Frequency-based metrics of evaluation of the performance of bias correction methods for original and corrected precipitation

Parameters	Catchment	Frequency indices	OBS	RCM	PT	LS	DT
PRECIP	Addis Ababa	Std	312.13	162.3	336.7	343.6	332.4
		Mean	185.14	87.46	185.1	185.2	183.07
		CV	1.69	1.86	1.82	1.86	1.82
	Boneya	Std	232.26	162.3	243	242.3	245.7
		Mean	130.55	87.47	130.6	130.6	130.5
		CV	1.78	1.86	1.86	1.86	1.88
	Bulbula	Std	243.99	99.06	275.3	275.3	259.3
		Mean	141.93	91.07	141.9	141.9	139.3
		CV	1.72	1.94	1.94	1.94	1.86
	Sebeta	Std	477.63	162.3	420.1	418.8	501.7
		Mean	225.68	87.47	225.7	225.7	223.9
		CV	2.12	1.86	1.86	1.86	2.24

Table 4 | Time series-based evaluation of the performance of bias correction methods for original and corrected precipitation at four stations

Parameters	Stations	Methods	MAE (mm)	PBIAS (%)	NSE (–)	R^2 (–)
Precipitation	Addis Ababa	RCM	2.82	26.4	−1.12	0.51
		PT	1.74	0.53	0.76	0.93
		LS	1.04	0.58	1.7	0.65
		DT	1.74	0.53	−2.2	0.58
	Boneya	RCM	1.37	15.02	−0.67	0.58
		PT	0.34	0.45	0.72	0.92
		LS	0.45	0.62	1.69	0.79
		DT	0.12	0.32	−1.3	0.52
	Bulbula	RCM	1.79	8.03	−1.36	0.49
		PT	0.42	0.51	0.67	0.90
		LS	2.53	0.42	0.64	0.84
		DT	0.31	1.02	−6.2	0.45
	Sebeta	RCM	1.41	10.2	−2.31	0.40
		PT	0.52	0.68	0.72	0.90
		LS	0.44	0.07	0.83	0.86
		DT	0.26	2.3	−1.32	0.55

when considering the average of all stations, with PBIAS, R^2, and MAE, respectively, rising to 23.16%, 0.58, and 0.60 mm. In general, the optimum values of times series-based metrics recommended for precipitation correction with MAE, PBIAS, NSE, and R^2 ranged between 0.12 mm/2.53 mm, 1.02%/0.68%, 2.31/6.2, and 0.45/0.93, respectively. Depending on these time series-based metrics, the performance of power transformation and linear scaling methods in correcting precipitation is much better than frequency-based metrics. While it is important to prioritize these methods based on both frequency-based and time series-based metrics, power transformation and linear scaling methods perform very well in both time series- and frequency-based metrics. Furthermore, in this study, which mainly concentrated on Akaki sub-basin, power transformation function is the best performing method in removing the RCM/GCM bias compared to the other methods.

3.4. Validation of corrected temperatures by frequency- and time series-based metrics

In the case of temperature bias correction, the linear scaling and variance scaling (VARI) methods demonstrate good performance. This clearly means that both methods were capable of correcting bias of RCM models for temperature when compared with observed data in terms of frequency-based and time series-based metrics. On the other hand, the daily translation method mostly underestimates and slightly overestimates temperature correction at almost all stations relatively. This is because, most probably, the time structure problem does not exist in temperature series. A study by Gumindoga *et al.* (2019) arrived at the same conclusion. When these two-pillar meteorological data were used in simulation of discharge by a hydrological model like SWAT, in this case the result was very good compared to when it was forced by RCM outputs except the daily translation method which performed poorly in removing bias from RCM models. As the analysis was applied to each method in terms of exceedance probability, frequency-based and time series-based metrics to predict the bias correction method's capability in simulating discharges, the result obtained by the daily translation method differed greatly between the simulated and observed discharge which showed the poor performance of this method.

On the same subject matter, Chen *et al.* (2013) arrived at a similar conclusion in which the daily translation method even underestimated compared with the discharge driven by RCM output. Hence, the daily translation method failed to show the expected performance in discharge modeling from corrected RCM precipitation and temperature. According to this analysis, corrected temperature by linear scaling and, especially by VARI methods, was acceptable for hydrological modeling because of their high capability in removing large biases from RCM models. Indeed, temperature exhibits a slightly worse performance than precipitation at the Addis Ababa station, which seriously overestimated when compared to the observed one, with an MAE of 2.57 °C and PBIAS of 42.3% (Table 5). According to the result obtained during calibration, all temperature bias

Table 5 | Prioritization of bias correction methods based on time series for original and corrected temperature on daily average scale at four stations

Parameters	Stations	Methods	MAE (mm)	PBIAS (%)	NSE (–)	R^2 (–)
Temperature	Addis Ababa	RCM	2.57	42.3	5.32	0.43
		VARI	1.3	−0.05	−0.74	0.79
		LS	1.01	−0.1	0.3	0.68
		DT	1.27	−0.05	−0.14	0.54
	Boneya	RCM	3.03	37.21	7.13	0.4
		VARI	2.4	−0.02	−1	0.43
		LS	1.08	0	0.04	0.82
		DT	0.85	0.49	−0.1	0.50
	Bulbula	RCM	1.23	−3.12	−4.62	0.42
		VARI	0.67	0.01	−0.28	0.75
		LS	0.42	−0.13	−0.02	0.69
		DT	0.26	−0.34	−0.18	0.52
	Sebeta	RCM	3.62	29.16	6.39	0.38
		VARI	1.02	0.08	1.75	0.78
		LS	0.38	−0.06	−0.25	0.71
		DT	1.02	−0.29	0.42	0.51

correction methods improve the performance of RCM-simulated temperature as PBIAS shows low underestimation and low overestimation to an acceptable value. The PBIAS was close to zero and the performance of these methods was good. Generally, the performance of the variance scaling method was much better at adjusting both frequency- and time series-based metrics in removing bias of temperature variable from RCM models.

In the same way, variance scaling and linear scaling methods were evaluated as the best temperature correction methods by frequency-based metrics. Especially when mean and coefficient of variation among those correction methods was considered, these two methods were ranked as the best performing. However, these methods overestimated standard deviation, not a great deal but to some extent at all stations, except for being exactly adjusted at Addis Ababa station by linear scaling. On the other hand, the daily translation method overestimates all frequency-based metrics (mean, STD, and CV) when compared to that of the observed one. This result clearly shows that daily translation performed less in adjusting mean, STD, and CV at all stations and was not suitable to remove bias for this river basin. Hence, variance scaling and linear scaling methods were ranked as the best performing temperature bias correction methods by frequency indices.

3.5. The performance of bias correction methods in simulating streamflow

In generating streamflow discharge through simulation, precipitation and maximum temperature large bias correction methods have been used in much research to remove bias from climate models. These methods were graded according to the capability of reducing bias from RCM in world climate regions with different characteristics and climate conditions. Depending on the regional climate scenario, bias correction methods most of the time assessed, prioritized, and evaluated through their performance to predict and generate discharge, precipitation and temperature variables by eventually minimizing bias under frequency- and times series-based metrics.

Based on the output of statistical methods, the discharges were simulated from the combined precipitation and temperature data forcibly applied to a SWAT model to evaluate the variation of results before and after the bias correction had been made and to suggest the consequences for water resource policymakers. These corrected precipitation and temperature data with linear scaling and daily translation methods for the simulation of discharge were significantly different to the reference. However, they are much better than the original RCM model that was too biased and underestimated the discharge. The simulated discharge driven by corrected discharge with power transformation for precipitation and variance scaling for temperature performed best. Furthermore, both climate variables corrected by linear scaling method apparently simulated the discharge much better than daily translation and the original RCM. Generally, power transformation and variance scaling methods for precipitation and temperature, respectively, were the best performing methods in removing bias from RCM/GCM of Akaki River basin meteorological data stations. Using the SWAT model output, the calibration and validation was done, which is to overcome any uncertainty remaining in bias correction on monthly time steps using the average measured streamflow, simulated before bias and after the application of bias correction.

Accordingly, these time series performed much better with monthly time series compared to the daily times series. As concluded from the result of calibrated discharge (Figure 7(a)) with uncorrected precipitation and temperature it possesses poor performance with RCM/RCA4 data of $R^2 = 0.53$, $NSE = 0.1$, $PBIAS = 0.51$, and $MAE = 5.91$ which was less than the minimum requirement. On the other hand, precipitation and temperature data corrected by daily translation method to simulate discharge was slightly better than RCM/RCA4, but not an acceptable result as $R^2 = 052 < 0.6$, $NSE = -3.62$, $PBIAS = 1.05$, $MAE = 4.08$ did not fit with the observed data. However, power transformation with the variance and linear scaling methods has the best performance in simulating discharge by removing an expected uncertainty from input data to the models. The time series metrics values of $R^2 = 0.87$, $NSE = 0.78$, $PBIAS = 0.24$, and $MAE = 3.17$ (Figure 7(c)) indicate that the linear scaling method is very good at removing bias from RCM models to reduce the misleading result. Furthermore, power

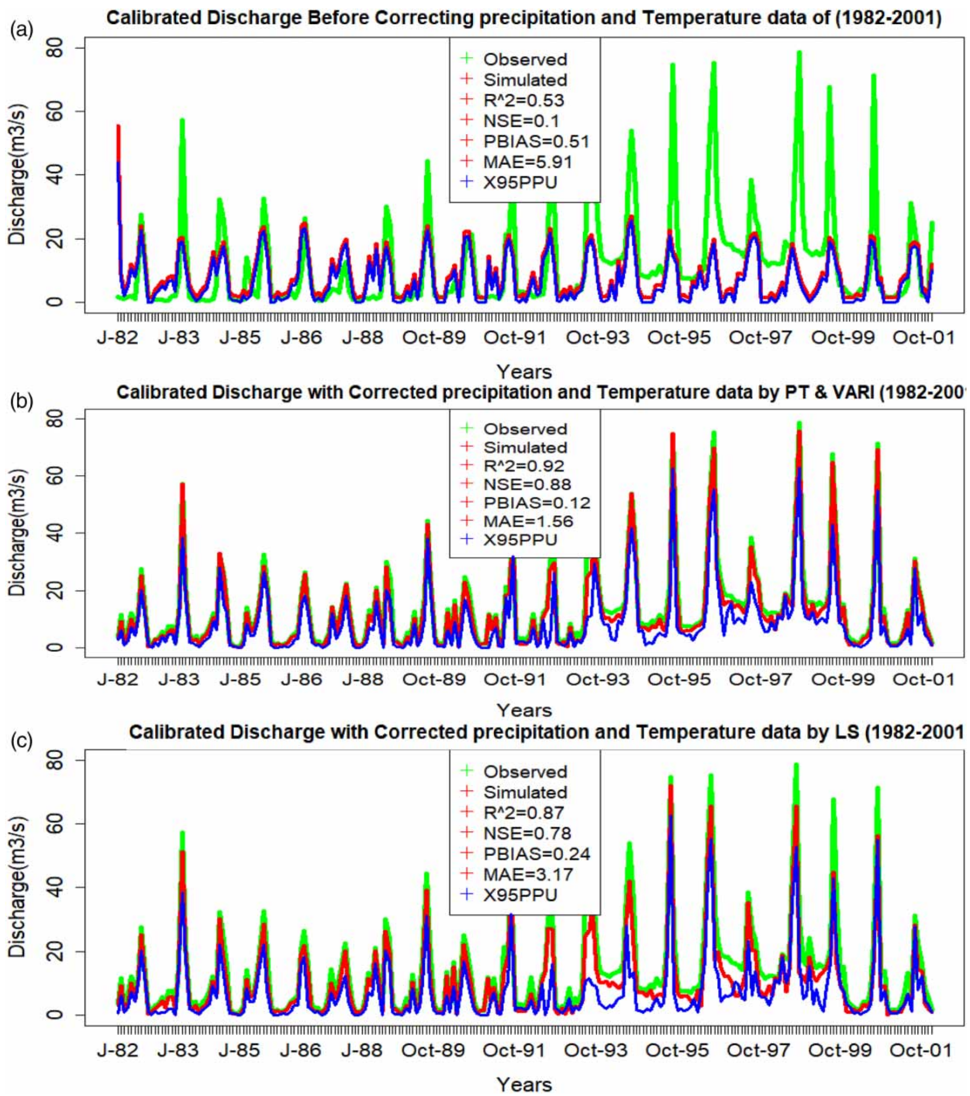


Figure 7 | The calibrated discharge with (a) original RCM, (b) after bias being removed by power transformation and variance scaling, (c) by linear scaling method.

transformation with variance scaling method was the best performing method in removing bias from RCM/RCA4 according to the result obtained during calibration and validation for streamflow.

Moreover, the time series-based metrics value provided here provided evidence for the performance of this method during calibration (Figure 7(b)) with $R^2 = 0.92$, NSE = 0.88, PBIAS = 0.12, and MAE = 1.56 and validation (Figure 8) $R^2 = 0.95$, NSE = 0.9, PBIAS = 0.09, and MAE = 0.9. In general, bias correction methods should be applied consciously with great care in order not to mislead the expected result when hydrological models are used. Even though it should be recognized that a good temporal structure of the original RCM simulations provides considerable assurance in model output, great care is needed in order not to be exposed to a misleading result for policymakers in mitigating climate change.

3.6. Performance of bias correction methods through developing spatial map

Spatial map is the most important way to identify deviation between the observed and simulated precipitation and temperature through developing a spatiotemporal map based on annual or monthly average rainfall and maximum–minimum temperature of the watershed. It is one of the most deterministic models in spatial interpolation which is relatively fast and easy to compute, and straightforward to interpret. Hence, the time series-based values indicated show that RCM performance in representing the sampled location from the neighboring station through simulation was poor. Other bias correction methods show relatively good performance in simulating and removing bias from RCM/GCM models (Table 6).

By applying six bias correction methods on rainfall and temperature spatial map analysis, power transformation with variance and linear scaling methods perform relatively better in removing uncertainty from models. This clearly shows that the simulated area with a limited range of precipitation and temperature values on the map corrected and represented by linear scaling was slightly underestimated. But the corrected value from power transformation and variance scaling function was better as the evidence of time series-based metrics ($R^2 = 0.68$, NSE = 1, PBIAS = 0, MAE = 0) and temperature ($R^2 = 0.72$, NSE = 0.8, PBIAS = −0.02, MAE = 0.08) gives good results.

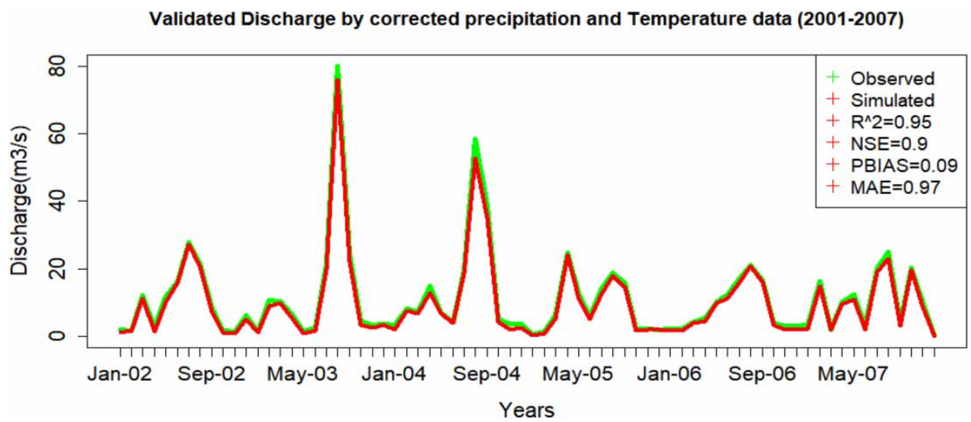


Figure 8 | Validated discharge after bias correction made for temporal precipitation and temperature under power transformation and variance scaling methods.

Table 6 | Performance of bias correction methods by developing spatial map from corrected and original RCM based on annual average precipitation and temperature

Statistical parameter	For precipitation (mm)				For temperature (°C)			
Time series metrics	Bias correction methods				Bias correction methods			
Series	RC	PT	LS	DT	RCM	VARI	LS	DT
R^2	0	0.68	0.57	0.40	0	0.72	0.64	0.52
NSE	−5.4	1	−1.62	0.748	0.36	0.8	0.37	−1.17
PBIAS	0.5	0	−0.11	0.096	−0.01	−0.02	0.01	0.02
MAE	80.5	0	35.69	14.243	0.21	0.08	0.20	0.06

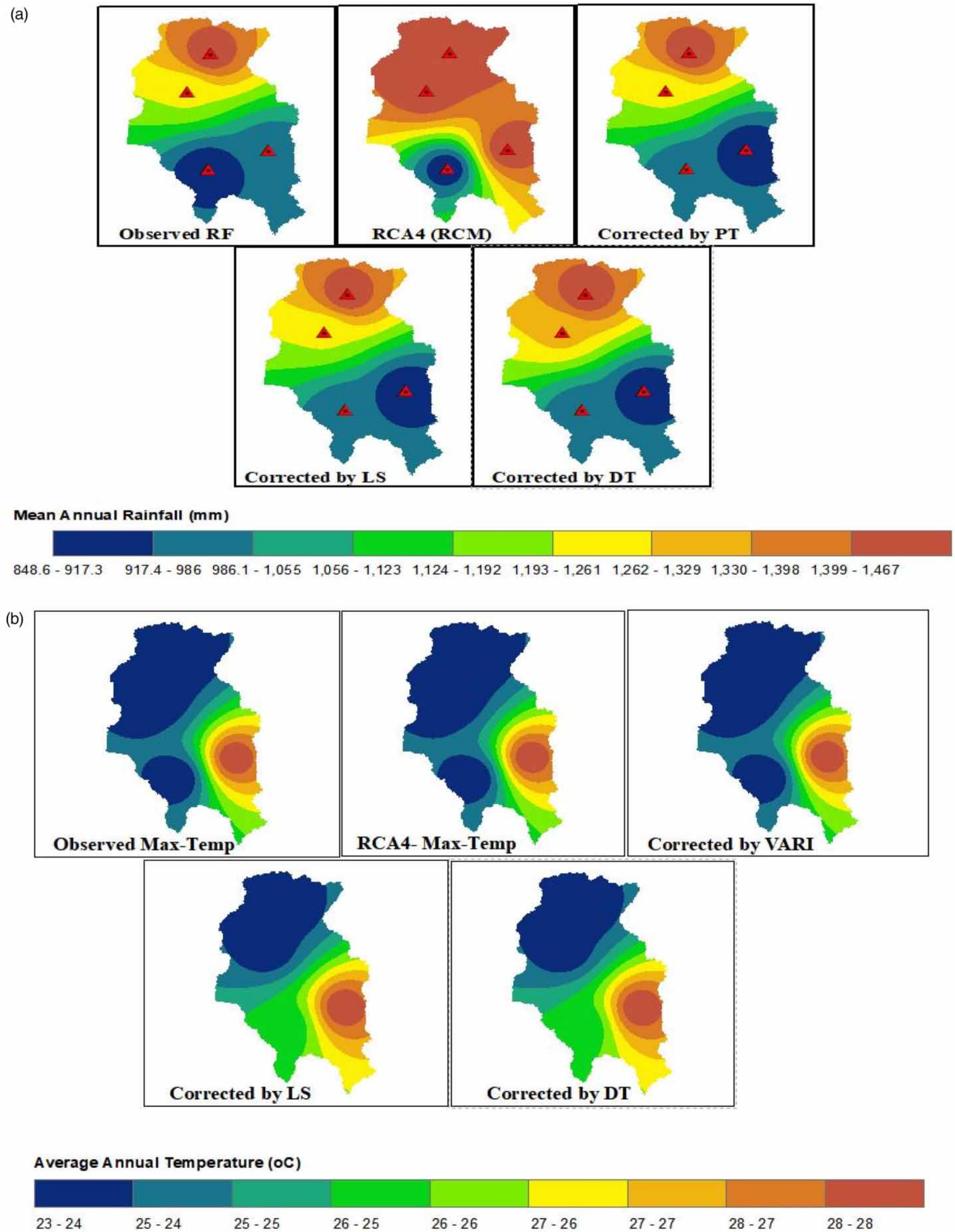


Figure 9 | Spatial map developed from (a) average precipitation and (b) temperature for Addis Ababa, Bulbula, Boneya, and Sebeta meteorological stations.

However, when the values of these time series calculated from the spatial map are compared to others like calibrated and validated values, they are slightly underestimated due to the spatial map being developed from annual average precipitation and temperatures entities (Figure 9). Furthermore, the variation clearly shows that the performance of bias correction methods mainly depends on seasonal values of meteorological parameters rather than corresponding average values. This means bias correction methods performed slightly better when monthly metrological data were used as opposed to daily, when times series metrics are used to evaluate their performance. Meanwhile, when daily metrological data were used, the bias correction methods performed very well when frequency-based metrics were used to evaluate them.

4. CONCLUSION

In this paper, six bias correction methods, three precipitations and three temperatures, were compared and evaluated by frequency-based and time series-based metrics considering their capability of removing bias from climate models for hydrological processes and simulations. In generating streamflow discharge through simulation, precipitation and maximum temperature, large bias correction methods were used in much research to remove bias from climate models. These methods were ranked according to the capability of reducing bias from RCM in world climate regions of different characteristics and climate conditions.

The SWAT model was used to identify the performances of bias correction methods by using original and corrected RCM data as raw inputs. The output of this hydrological method was analyzed by statistical methods along with recorded streamflow and realized the existence of significant bias. This bias is fundamentally merged from regional climate models during simulating precipitation and temperature over the river basin. Referring to this evidence, bias correction methods are very important for fixing the deviation between simulated and observed climate variables in order not to mislead the hydrological model outputs for policymakers to better mitigate climate change consequences. Therefore, this study concludes power transformation and variance scaling method are the most suitable bias correction methods for precipitation and temperature at upper Awash basin, respectively.

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DECLARATION OF COMPETING INTEREST

The author declares no conflicts of interest at all.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information. All necessary data were incorporated and included in the paper.

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