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Research Article

Assessment of LARS-WG and Change Factor Downscaling Models in Simulating Climate Variables (Case study: Golmakan station)

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Abstract

Today, climate change caused by the increase in greenhouse gases is considered one of the important global issues and has led to anomalies in the global climate system. Downscaling methods play a fundamental role in improving the accuracy of General Circulation model outputs (GCMs). Among these, statistical downscaling methods have more efficiency due to their easy and inexpensive calculations compared to dynamic downscaling methods and are used more. In this study, the results of two statistical downscaling models, LARS-WG and Change Factor (CF) or Delta, in simulating temperature and precipitation parameters under three emissions scenarios (RCP2.6, RCP4.5, and RCP8.5) shortly period (2021-2040) were considered based on observational data from the Golmakan synoptic station in the base period (1975-2005). To evaluate the accuracy of the mentioned methods in estimating the variables, statistical evaluation criteria such as Nash-Sutcliffe efficiency, Root Mean Square Error, and correlation coefficient were used. Ultimately, based on the research findings, the LARS-WG model showed less error in simulating minimum and maximum daily temperature and precipitation in the study area and performed better compared to the Change Factor method in climate prediction.

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1- Introduction

In recent years, researchers in atmospheric and climate science have considered climate change caused by greenhouse gas emissions and global warming and the resulting future climate conditions on Earth as the most important concern (Li et al., 2013). Climate change is a global challenge with its long-term adverse effects hindering the process of achieving sustainable development worldwide. Currently, researchers focus on simulating climate variables using general circulation models (Barrow and Yu, 2005). The main objective of these models is to calculate three-dimensional climate indices on specified grids. These models are effective tools for studying and evaluating the risks of climate change. Furthermore, utilizing the approved approaches of the Intergovernmental Panel on Climate Change (IPCC), they can create long-term time series of precipitation, minimum temperature, maximum temperature, and evapotranspiration at a daily scale (Nasiri and Yarmoradi, 2017).

General Circulation Models (GCMs) are not suitable for practical studies with smaller scales, and their outputs have low accuracy (Minville et al., 2008). Downscaling is the process by which coarse-resolution GCM outputs are translated into finer-resolution climate information so that they better account for regional climatic influences. Downscaling can be done through dynamic and statistical methods. Despite the suitable spatial accuracy of dynamic models, they are often disregarded due to their high cost, time-consuming nature, and need for high-speed laboratory equipment that many countries lack. However, statistical downscaling has gained attention from researchers due to its low computational cost, economic efficiency, simplicity, and high speed in the regional downscaling process compared to other methods (Wilby et al., 2005). Numerous studies have been conducted on downscaling and predicting future data for various regions worldwide using different models.

Helmi et al. (2024) investigated the downscaling of precipitation and temperature data using LARS-WG, SDSM, and ANN models in two different climates in Khorasan Razavi. The results showed that the performance of the LARS-WG model is acceptable. Salehnia et al. (2013) examined the accuracy of two statistical downscaling models, LARS-WG and ASD, at three stations in Mashhad, Bojnourd, and Birjand. The results indicated that the mean absolute error for minimum and maximum temperature values in the LARS model is less compared to ASD. Zahiri et al. (2020) also compared the LARS-WG and SDSM models on the statistical downscaling data of general circulation models. According to the results of this study, no precise superiority can be stated for each of the models, but generally, the prediction results of the two models differ significantly in most cases. In another study, Sharghi et al. (2017) studied the performance of the LARS-WG method and Change Factor (CF) in the Tabriz study area (Iran). The results indicated satisfactory performance of both models. In the research by Jafary Godeaneh et al. (2020), the statistical downscaling of precipitation and temperature data in Kerman (Iran) using the LARS-WG model for the period 2020-2050 was done. The results showed the suitable performance of this model.

In conclusion, the LARS-WG model has proven to be a reliable and efficient tool for statistical downscaling of precipitation and temperature data in various climates across Iran. The model's advantages include its ability to generate synthetic weather data, its simplicity, and its relatively low computational requirements. However, the development of this method has been halted due to the lack of funding and support for research in this area. To overcome this challenge, it is essential to prioritize funding for climate change research and encourage collaboration between researchers and policymakers to ensure the continued development and improvement of downscaling models like LARS-WG.

Concerning previous research studies, the importance of temperature and rainfall conditions for proper water planning in different regions becomes evident. On the other hand, less research has been conducted in this regard in the studied region.

The Golmakan station is a significant region for climate change research due to its unique geography and climate. The region's high elevation and proximity to the Caspian Sea make it susceptible to extreme weather events, such as heavy precipitation and temperature fluctuations.

This station is significant for several reasons. Firstly, its unique geography and climate make it susceptible to extreme weather events, such as heavy precipitation and temperature fluctuations. Secondly, the region is home to several important agricultural and industrial activities, which are vulnerable to climate change impacts. Finally, the region is also home to several important cultural and historical sites, which are vulnerable to climate change impacts. Understanding the future climate projections for this region is crucial for effective planning and mitigation strategies. This study aims to simulate daily precipitation and minimum and maximum temperature parameters for the Golmakan station from 2040 to 2021 using the LARS-WG6 model.

The simulation was based on twenty years of precipitation, minimum and maximum daily temperature data for the mentioned station (years 1975-2005), and data from the fifth report of models under Representative Concentration Pathway scenarios (RCP2.6, RCP4.5, and RCP8.5). However, due to the lack of updating the LARS-WG model to provide new RCP scenarios, incorporating the downscaling technique through the CF or Delta Method has been addressed to reduce total uncertainty.

2- Material and methods

2-1- Study Area

The study area, Golmakan Station, is located in the Chenaran in Khorasan Razavi Province with an area of 2000 Hectares. Golmakan is located at latitude 36.29, longitude 59.17, and at an elevation of 1176 meters. Its climate, according to the De Martonne, is classified as a cold desert and is also classified as a cold, dry climate according to the Emberger classification (Eftekhari et al., 2023). It has cold and moist winters and dry summers. The location of the study station in Iran and the province is shown in Fig. 1.

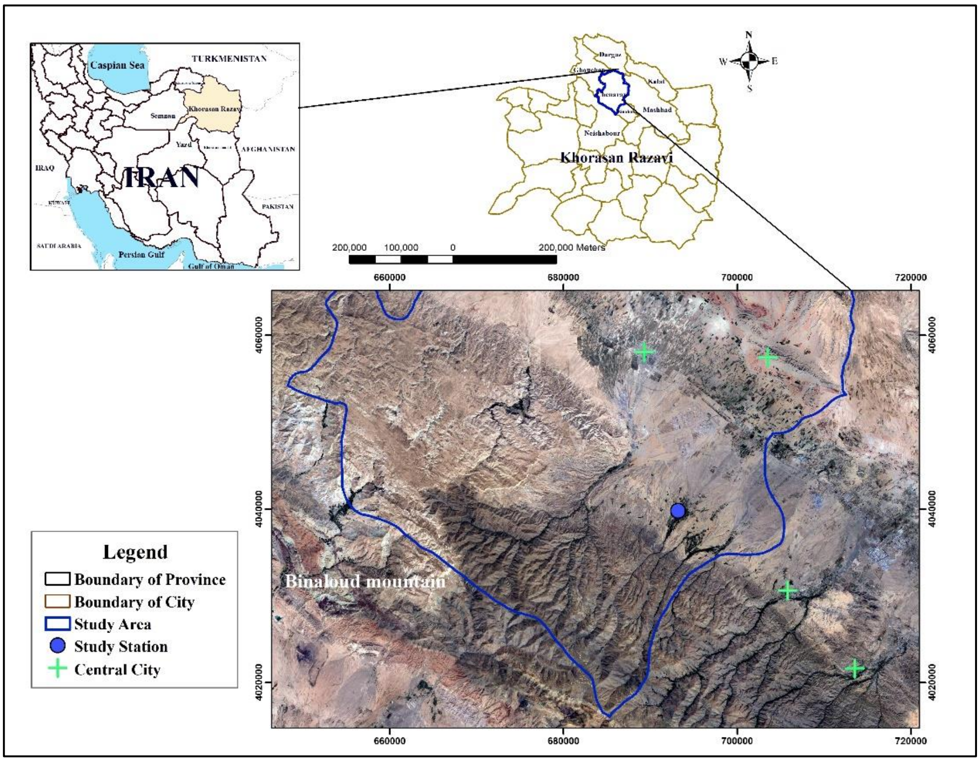

Figure 1. Location of the study area in the Country and the Province

2-2- Data Preparation

The data of 30 years of daily precipitation and temperature (2005-1975) were collected from the Golmakan station in Khorasan Razavi province, Iran. After preprocessing the data, the run test method was used to assess the homogeneity of the data. Additionally, the trend was examined using the Mann-Kendall and Sen's slope methods.

The Mann-Kendall test is robust to outliers and missing values in the data, making it useful for analyzing real-world datasets that may contain irregularities. It is also effective in detecting monotonic trends, which are trends that consistently increase or decrease over time without necessarily being linear.

On the other hand, Sen's slope method provides an estimate of the magnitude of the trend, which is useful for quantifying the rate of change in the data over time.

By employing the Mann-Kendall and Sen's slope methods, researchers can gain insights into the presence, direction, and magnitude of trends in their data, even if the data does not meet strict parametric assumptions or contains irregularities. This information can be valuable for understanding the underlying processes driving the observed changes and making informed decisions based on the trend analysis (de Assis Paiva, D., and Sáfadi, 2021).

Statistical tests are used to examine the presence of random patterns based on the number of runs in the data. The run refers to a consecutive set of data points that are either greater or smaller than the mean (Setoudeh, 2014).

The main steps of the run test include:

1- Calculating the number of runs (a consecutive run of data points can be either increasing or decreasing).

2- Calculating the expected value and variance of the number of runs based on a random distribution (such as a binomial distribution).

4- Comparing the observed and calculated data using test statistics (such as the Chi-square test).

5- Confirm the presence or absence of random patterns in the data based on the test statistic and the specified significance level (0.05) (Setoudeh, 2014).

2-3- Mann-Kendall Trend Test

The Mann-Kendall method was initially introduced by Mann (1945) and later extended and developed by Kendall (1970) (Khazaei et al., 2019). The Mann-Kendall test is a non-parametric statistical method used to analyze trends in time series data (such as temperature and precipitation observational series). This method analyzes the existence of a significant trend in the climatic variable time series. The null hypothesis of the test suggests random fluctuation and the absence of a trend in the data, while the alternative hypothesis accepts the presence of a significant trend in the data (Jahangir et al., 2019).

The equations for determining the Mann-Kendall statistic values are as follows (Bakhtiari et al., 2021).

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\operatorname{sgn}\left(X_j-X_i\right) \qquad |(1)$$

$$sgn(\theta)=\begin{cases}+1 & if\ \theta>0\\ 0 & if\ \theta=0\\ -1 & if\ \theta<0\end{cases} \qquad (2)$$

$$F=\begin{bmatrix} n(n-1)(2n+5)-\\ -\sum_{i=1}^{m}t_i(t_i-1)(2t_i+5)\end{bmatrix} \qquad (3)$$

$$V(S)=\frac{F}{18}$$

$$Z_M=\begin{cases}(S-1)\big/\left(\sqrt{VAR(S)}\right) & if\ S>0\\ 0 & if\ S=0\\ (S+1)\big/\left(\sqrt{VAR(S)}\right) & if\ S<0\end{cases} \qquad (4)$$

In the equations above, n is the number of observed data (length of the statistical period), Xi and Xj are the i-th and j-th smallest observed data, and Q is the number of groups created (with data equal to or more than two members), tp is the number of equal data in the p-th group, and Z_M is the value of Kendall's statistic (Bakhtiari et al., 2021).

Let Z be the statistic of the standard normal distribution and $Var(S)$ be the variance of parameter S. This parameter is obtained from Eqs. (1) to (4).

2-4- Sen's Slop Test

Sen's slope test is an analytical and non-parametric method for identifying changes in time series graphs, first introduced by Theil in 1950 and later expanded by Sen in 1968. This method is based on the analysis of differences between observations in a time series and is used when the time series trend is linear. (Eblaghian et al., 2019).

$$\beta=Median\left(\frac{x_j-x_i}{j-i}\right) \qquad \forall i<j \qquad (5)$$

Where, β is slope and other parameters are similar to prevois equations (see Mahmoudi et al., 2016 for more informatons).

2-5- Downscaling process

Climate change downscaling involves the production of detailed climate information from lower-resolution GCMs. This is typically needed because GCMs have a resolution of 150-300 km by 150-300 *km*, whereas many impact models require data at scales of 50 km or less. Downscaling can be accomplished through statistical techniques that establish relationships between observed small-scale variables (often station-level) and larger-scale GCM variables. This is achieved using methods like analog, regression analysis, or neural network techniques. The relationships are then used to estimate the finer-scale details of future climate based on future GCM projections. This approach is often used when impact models require small-scale data and relevant observed data is available to calibrate and validate the statistical models. The primary output of statistical downscaling is detailed information on future climate or climate change, such as maps or data. The main inputs required for statistical downscaling are suitable observed data to calibrate and validate the statistical models, as well as GCM data for future climate to drive the models (Gumus et al., 2023).

2-5-1- LARS-WG Model

The LARS-WG model is a stochastic weather generator used for simulating the weather conditions of a site under both current and future climate scenarios. This multivariate regression model utilizes statistical techniques to generate weather data. In this research, the LARS-WG5 software was used for this purpose.

The steps involved in working with this model are as follows:

1- Statistical properties of observational data are determined and analyzed in this step.

2- The model reproduces the data using observational data and determines the statistical characteristics of the synthetic data. The model uses an empirical distribution to represent the empirical distribution of observational data.

3- The model analyzes the observational and reproduced data from a statistical perspective.

4- To simulate future climatic conditions at the desired location, the model simulates future climate changes by inputting greenhouse gas emission scenarios and outputs from climate models into the reproduced baseline data. It is important to note that emission scenarios and outputs from climate models are defined within the model, eliminating the need for a database (Wilby et al., 2005).

2-5-2- Change Factor Method

One of the simplest methods of fine-scale statistical downscaling of General Circulation Models (GCMs) is the use of the delta or CF method. The CF is the ratio between future climate simulations and the present climate in a GCM. In calculating this ratio, observational data have no impact, and the CF is obtained using baseline and future GCM model data series. This ratio is multiplicative for precipitation and additive for temperature.

2-6- Evaluation of downscaling method

To investigate and compare the results obtained from the LARS-WG and CF models, the statistical metrics of Nas-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Correlation Coefficient (R) according to Eqs. 12 to 14 have been used.

$$NSE = 1 - \frac{\sum_i^n (P_o - P_m)^2}{\sum_i^n (P_o - \bar{P}_o)^2} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_i^n (P_m^i - P_o^i)^2}{n}} \quad (13)$$

$$R = \sqrt{\frac{\sum_i^n \left(P_o - \overline{P_o}\right) \sum_i^n \left(P_m - \overline{P_m}\right)}{\sum_i^n \left(P_o - \overline{P_o}\right)^2 \sum_i^n \left(P_m - \overline{P_m}\right)^2}} \quad (14)$$

In these equations, P_m and P_o are computational and observational data, $\overline{P_0}$ is the average of observational data, and n is the size of the data.

The changes of NSE are from -1 to +1 and the optimal value of this index is one. The value of RMSE varies between zero and infinity. The Correlation Coefficient (R) varies between zero and one, and the optimal value is one.

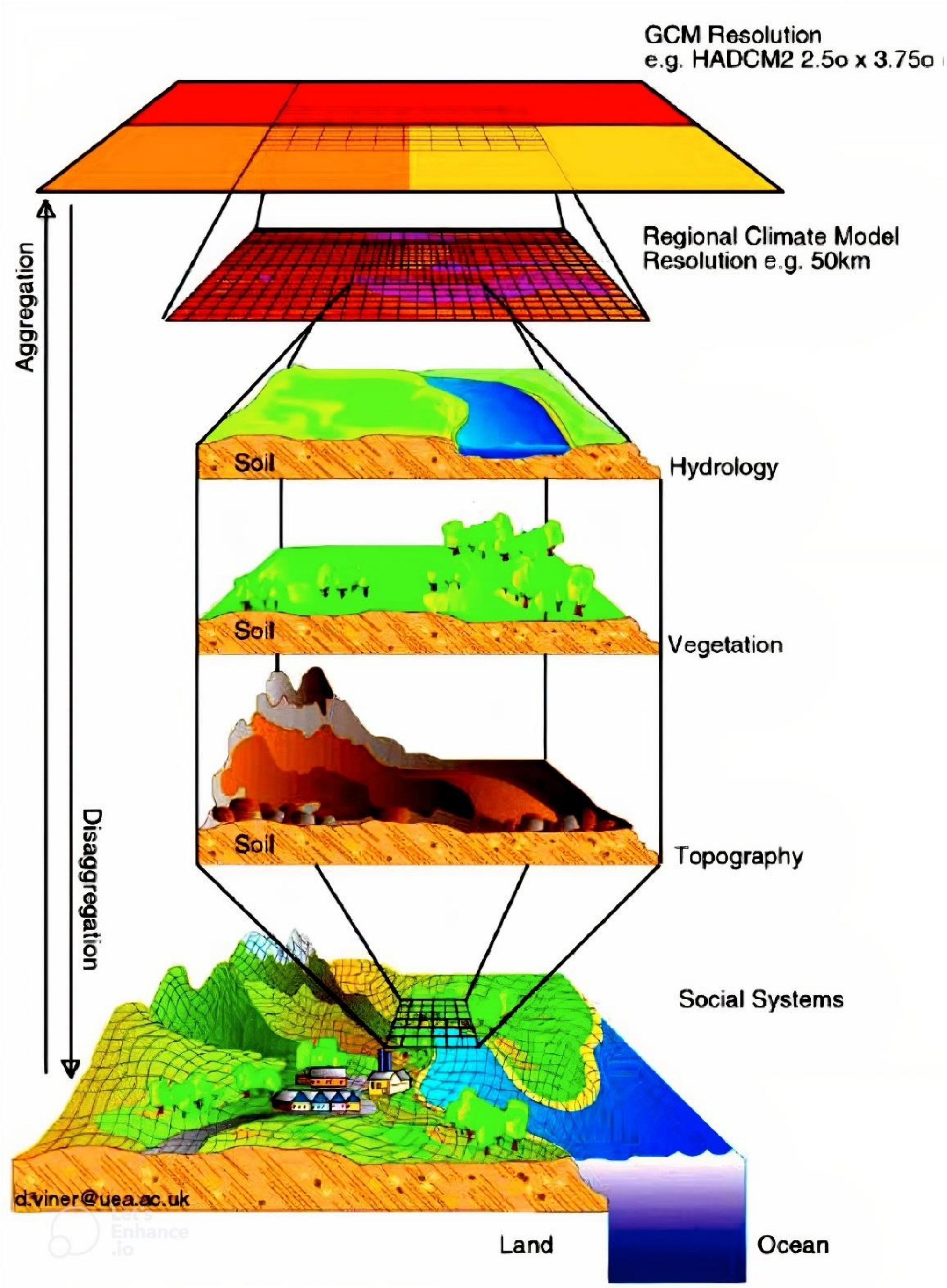

Figure 2. Schematic diagram of the downscaling process (Viner, 2012).

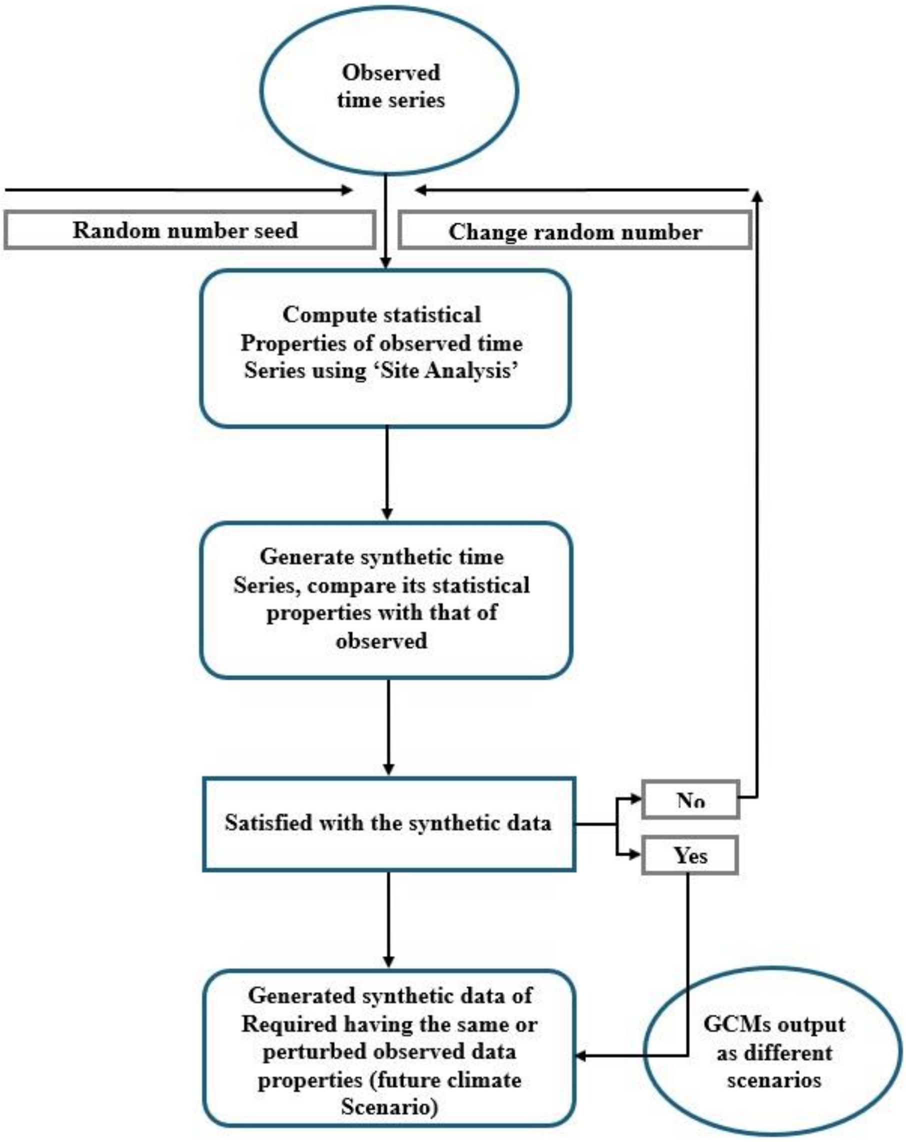

Figure 3. Schematic diagram of the downscaling process (adopted from Fenta Mekonnen and Disse, 2018).

3- Results and Discussion

Using robust statistical metrics, namely the NSE, RMSE, and R, we conducted a comprehensive performance evaluation of two downscaling models, namely LARS-WG and CF. The evaluation focused on their ability to simulate minimum and maximum temperature as well as precipitation data at the Golmakan station. The evaluation results are presented in Table 1.

The LARS-WG model has demonstrated superior accuracy in simulating the minimum temperature parameter at the Golmakan station, with an acceptable level of error.

The results of the present study align with previous research evaluating the efficacy and precision of the LARS-WG model for downscaling climate data. Specifically, they are consistent with findings from Hashemi et al. (2011), who compared the SDSM and LARS-WG models in a catchment area in southern New Zealand. They observed that both methods produced very similar results in modeling climate variables, suggesting that both SDSM and LARS-WG can serve as effective tools for climate change analyses.

Additionally, Zarfeshani and Jahangir (2021) utilized the LARS-WG model in Isfahan province, Iran, to predict temperature and precipitation, comparing it with SDSM and artificial neural networks. Their findings also indicated that LARS-WG performed well in simulating regional temperatures and precipitation.

Thus, the results of the present study underscore the reliability of the LARS-WG model in downscaling climate data. Its accuracy in modeling temperature and precipitation makes it a valuable asset for climate change studies and impact assessments. Future research could focus on comparing LARS-WG with newer downscaling methods, assessing its effectiveness under various climate change scenarios, and enhancing its application for specific regions.

Table 1. The results of LARS-WG and CF downscaling model in the monthly simulation of climatic parameters of Golmkan.

Model	Parameter	(R)	(RMSE)	NSE
LARS-WG	Max Temperature (°C)	0.58	1.74	0.35
	Min Temperature (°C)	0.61	1.71	0.37
	Precipitation (mm)	0.54	1.79	0.30
CF	Max Temperature (°C)	0.51	2.88	0.28
	Min Temperature (°C)	0.56	2.79	0.29
	Precipitation (mm)	0.49	2.98	0.25

The p-value values and the KS-test of the Kolmogorov-Smirnov test indicate that the simulated and observed minimum and maximum temperatures do not significantly differ for all months, except in the summer months. This difference is due to the mismatch between the precipitation predicted by the GCM models for the summer months at the station and the results of the synoptic station.

According to the results obtained from Table 1 and the value of the R, RMSE and NSE for the LARS-WG, this method is the superior method, which can be seen in Fig. (4) to Fig. (6) of its future prediction.

In the Fig. 4 to 6, the amounts of precipitation, minimum and maximum temperature predicted in the three scenarios (RCP 2.6, RCP 4.5 and RCP 8.5) are presented. The LARS-WG model has a suitable ability to simulate observational data for downscaling and also has greater simplicity and speed of operation and more appropriate efficiency. The results of this model can be used in studying climate changes and simulating climate parameters.

Table 2. Analysis table of monthly scenarios produced by LARS-WG model

Month	ks-test			p-value		
	Max Temperature	Min Temperature	Precipitation	Max Temperature	Min Temperature	Precipitation
Jan	0.158	0.106	0.126	0.91	0.99	0.99
Feb	0.158	0.053	0.042	0.91	1.0	1.0
Mar	0.105	0.053	0.051	0.99	1.0	1.0
Apr	0.106	0.106	0.074	0.99	0.99	1.0
May	0.106	0.105	0.033	0.99	0.99	1.0
Jun	0.106	0.106	0.135	0.99	0.99	0.97
Jul	0.106	0.106	0.218	0.99	0.99	0.59
Aug	0.158	0.158	0.224	0.99	0.91	0.67
Sep	0.053	0.053	0.261	1.0	1.0	0.36
Oct	0.106	0.106	0.090	0.99	0.99	1.0
Nov	0.106	0.053	0.042	0.99	1.0	1.0
Dec	0.053	0.053	0.073	1.0	1.0	1.0

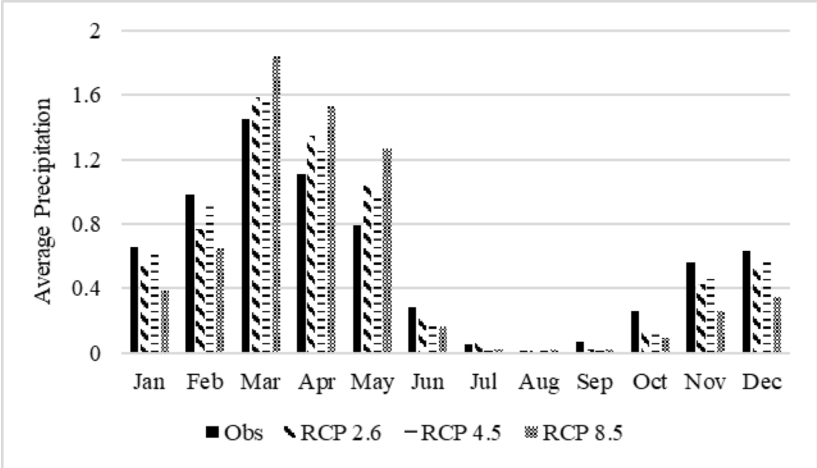

Figure 4. Mean monthly observations and predicted precipitation for the future (2021-2040) under RCP 2.6, RCP 4.5 and RCP 8.5 scenarios

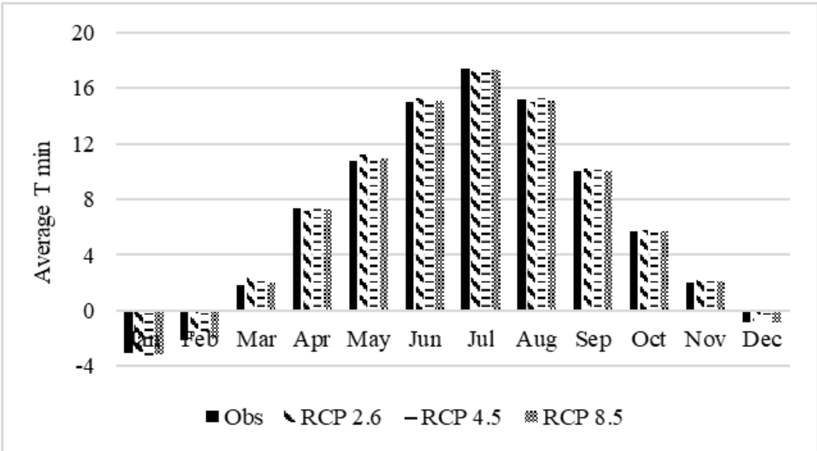

Figure 5. Mean monthly observations and predicted minimum temperature for the future (2021-2040) under RCP 2.6, RCP 4.5 and RCP 8.5 scenarios

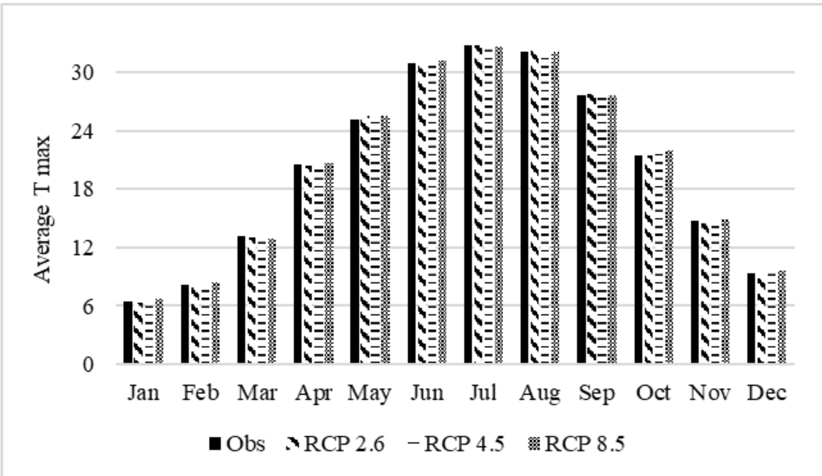

Figure 6. Mean monthly observations and predicted maximum temperature for the future (2021-2040) under RCP 2.6, RCP 4.5, and RCP 8.5 scenarios

4- Conclusions

This study aimed to evaluate the performance of two statistical downscaling models—LARS-WG and CF —in simulating daily precipitation, as well as daily minimum and maximum temperatures at the Golmakan station. Climate variables, including temperature and precipitation and their inherent variability, play a significant role in influencing the distribution of other climatic elements. Given their importance, accurate predictions of climate change are vital for effective water resource planning and management. While General Circulation Models (GCMs) are among the most advanced tools available for simulating climate change, they are still evolving and require further refinement.

The results of this study indicated that the LARS-WG model outperformed the CF method in simulating both daily minimum and maximum temperatures, as evidenced by consistently lower error values across all evaluation criteria. This highlights the superior capability of the LARS-WG model in providing reliable climate predictions for temperature-related variables.

However, the LARS-WG model does face certain limitations that must be addressed to enhance its overall effectiveness. One significant challenge is its dependence on high-quality, time-series climate data, which is essential for accurate simulations. Improving the availability and accessibility of reliable climate datasets will be crucial for enhancing the model's performance. Scalability is another key concern, as the computational demands of the model increase significantly with larger datasets or a greater number of study subjects. Optimizing the model to handle larger datasets more efficiently would address this issue, improving both its usability and performance.

Looking forward, future research could focus on broadening the application of the LARS-WG model to encompass additional climate variables, diverse geographic regions, and extended time frames. Such expansions would increase the model's versatility and applicability to a wider range of climate studies. Another important direction for future work would be the integration of higher-quality climate data, including more advanced GCM outputs, to improve the model’s predictive accuracy. Addressing these challenges will further strengthen the LARS-WG model's role as a valuable tool in climate change research and water resource management.

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Competing interest

The authors declare that there are no conflicts of interest.

Authors' contribution

M.H.: Conceptualization, methodology, and data analysis. S.Z.N.: Literature review, data collection, and interpretation of results. M.Y.: Supervision, critical revision, and writing of the manuscript. Additionally, all authors have reviewed and approved the final version of the manuscript.

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