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

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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 (i.e., LARS-WG, SDSM) was employed for assessing the fluctuations of temperature predictand for Tabriz city, Iran. 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. The result of climate projection for the temperature predictand by both approaches revealed the point that the city will experience an increasing trend in minimum and maximum temperatures for the horizon of 2041-2060. The average temperature will increase by 2.9 and 3.7 (°C) under RCP4.5 and 8.5, respectively. Also, the results disclosed that both models represented the same performance for minimum and maximum predictands, although the monthly correlation of observed and simulated during the baseline period in LARS-WG model was slightly higher than the SDSM.

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, SDSM, and afterward, ANN are widely used for climate projections, Khan et al. (2006) analyzed the uncertainties retrieved from various downscaling schemes (i.e., LARS-WG, SDSM, and ANN) over a region in Canada. They concluded that SDSM indicated the best performance 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. Results of the study revealed the point that for minimum and maximum temperatures, SDSM represented a higher performance whereas for simulating precipitation, LARS-WG was preferred. Hassan et al. (2014) examined the application of SDSM and LARS-WG to simulate rainfall and temperature in Peninsular Malaysia. The results showed SDSM has a better performance compared to LARS-WG. Despite the time series generated by both approaches, the trend of daily temperature was increasing. Meanwhile, SDSM represented a relatively higher fluctuation of annual rainfall in comparison with LARS-WG. Vallam and Qin (2017) employed three statistical downscaling approaches (i.e., LARS-WG, Bias Corrected Disaggregation (BCD) and SDSM) to predict upcoming temperature and rainfall predictands in diverse study areas. As a result, the divergence between the predictions of various models derived from the regions experiencing severe precipitation intensities. 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 scheme 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 multilinear one.

Given the conflicting results of over-mentioned studies on the performance of various downscaling methods, 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 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, MIROC, 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° × 2.5° were extracted to link the dimensions of the GCM. The periods of 1961-2005 and 2041-2060 was utilized as the baseline and simulation period, respectively.

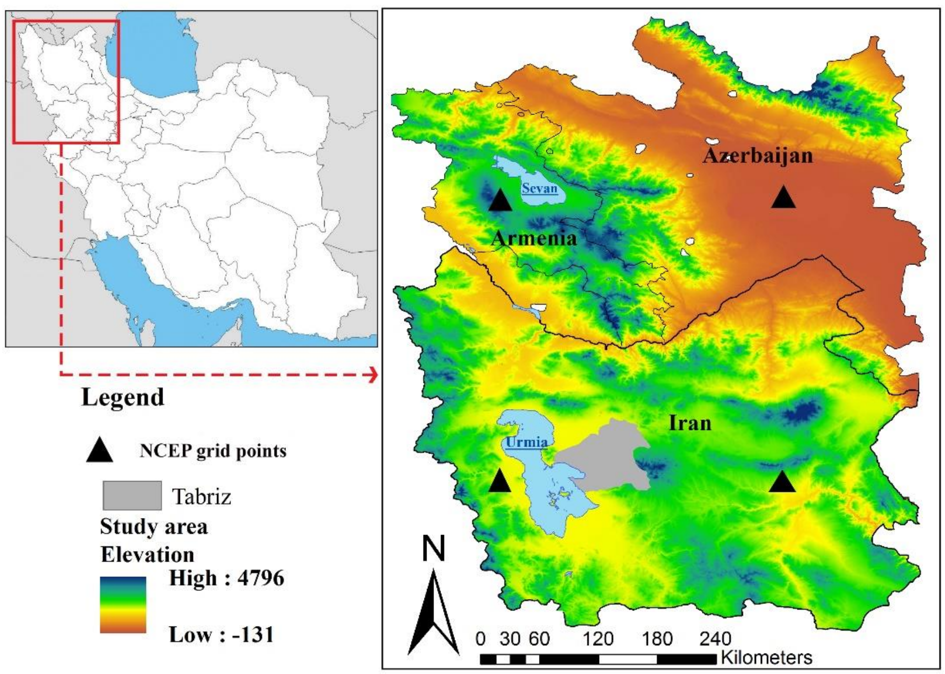


Fig 1. Topography of the study area and its position on Iran's map.

Table 1. Climate stations and GCM grid point information.

No	Global Climate Model	Centre	Centre acronym	Country	Grid resolution
1	EC-EARTH	Numerical weather prediction	ESM	Europe	1.1° x 1.1°
2	HadGEM2	UK Met. Office	UKMO	UK	2.5° x 3.75°
3	MIROC5	Met Research Institute, Japan	NIES	Japan	1.1° x 1.1°
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 are considered as stochastic processes with daily mean and standard deviation through the process of downscaling by LARS-WG. Seasonal averages are modeled by the finite series 3-order Fourier series and the residuals of the model are approximated by the normal distribution. The periods of 1961-1990 and 1991-2005 was considered as the baseline and validation periods for downscaling by LARS-WG, respectively. Afterward, SDSM as the second downscaling approach requires a proper selection of predictors which establish a relationship between predictors and predictand based on partial correlation coefficients. Since the involvement of a complete set of potential variables simultaneously in a downscaling model could negatively impact the results due to redundant data, the lack of general guidelines makes it necessary to carry out pervasive assessments of the selection of particular predictors. Important predictor selection among four GCMs was implemented in this study. In this way, the collection of four various GCMs was conducted in the screening phase prior to downscaling, Nevertheless, all of the considered predictors from four grid points of four GCMs (i.e., in total 16 sources of predictors) were integrated into the screening procedure to pick the fundamental variables which have a direct impact on the Tabriz temperature generation. Since the chosen variables related to various GCMs at distinct grid points, it was named a multi-GCM ensemble procedure. 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. The large-scale variables were extracted for the periods of 1961-1990 and 1991-2005 as the baseline and validation period, respectively.

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 relationships 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, through the training and validation steps, three criteria containing root mean square error (RMSE), a non-parametric test (i.e., Mann-Whitney U Test), and Spearman’s correlation test are utilized.

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) are assigned to choose the dominant predictors. In this regard, important climate variables of all the GCMs were identified.

3.1 First step-input screening

For the purpose of screening the predictors by SDSM, the daily regression models are produced between the chosen NCEP predictors and predictand at each station. Analysis indicated that the dominant predictors for minimum and maximum temperatures were large-scale variables (i.e., mean sea level pressure (Mslp), 500 hPa geopotential height (p500), 850 hPa geopotential height (P850) and Mean temperature at 2 m (p_temp)).

3.2 Second step-performance of downscaling techniques

In this step, the performance of two approaches (e.g. LARS-WG, DSDM) for downscaling predictands (i.e., minimum and maximum temperature) were assessed comprehensively. To do so, by using the absolute difference index, the difference between simulated and observed data was compared. For the minimum temperature, LARS-WG scheme represented the least difference between simulated and observed data for the station, indeed LARS-WG has represented a better performance compared to SDSM. Although in January and December the difference between simulated and observed data in LARS-WG is slightly higher than SDSM, indicating a low performance of LARS-WG tool during these months. Due to the outputs of evaluation criteria for maximum temperature, the performance of LARS-WG model is much better than the SDSM model. Overall, the results revealed the point that the performance of LARS-WG in downscaling minimum and maximum temperatures is more reliable compared to SDSM. Fig. 2.

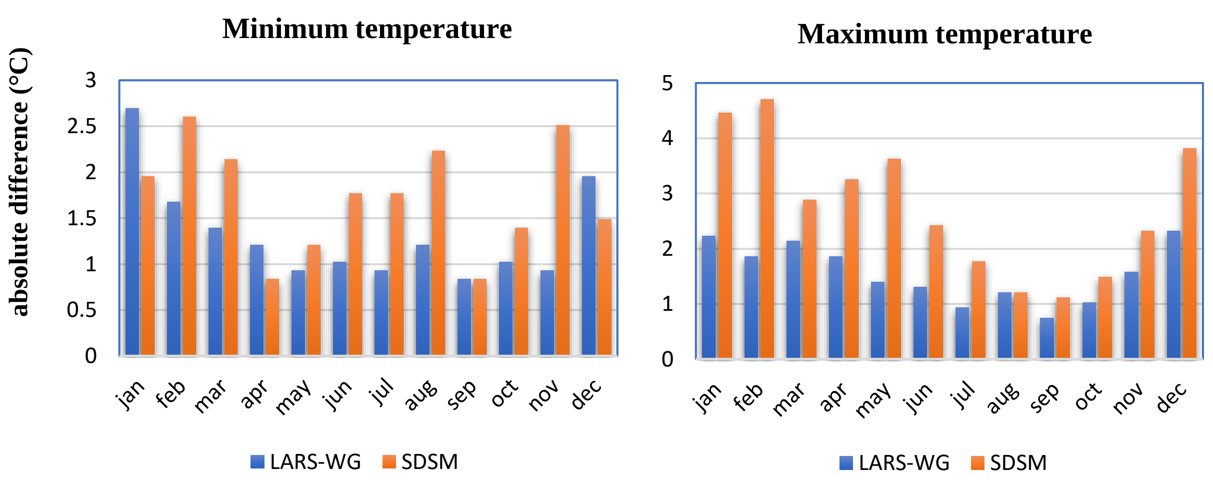


Fig 2. The monthly Mean absolute difference between simulated and observed data, 1991-2005.

In order to select the best downscaling model and eliminate the spatial-geographical factors, three criteria are utilized to compare the performance of both models over Tabriz city, including the Mann-Whitney comparison test, Spearman correlation test, and RMSE index. The results of the criteria tests and calculation of RMSE are represented bellow for predictands (i.e., minimum and maximum temperature). Shown in Tables 2.

Mann-Whitney criteria express the number of months in which the difference between generated and observed data are significant. According to the outputs of Mann-Whitney criteria in Tabriz station the difference between observed and generated data were significant by both approaches. In this way, Tabriz station is well-respond for both models, which indicated a significant difference between observed and generated data through one and two months, indicating a reliable performance of both models over the study area. In terms of comparing the two models, the Mann-Whitney test reveals the point that the performance of both approaches is fairly similar for minimum temperature. Also, outputs of the Spearman correlation test for minimum temperature indicated that the number of months in which the correlation between simulated and observed data is significant for LARS-WG model is nine months per year on average, which indicate a better performance of LARS-WG tool compared to SDSM, whereas, SDSM model represented an average performance with a six months significant correlation.

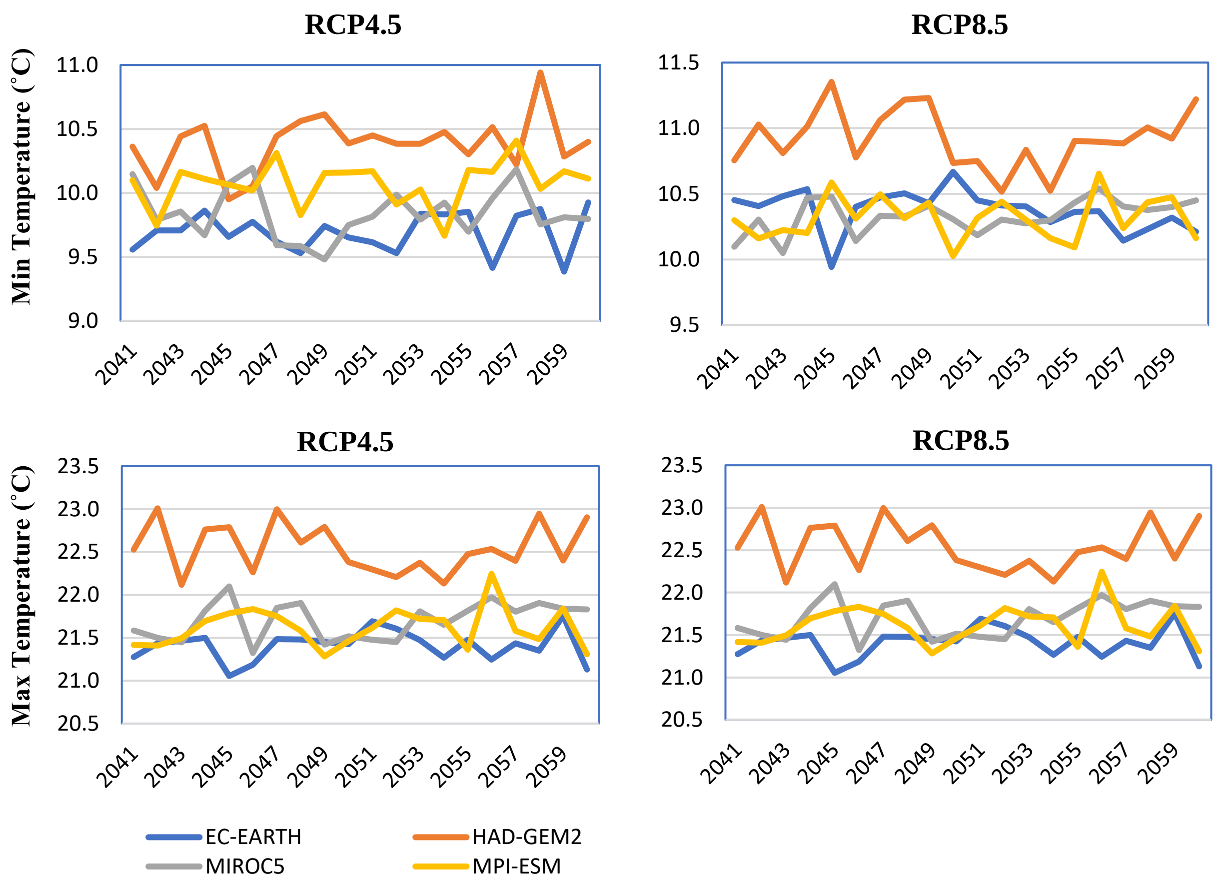
The result of Mann-Whitney criteria for maximum temperatures indicated that the number of months with a significant difference for the Tabriz station was one and three months for LARS-WG and SDSM, respectively. Indeed, from the perspective of downscaling models, both models played similar performances. Also, Spearman correlation test indicated that the number of months with significant correlation for maximum temperature parameter was not much more different, but the comparison of models showed the number of months with significant correlation is ten months for LARS-WG, which this issue Indicated a high correlation between simulated and observed data whereas SDSM comprise the number of months with significant correlation of eight months indicated a low performance of SDSM compared to LARS-WG. Overall, it concluded that both downscaling methods played a similar performance for minimum and maximum temperatures in Tabriz City. Accordingly, the results of LARS-WG were slightly better than the SDSM approach.

Table 2. Results of comparative tests, correlation and monthly RMSE index of the mean minimum and maximum temperatures (1991-2005).

Stations	**Mann-Whitney**		**Spearman correlation**		**RMSE**	
	LARS-WG	SDSM	LARS-WG	SDSM	LARS-WG	SDSM
MIN Temp	1	2	9	6	1.91	1.76
MAX Temp	1	3	10	8	2.47	4.53

3.3 Third step-temperature projection for future

For the purpose of future climate projection, two statistical methods (i.e., LARS-WG, SDSM) was employed over the region, in this regard, outputs of four GCM models (i.e., EC-EARTH, HADGEM2, MIROC5, MPI-ESM) of CMIP5 under RCP4.5 and 8.5 scenarios are utilized for the horizon of 2041-2060. The results of combined projection for temperature predictand over the region by both methods revealed the point that the city will experience an increasing trend in minimum and maximum temperatures. The mean temperature will increase by 2.9 and 3.7 (°C) under RCP4.5 and 8.5 for mean temperature, respectively. The results of this study correspond with the research of (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.



4. CONCLUSIONS

The evaluation of climate projection 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. The findings of both simulations disclosed the fact that, temperature predictand will experience an increasing trend within the study area. With respect to the results of the evaluation Criteria, it concluded that for the purpose of future climate projection, LARS-WG tool revealed better performance for temperature predictand compared to SDSM. Of course, It is proposed several approaches should be used simultaneously to reduce uncertainty, instead of employing a specific downscaling scheme.

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