Statistical Downscaling and Projection of Future Temperature Change for Tabriz City, Iran

Aida Hosseini Baghanam, Vahid Nourani, Ali Sheikhbabaei and Arshia Jedary Seifi

November 8, 2019

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Aida Hosseini Baghanam[1], Vahid Nourani[2], Ali Sheikhbabaei[3], Arshia Jedary Seifi[3]
[1] Assistant Prof. Dept. of Water Resources Eng., Faculty of Civil Eng., Univ. of Tabriz, Iran
[2] Prof. Dept. of Water Resources Eng., Faculty of Civil Eng., Univ. of Tabriz, Iran; Faculty of Civil and Environmental Eng., Near East University, Lefkosa, TRNC, Cyprus
[3] M.Sc. Dept. of Water Resources Eng., Faculty of Civil Eng., Univ. of Tabriz, Iran
Email: hosseinibaghanam@gmail.com

ABSTRACT

In the 21st century, Climate change has become one of the prominent global challenges which threats the world, and the changes in climate extremes are estimated to have catastrophic consequences on human society and the natural environment. To overcome the spatial-temporal inadequacy of the GCMs, Linking large-scale General Circulation Model (GCM) data with small-scale local climatic data highly comes to the fore. In this paper, two statistical downscaling techniques encompass LARS-WG and SDSM were employed for assessing the fluctuations of temperature predictand in Tabriz city, Iran. In order to choose the well-response GCMs a Multi-GCM ensemble approach was utilized by EC-EARTH, HadCM2, MIROC5, MPI-ESM GCMs from the CMIP5. To study the impact of climate change over the region, the periods of 1961-1990 and 1991-2005 were used as the baseline and validation period, respectively. Results of evaluation criteria disclosed the superior performance of Multi-GCM ensemble for predicting temperature predictand compared to single GCM models. Furthermore, the result of climate projection for the temperature predictand by both models revealed that the city will experience an increasing trend in temperatures for the horizon of 2021-2080. The average temperature will increase by 2.9 and 3.7 (°C) under Representative Concentration Pathways (RCPs) (i.e., RCP4.5 and 8.5), respectively.

Keywords: *Climate change, General Circulation Models, Statistical downscaling, Tabriz city temperature*

1. INTRODUCTION

Regarding the spatiotemporal inadequacy of General Circulation Models (GCMs), Connecting large-scale GCM data with small-scale local climatic data is of great importance. To overcome this issue, various downscaling approaches are being applied to increase the accuracy of the GCM-based impact models. Indeed downscaling is an approach to derive high-resolution data from low-resolution GCMs and classified into two primary categories, i.e., dynamical and statistical (Hassanzadeh et al. 2014).

Dynamical downscaling is a technique to derive smaller-scale climatic data over a bounded area which are nested within the coarser scale climatic information via a high-resolution regional climate model (RCM) driven by boundary conditions from GCMs, whereas statistical downscaling involves empirical links between coarse-scale predictors and local climate data predictand (Wilby and Wigley 1997). Statistical downscaling approaches are divided into the following subcategories; weather generators, e.g., Long Ashton Research Station-Weather Generator (LARS-WG) (Racsko et al. 1991); linear regression models, e.g., statistical downscaling model (SDSM) (Wilby et al. 2002); nonlinear regression models, e.g., artificial neural network (ANN) (Zorita and Von Storch 1999), support vector machine (SVM) (Tripathi et al. 2006), relevance vector machines (RVM) (Ghosh & Mujumdar 2008) and gene expression programming (GEP) (Sachindra & Perera 2016).

In order to investigate downscaling methods precisely, Trzaska & Schnarr (2014) represented a thorough review of downscaling methods for climate change projections. LARS-WG and SDSM are widely used for climate projections, Khan et al. (2006) analyzed the uncertainties retrieved from various downscaling models (i.e., LARS-WG, SDSM, and ANN) over a region in Canada. The results revealed the superiority of SDSM model for predicting minimum and maximum temperature, precipitation (i.e., predictands). King et al. (2012) employed two statistical downscaling schemes (i.e., LARS-WG and SDSM) on the projection of future climate over the Thames River which resulted in preference of SDSM to LARS-WG for Minimum and maximum temperatures while for forecasting precipitation LARS-WG represented a superiority performance. Hassan et al. (2014) examined the application of SDSM and LARS-WG in order to forecast temperature and precipitation in Peninsular Malaysia. The results showed SDSM has a better performance compared to LARS-WG. Despite the time series simulated by both tools, the trend of daily temperature was increasing. Meanwhile, SDSM represented a relatively higher fluctuation of annual precipitation compared to LARS-WG. Vallam and Qin (2017) employed three statistical downscaling approaches (i.e., LARS-WG, Bias Corrected Disaggregation (BCD) and SDSM) to predict temperature and precipitation predictands in diverse study areas. As a result, the divergence between the predictions of various models derived from the regions experiencing severe precipitation intensities. Mekonnen and Disse (2018) used two statistical downscaling methods (i.e., LARS-WG and SDSM) in order to downscale future climate scenarios of the Upper Blue Nile River basin. The used a multimodal average of LARS-WG and individual model results from SDSM which let to preference of LARS-WG to SDSM. Baghanam et al. (2019) demonstrated that the application of ANN tool in downscaling without pre-processing of data is the principle reason for the drawback of such a data-based model. In this way, they developed an ANN-based statistical downscaling model using wavelet entropy and clustering methods to pre-process GCM data. Unlike the study of Khan et al. (2006), they concluded that the performance of the nonlinear ANN model with pre-processing is better than the multi-linear one.

Given the contrary outputs of over-mentioned studies on the performance of various downscaling methods in diverse study areas, regarding the high environmental sensitivity of the city, projection of future climate by different downscaling methods highly comes to the fore. The following study sought to investigate whether the various downscaling schemes with multi GCM ensemble models reflect contradictory outcomes in climate projection over the study area or not.

2. MATERIAL AND METHODS

2.1 Case study and data set

The present study encompasses a mountainous region in the northwest of Iran, Tabriz metropolis is the capital city of East Azerbaijan province and is located in the valley of a seasonal river. The study area is situated at 38 ˚08′N latitude and 46˚ 29′ E longitude (Figure 1). The city lies on the Tabriz plain with a mild slope and at 60 km west ends on the east bank of the Urmia Lake (Hassanzadeh et al. 2012). The altitude of the city ranges from 1,350 to 1,600 meters above sea level. The annual mean temperature and precipitation are 12.2°C and 280 mm, respectively. Also, the Climate of the region is changed from semi-arid to arid based on the De Martonne aridity index (Zarghami et al. 2011). Overall, the city's weather is mild and fine in spring, dry and semi-hot in summer, humid and rainy during fall, and cold with snowfall in winter. During the last decades drying of the lake became the prominent environmental crisis in which the ecosystem of the region threatens.

Nevertheless, The synoptic station of Tabriz city was chosen to reflect the spatial variability of the climate. For the downscaling purpose, Large-scale GCM models were used (i.e., EC-EARTH, HadCM2, MIROC5, MPI-ESM) from the 5th Coupled Model Intercomparison Project (CMIP5) under RCP4.5 and 8.5 scenarios. Table 1.

In order to validate GCM-based downscaling, daily reanalysis datasets of the National Center for Environmental Prediction (NCEP) with the resolution of $2.5° \times 2.5°$ were extracted to calibrate downscaling models. The periods of 1961-2005 and 2041-2060 was utilized as the baseline and simulation period, respectively.

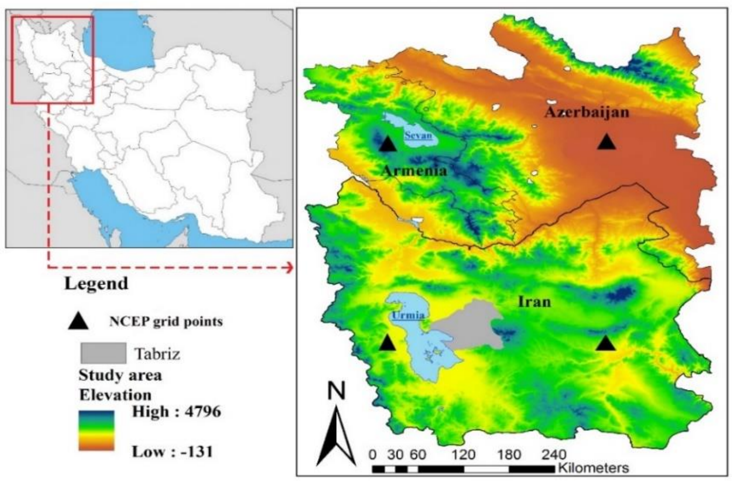

Figure 1. Topography of the study area and its position on Iran's map.

Table 1. Climate stations and GCM grid point information.

No	Global Climate Model	Centre	Centre acronym	Country	Grid size (approximately)
1	EC-EARTH	Numerical weather prediction	ESM	Europe	1.1° x 1.1°
2	HadGEM2	UK Met. Office	UKMO	UK	1.4° x 1.9°
3	MIROC5	Met Research Institute, Japan	NIES	Japan	1.2° x 2.5°
4	MPI-ESM	Max-Planck Met Institute	MPI-M	Germany	1.9° x 1.9°

2.2 proposed methodology

For the purpose of downscaling, two statistical downscaling methods (i.e., LARS-WG, SDSM) were applied by considering predictands comprises minimum and maximum temperature over a semi-cold region in the northwest of Iran.

Firstly, the daily data of stations were quality controlled. Minimum and maximum daily temperatures were considered as stochastic processes with daily mean and standard deviation through the process of downscaling by downscaling models. Seasonal averages were modeled by the finite series 3-order Fourier series and the residuals of the model were approximated by the normal distribution. The periods of 1961-1990 and 1991-2005 were considered as the baseline and validation periods for downscaling by LARS-WG, respectively. Afterward, SDSM as the second downscaling approach which required a proper selection of predictors established a relationship between predictors and predictand based on partial correlation coefficients. Since the involvement of potential GCMs simultaneously in downscaling models could help to extract hidden information in each GCM, the ensemble approach can positively impact the results. Important predictor selection among GCMs was implemented in LARS-WG and SDSM models. It should be noted that in order to ensemble GCMs the average values of each predictor from four GCMs were calculated and used in downscaling models. Also, throughout the process of calibration in SDSM, parameters such an event threshold, corrected skew and variance inflation utilized to determine the best statistical fit between observed and simulated climate variables.

2.2.1 Lars-WG

The Long Ashton Research Station Weather Generator (LARS-WG) is a stochastic weather generator that produces synthetic daily time series of climate variables to derive finer-resolution spatial climate data from coarser-resolution GCM output, drawing on observed climatic data in the baseline period and climate change pattern (Semenov & Barrow 1997).

2.2.2 SDSM

The Statistical Downscaling Model (SDSM) is a hybrid model based on multiple linear regression (MLR) and the stochastic weather generator (SWG), (Harpham & Wilby 2005). MLR represents statistical-empirical relevancy between NCEP large-scale climate variables (predictors) and local scale weather data (predictand) along the process of screening predictors and the calibration of SDSM which results in producing several regression parameters.

2.3 Evaluation criteria

Due to examining the efficiency of the proposed downscaling techniques, two evaluation criteria containing Correlation coefficient (CC), and root mean square error (RMSE), was employed. CC (as Eq. 1) as the most commonly used method to calculate the relevancy between calibrated and observed data ranging between -1 to +1, the greater CC represents to the better coefficient, while zero states no association between the two variables.

$$\mathrm{CC} = \frac{\mathrm{N}(\sum \mathrm{OC}) - (\sum \mathrm{O})(\sum \mathrm{C})}{\sqrt{[\mathrm{N}\sum \mathrm{O}^2 - (\sum \mathrm{O})^2]\,[\mathrm{N}\sum \mathrm{C}^2 - (\sum \mathrm{O})^2]}} \quad (1)$$

RMSE as a measure to assesses the accuracy of downscaling models in predicting temperature (see Eq. 2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(R_i - Z_i)^2}{N}} \tag{2}$$

3. RESULTS AND DISCUSSION

The purpose of this study is to predict the performance of two statistical downscaling techniques (i.e., LARS-WG, SDSM) in downscaling predictands including minimum and maximum temperatures over a semi-cold region in northwestern Iran. Four GCMs (i.e., EC-EARTH, HadCM2, MIROC, MPI-ESM) separately and with multi-GCM ensemble approach were assigned to choose the dominant predictors. In this regard, important climate variables of all the GCMs were identified.

To enjoy effective characteristics of each GCM in future temperature simulation, an ensemble of four GCMs (i.e., EC-EARTH, HadCM2, MIROC5, MPI-ESM GCMs) is utilized in the proposed downscaling. Since various GCMs are developed according to different structures, climate downscaling and projection using different GCMs can lead to diverse results. Application of a multi-GCM approach can lead to efficient results since there is the opportunity to select dominant variables among various GCMs with different structural inherence than being forced to select from one specific GCM. In this way, two downscaling models were performed by using ensemble of GCMs and reanalysis data (i.e., NCEP). Outcomes of temperature downscaling at Tabriz station based on LARS-WG and SDSM models for single and multi-GCM approaches shown in Table 2.

Table 2. Downscaling results at Tabriz station based on LARS-WG and SDSM models for single- and multi-GCM approaches

Downscaling models	**GCM Models**	**Evaluation Criteria**	
		CC	N[1] .RMSE
LARS-WG	EC-EARTH	0.41	0.80
	HADGEM2	0.28	0.90
	MIROC5	0.67	0.71
	MPI-ESM	0.55	0.73
	Ensembles of GCMs	0.73	0.65
SDSM	Ensembles of GCMs	0.71	0.69

[1] N-RMSE denotes normalized RMSE values.

According to the results of evaluation criteria, multi-GCM ensembles revealed a superior performance compared to single GCMs. To have a visual vision toward the performance of applied GCMs for temperature predictand, mean annual temperature of the observed and calibrated temperature for the single and ensemble multi-GCMs approach shown in Figure 2. Also the distribution of mean annual temperature Boxplot of the Observed, Calibrated and Simulated Temperature shown in Fig 3.

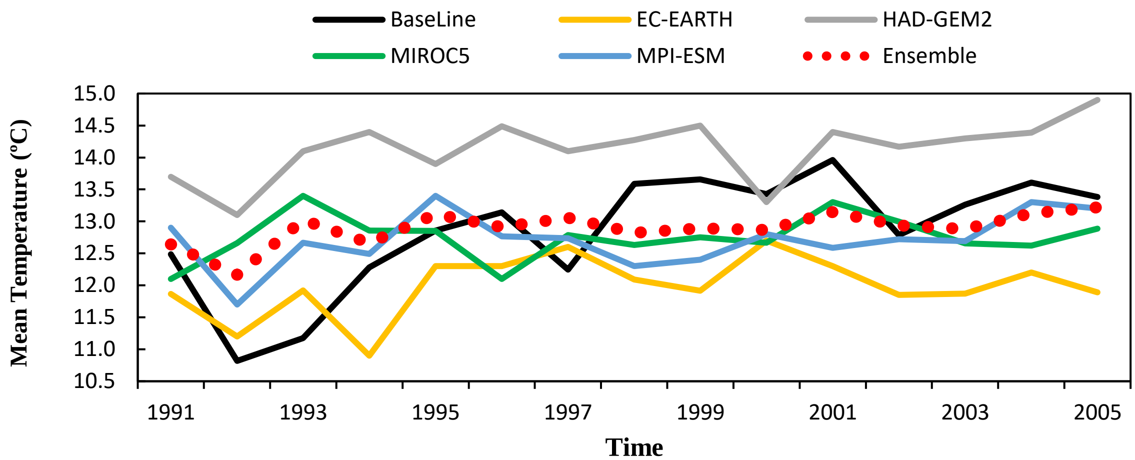

Figure 2. Mean annual temperature of the observed and calibrated temperature for the single and ensemble of multi-GCM approach

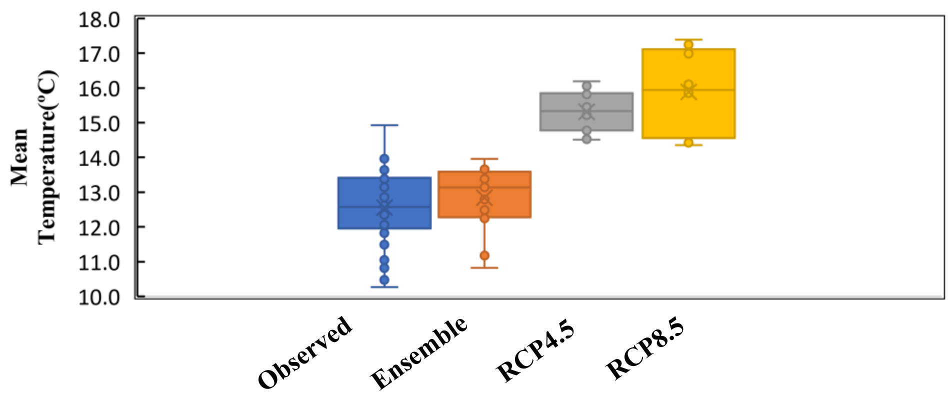

Figure 3. Mean Annual temperature Boxplot of the Observed, Calibrated and Simulated Temperature

Also, for the purpose of future climate projection, two statistical methods (i.e., LARS-WG, SDSM) was employed. In this regard, outputs of the ensemble multi-GCM models (i.e., EC-EARTH, HADGEM2, MIROC5, MPI-ESM) of CMIP5 under RCP4.5 and 8.5 scenarios were utilized for the horizon of 2021-2080. The results of the combined projection of models for the temperature predictand revealed the point that the city will experience an increasing trend in temperatures. The mean temperature will increase by 2.9 and 3.7 (°C) under RCP4.5 and 8.5 scenarios, respectively. The mean annual temperature variation during the baseline and simulated horizons has shown in Fig. 4. The results of this study corresponds with previous researches like Nourani et al. (2018) and Zarghami et al. (2011). In their study, they employed the LARS-WG tool as a statistical downscaling method in East Azerbaijan province, Iran. Their projection concluded that, the average temperature rise of ~ 2.3 °C in about 2050.

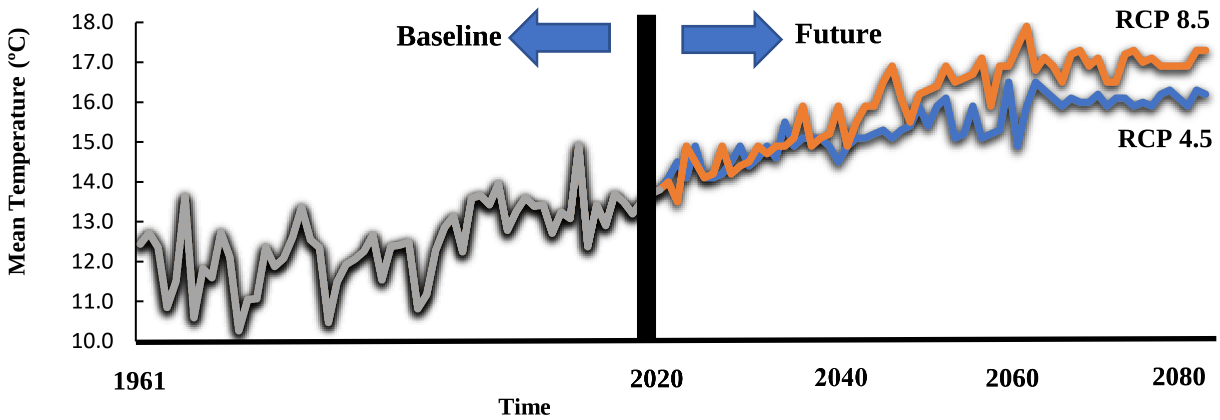

Figure 4. Mean annual temperature variation during 1961–2080

4. CONCLUSIONS

Since temperature is an important factor in developing climate impact studies for the future horizons, temperature forecasting of the Tabriz stations was assessed by various statistical GCM-based downscaling models. four different GCMs with the single and multi-GCM input approaches were employed in downscaling models under the RCPs 4.5 and 8.5. Outcomes of the simulations disclosed that, according to intermediate and high emission scenarios, the Tabriz station temperature will decrease in average (i.e., 2.9 and 3.7°C) under RCP 4.5 and 8.5 scenarios, respectively. The projection of climate in diverse climates through the use of various downscaling schemes has been contradictory. To achieve reliable results, different downscaling methods require to implement. In this research, the output of two statistical downscaling techniques (i.e. LARS-WG, SDSM) was analyzed for Tabriz city in northwestern Iran. Overall, the results of this study provide promising evidence for statistical downscaling and more specifically, the ensemble of multi-GCM models that utilized the hidden information of GCM demonstrated the superior performance of this approach compared to using a single GCM.

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