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Performance analysis of LARS-WG and SDSM downscaling models in simulating temperature and precipitation changes in the West of Iran

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Abstract

The outputs from general circulation models (GCMs) lack spatial and temporal accuracy for local and regional studies due to their large-scale networks. Therefore, there is a need to make the scale of outputs from these models smaller to the station and point scales. This has led to the development of regional and statistical models that have wide applications in climate change studies from the beginning of their introduction and decision-making for facing and adapting to the consequences of climate change in recent years. The models based on statistical methods are more popular and applicable due to their ease of use and because they do not need high computational power. Among the statistical methods, LARS-WG and SDSM are the most commonly used and valid downscaling models. In this study, the results of our analysis related to the performance of these two models in simulating temperature and precipitation changes in western Iran are presented. The weather stations under study include 17 stations with a long-term statistical period (1989–2018) in three provinces of Kurdistan, Kermanshah, and Ilam. To evaluate the performance of the models, MSE, RMSE, MAE, and R^2 are used. The results show that the two models have an acceptable level of ability in simulating temperature and precipitation changes in the area under study. However, different results are reported for different stations and within different weather parameters. A comparison between the performance of the two models in simulating temperature and precipitation changes reveals that both of them have higher accuracy in simulating temperature than precipitation. Furthermore, the SDSM model is more successful in a monthly simulation of temperature and precipitation with lower uncertainty. However, it has a time-consuming and complicated simulation process. The LARS-WG model is more efficient in simulating annual precipitation and is simpler with a higher performance speed. In a nutshell, none of these models is better than the other and despite the differences in simulation, they can both be useful for examining climate changes. There is a need to use different models for examining the uncertainty of climate change.

Keywords Iran · Precipitation · Climate changes · Temperature · LARS-WG · SDSM

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Introduction

The increase in greenhouse gases and the changes in climatic parameters have significant negative effects on different systems such as water resources, the environment, industries, health, agriculture, and all the other systems interacting with the climate system (Intergovernmental Panel on Climate Change (IPCC), 2007). The negative consequences of this phenomenon for humanity are such that among the ten factors threatening human beings in the twenty-first century such as poverty, nuclear weapons, and food shortages, climatic change comes first (IPCC 2001). Among the climatic elements, temperature and precipitation are of high importance due to their wide effects on other factors, especially the effects they have on human

activities. So that almost all of the climate change on the Earth's surface has been focused on these two parameters (Tabatabaei and Hosseini 2003; Salimi et al. 2018). Therefore, long-term predictions of climatic variables have been the focus of many scientific assemblies to know about the extent of changes in them and make the required preparations to moderate the negative effects caused by climatic changes. On this basis, GCM models have been developed (Qian et al. 2004). Although these models demonstrate meaningful results at the spatial atmospheric and continental scale and combine a major part of the complexity of the earth, they are not able to show the dynamics and shapes with a small-grid local scale (Carter et al. 1994; Wigley et al. 1990; Sharma et al. 2007). Therefore, evaluating the effect of climate change at the local scale requires an approach that fills the temporary spatial gap between large-scale climatic variables and meteorological variables at the local scale. In this case, the basic approach is to use downscaling techniques (Wilby et al. 2002). In fact, general circulation models (GCMs) can be never directly used for regional or point predictions. They are classified into statistical and dynamic models. The former is different from the latter for two major reasons: (1) it requires the observational (past) behavior of the station under study and (2) modeling these 2–3 months is done in a fraction of a second (Shamsipour 2013). Therefore, the most valid instrument for downscaling the GCM data is the statistical method. In this regard, Semenov et al. (1998) compared LARS-WG and WGEN models in 18 stations located in the United States, Europe, and Asia. Their results show that the LARS-WG model was better at producing different climate data including different severe weather events. Khan et al. (2006) analyzed uncertainty in three downscaling models including SDSM, LARS-WG, and ANNs. The results of their analysis show that SDSM and LARS-WG models yield better results, compared to the ANN model with lower accuracy. Hashemi et al. (2010) compared LARS-WG and SDSM models in simulating heavy precipitation in Clutha in the southern island of New Zealand. Their findings indicate that the two models have an equally good ability in simulating heavy precipitation and can be used for climatic predictions. Sunyer et al. (2015) compared well-known downscaling methods to examine extreme rainfall events in Europe. They found that statistical downscaling models had a higher accuracy. Ababayi et al. (2011) evaluated the performance of the LARS-WG model in simulating precipitation, temperature, and sunlight in the stations of the southern and northern coasts of Iran. They discovered that this model had an acceptable performance in simulating daily distribution and annual and seasonal distribution of most of the series. Aghashahi et al. (2012) introduced and compared the LARS-WG and SDSM models to downscale the environmental parameters

in the studies on climate change. Their results showed that the SDSM model had a lower uncertainty and a more complicated simulation process while LARS-WG had more simplicity and a higher performance speed. Abkar et al. (2013) examined the efficiency of the SDSM model in simulating temperature indices in arid and semi-arid areas showing that the SDSM model has the required capability for simulating temperature indices. Hajjarpour et al. (2014) made a comparison between three models including LARS-WG, Weatherman, and CLIMGEN in simulating climatic parameters in three different climates in Gorgan, Gonbad, and Mashhad, Iran. Their findings were indicative of the higher efficiency of LARS-WG in simulating minimum temperature parameters. Goudarzi et al. (2015) evaluated the performance of downscaling models of SDSM and LARS-WG in the Urmia Lake basin in the northwest of Iran. Their findings were indicative of no absolute superiority of one model over the others. Sobhani et al. (2017) compared three downscaling models including SDSM, ANN, and LARS-WG in simulating temperature and precipitation changes in the northwest of Iran. The findings of their study showed that the performance of models varied depending on the type of regional climate. Ouji (2018) compared one-station and multi-station extreme temperature and precipitation events in the southern coasts of the Caspian Sea. Based on their findings, the performance of the multi-station downscaling method, particularly in downscaling of temperature indices, was better than the one-station method. Heydari Tasheh Kabood (2020) studies the effects of climate change on stream flows of the Urmia Lake basin in Iran using the LARS-WG model. The results showed that this model has high accuracy in simulating temperature and precipitation changes.

Based on the literature, among the statistical downscaling models used in examining climate change, SDSM and LARS-WG models are the highly used ones. This article presents the results of our analysis related to the performance of these two downscaling instruments in simulating temperature and precipitation changes in western Iran.

Data and methodology

The area under study included three provinces of Kurdistan, Kermanshah, and Ilam in the west of Iran. The analyzed data included the least temperature, maximum temperature, and precipitation in 17 selected weather stations across the region under study during the statistical period 1989–2018 on a daily basis. The geographical position and meteorological station study is demonstrated in Fig. 1. The geographical characteristics of the meteorological stations are presented in Table 1.
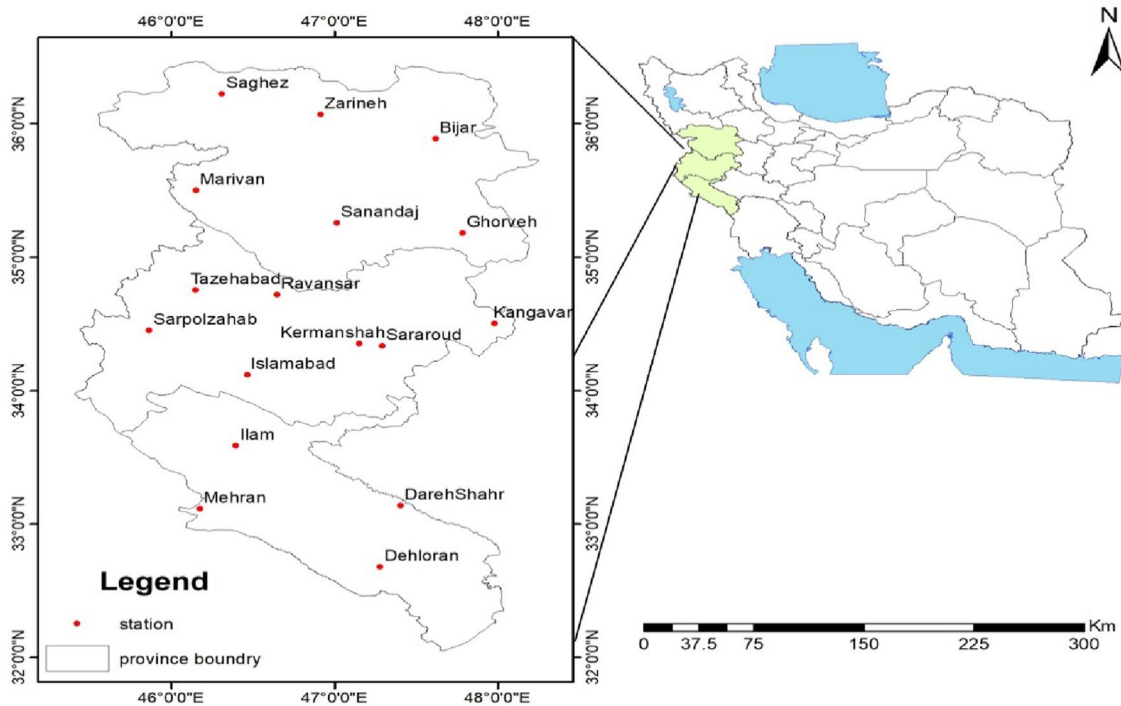
Fig. 1 The geographical location of the study area and the meteorological stations

Table 1 Geographic characteristics of the studied meteorological stations

Station	Station type	lat	lon	Elevation (m)
Bijar	Synoptic	35.89	47.62	1883.4
DarehShahr	Synoptic	33.14	47.41	670
Dehloran	Synoptic	32.68	47.28	232
Ghorveh	Synoptic	35.18	47.79	1906
Ilam	Synoptic	33.59	46.40	1337
Islamabad	Synoptic	34.12	46.47	1348.8
Kangavar	Synoptic	34.50	47.98	1468
Kermanshah	Synoptic	34.35	47.15	1318.5
Marivan	Synoptic	35.50	46.15	1287
Mehran	Synoptic	33.11	46.18	150
Ravansar	Synoptic	34.72	46.65	1380
Saghez	Synoptic	36.22	46.31	1522.8
Sanandaj	Synoptic	35.25	47.01	1373.4
Sararoud	Agriculture	34.33	47.29	1361.7
Sarpolzahab	Synoptic	34.45	45.87	545
Tazehabad	Synoptic	34.75	46.15	1226
ZarinehObatou	Synoptic	36.07	46.92	2142.6

The model examined

The LARS-WG model is a random model for producing weather data using statistical downscaling techniques (Wilks 1992; Wilks and Wilby 1999). The first version of this model was presented as an instrument for statistical downscaling in Budapest in Hungary in 1990. As a downscaling model, this model has a high ability in predicting climate change despite the lower complexity of the simulation process and the input and output data (Semenov and Stratonovitch 2010). The input data for the model includes minimum temperature, maximum temperature, precipitation and the level of sunlight on a daily basis. This data should have a period of at least 30 years; in this study, the period 1989–2018 is considered as the base period. To use this model, the observed data of the basic period were received and examined to extract the statistical features of the data. To validate the data and ensure the ability of the model in the basic period, it is executed to create a series of synthetic data in the base period. Subsequently, the outputs are compared with the statistical features observed in the 30 years to evaluate the performance of the model in recreating the data. In this study, the latest version of this model, i.e. the sixth version (LARS-WG6) developed in 2018 for downscaling the Fifth Assessment Report (AR5), was used. This model produces weather parameters on a daily basis at the station scale by receiving meteorological data of the statistical period and output from the general circulation model in a period similar to the present and future statistical periods.

The SDSM downscaling model was developed by Wilby et al (2002) in England. It is based on the use of a combination

of regression methods and the production of weather data. It was initially developed for producing climate change scenarios at a small scale, but with the effects of climate change becoming more apparent and passing from the static to the decision-making phase; it was used as decision-making software (Houshyar et al. 2018). The input data for the model included daily meteorological data related to the parameters under study and observational data related to the National Center for Environmental Prediction (NCEP). Since the output related to the large-scale predictors or NCEP variables have many variables, the most appropriate predictors related to the station of interest should be selected out of these variables. During this process, which is referred to as screening, the SDSM model carries out tests of correlation, partial correlation, and correlation between the predictor and predicted (generally precipitation and temperature) variables. Using these tests, the predictors that have a good correlation with the predicted variables are selected as the future climate predictors (Aghashahi et al. 2012). In this analysis, the 30-year NCEP data were used from 1989 to 2018, which included 26 independent atmospheric variables for validation and evaluation of the model to simulate temperature and precipitation parameters in the basic period.

The temperature and precipitation data of the meteorological stations studied were received from the Iran Meteorological Organization and NCEP predictor variables were downloaded from the https://sdsm.org.uk/data.html

Evaluation of model performance

For evaluating and analyzing the performance of the estimation and prediction models, there are different performance indices. In the following section, the indices used in this study will be briefly explained. The coefficient of determination (R^2) is a dimensionless criterion and its best value is 1. Equation (1) shows how it is calculated (Salahi et al. 2017). Mean square error (MSE) can vary from 0 to infinity in an excellent performance, which is defined in the form of Eq. (2) (Helali et al. 2020). RMSE is used as an index for showing the difference between the simulated values and the measured values. This criterion, which is defined as Eq. (3), is used as the most common error index (Lin et al. 2006). Mean absolute error (MAE) is also utilized for comparing the case to case relative error of simulated values based on the measured values, which is expressed in Eq. (4) (Hu et al. 2001):

$$R^2 = \frac{\sum_{i=1}^{N} X_o X_S}{\sum_{i=1}^{N} X_o^2 \sum X_S^2} \tag{1}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_o - X_S)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X_o - X_S)^2}{N}} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{N} |X_o - X_S|}{N} \tag{4}$$

In the above equations, X_o indicates observed data, X_s represents simulated data and N shows the amount of data.

Results and discussion

To calibrate and ensure the accuracy of the LARS-WG model, it was first executed for the basic statistical period (1989–2018). Then the outputs from the model including the least temperature, maximum temperature, monthly precipitation, and standard deviation were compared with the observed data in the station under study. To ensure the accuracy of the SDSM downscaling model, the simulated parameters were evaluated using NCEP variables and real data for the basic statistical period. Based on the results from examining the correlation between NCEP variables and the observed data, the variables of average sea-level pressure, the geo-potential height of 500 hpa and mean temperature at the height of two meters had the highest correlation with the examined parameters (temperature and precipitation) in the study area. The results of an evaluation of the observed and simulated precipitation data by the two downscaling models including the LARS-WG and SDSM based on different statistical indices are presented in Table 2. The findings are indicative of the accuracy of the investigated models in different stations and areas. On average, the highest accuracy of the models in simulating precipitation was related to the Kangavar station and the least accuracy was in the Tazehabad and Marivan stations.

The results related to the performance of the downscaling model in simulating minimum temperature show that this model has high accuracy in simulating temperature that comparing the error between the observed and simulated data is very small and all the stations have an R^2 value of 0.99. Based on the findings, the lowest error of the model concerning the least temperature was in the Kangavar station and the highest error was in Bijar and Tazeh Abad stations (see Table 3).

The results of analysis related to maximum temperature using different indices show that the LARS-WG model also had a high accuracy in downscaling maximum temperature. The highest and lowest accuracy of the models in this respect was in the Ghorveh and Tazehabad stations, respectively (see Table 4).

The results showed that the accuracy of the models varied in different stations and parameters. Both models had

Table 2 Evaluation of the performance of LARS-WG and SDSM models in simulating precipitation

Station	RMSE		MSE		MAE		R^2	
	SDSM	LARS	SDSM	LARS	SDSM	LARS	SDSM	LARS
Bijar	6.11	4.4	37.3	19.2	5.16	3.6	0.99	0.95
DarehShahr	2.6	5.8	6.9	33.6	2.03	3.9	0.99	0.96
Dehloran	1.7	4.4	2.88	19.5	1.32	2.9	0.99	0.96
Ghorveh	3.26	4.1	10.64	15.5	2.7	3.5	0.99	0.96
Ilam	3.72	7.6	14.22	58.2	3.18	5.2	0.99	0.96
Islamabad	4.2	5.2	17.7	26.5	3.28	3.1	0.99	0.97
Kangavar	2.9	3.4	8.5	11.6	2.33	2.5	0.97	0.98
Kermanshah	2.44	6.1	5.97	37.1	2.1	4.2	0.99	0.95
Marivan	8.7	7.8	76	60.5	6.65	6.3	0.99	0.99
Mehran	4.8	3.6	21.8	12.7	4	2.4	0.94	0.99
Ravansar	3.1	5.9	9.7	34.5	2.5	5	0.99	0.97
Saghez	4.4	5.6	19.7	31.7	3.8	4.1	0.99	0.97
Sanandaj	0.93	4.4	0.86	18.9	0.7	2.5	0.99	0.97
Sararoud	5.1	3.8	25.7	14.5	3.9	2.6	0.99	0.98
Sarpolzahab	4.3	6.5	18.7	42.3	3.4	4.4	0.99	0.97
Tazehabad	4.35	10.7	18.9	115.6	3.6	6.3	0.99	0.93
ZarinehObatou	5.25	4.9	27.6	24.3	4.35	3.3	0.99	0.98

Table 3 Evaluation of the performance of LARS-WG and SDSM models in simulating minimum temperature

Station	RMSE		MSE		MAE		R^2	
	SDSM	LARS	SDSM	LARS	SDSM	LARS	SDSM	LARS
Bijar	0.03	0.35	0.00	0.12	0.02	0.27	0.99	0.99
DarehShahr	0.1	0.29	0.01	0.08	0.08	0.25	0.99	0.99
Dehloran	0.03	0.22	0.00	0.05	0.02	0.18	0.99	0.99
Ghorveh	0.03	0.23	0.00	0.05	0.02	0.19	0.99	0.99
Ilam	0.02	0.2	0.00	0.04	0.02	0.14	0.99	0.99
Islamabad	0.03	0.17	0.00	0.03	0.02	0.14	0.99	0.99
Kangavar	0.03	0.1	0.00	0.01	0.02	0.08	0.99	0.99
Kermanshah	0.03	0.23	0.00	0.05	0.02	0.17	0.99	0.99
Marivan	0.04	0.23	0.00	0.05	0.03	0.19	0.99	0.99
Mehran	0.12	0.24	0.01	0.06	0.08	0.18	0.99	0.99
Ravansar	0.03	0.13	0.00	0.02	0.03	0.1	0.99	0.99
Saghez	0.03	0.3	0.00	0.09	0.02	0.21	0.99	0.99
Sanandaj	0.04	0.18	0.00	0.03	0.03	0.14	0.99	0.99
Sararoud	0.1	0.23	0.01	0.05	0.07	0.18	0.99	0.99
Sarpolzahab	0.03	0.3	0.00	0.1	0.02	0.26	0.99	0.99
Tazehabad	0.12	0.31	0.01	0.1	0.1	0.27	0.99	0.99
ZarinehObatou	0.03	0.14	0.00	0.02	0.02	0.11	0.99	0.99

better accuracy in simulating temperature compared to precipitation. Besides, in simulating monthly precipitation, the SDSM model had a lower accuracy compared to the LARS-WG model in most of the stations, but in terms of simulating temperature parameters, it had a higher accuracy. In simulating temperature parameters also, both models were more successful in simulating maximum temperature than minimum temperature through the SDSM model had a higher accuracy compared to the LARS-WG model. Overall, the results of analysis related to the error measurement indices indicated that the SDSM downscaling model was more accurate in downscaling climatic parameters at the monthly scale, particularly concerning temperature indices in the area under study, which is consistent with earlier results of Aghashahi et al. (2012), Goudarzi et al. (2015) and Sobhani et al. (2017) studies.

To better illustrate the findings and ensure accuracy of the results from the investigated models, the simulated and

Table 4 Evaluation of the performance of LARS-WG and SDSM models in simulating maximum temperature

Station	RMSE		MSE		MAE		R^2	
	SDSM	LARS	SDSM	LARS	SDSM	LARS	SDSM	LARS
Bijar	0.02	0.21	0.00	0.05	0.02	0.18	0.99	0.99
DarehShahr	0.12	0.33	0.01	0.11	0.07	0.27	0.99	0.99
Dehloran	0.03	0.2	0.00	0.04	0.02	0.15	0.99	0.99
Ghorveh	0.03	0.18	0.00	0.03	0.03	0.12	0.99	0.99
Ilam	0.03	0.2	0.00	0.04	0.02	0.16	0.99	0.99
Islamabad	0.03	0.19	0.00	0.04	0.02	0.16	0.99	0.99
Kangavar	0.03	0.21	0.00	0.05	0.02	0.17	0.99	0.99
Kermanshah	0.03	0.25	0.00	0.06	0.02	0.21	0.99	0.99
Marivan	0.04	0.22	0.00	0.05	0.03	0.16	0.99	0.99
Mehran	0.14	0.19	0.02	0.04	0.09	0.14	0.99	0.99
Ravansar	0.03	0.32	0.00	0.1	0.02	0.25	0.99	0.99
Saghez	0.03	0.29	0.00	0.08	0.03	0.22	0.99	0.99
Sanandaj	0.03	0.2	0.00	0.04	0.02	0.16	0.99	0.99
Sararoud	0.08	0.25	0.01	0.06	0.06	0.22	0.99	0.99
Sarpolzahab	0.03	0.23	0.00	0.05	0.02	0.19	0.99	0.99
Tazehabad	0.18	0.36	0.03	0.13	0.14	0.32	0.99	0.99
ZarinehObatou	0.02	0.24	0.00	0.06	0.02	0.18	0.99	0.99

observed minimum and maximum temperature and precipitation values were compared using comparative figures on a monthly and annual basis during the period under study in the stations of interest. Examining the maximum temperature pointed to the fact that in most of the months and annually, in all the stations, the SDSM model had a better performance than the LARS-WG model (see Figs. 2 and 3). Concerning the monthly figures, only the stations at the center of the provinces (Ilam, Sanandaj, and Kermanshah) are presented, due to a large number of stations.

A comparison between the means of the observed and simulated monthly and annual minimum temperature also showed that despite the high accuracy of the two models, the SDSM model is more successful (see Figs. 4 and 5). In a nutshell, based on the results related to temperature, the SDSM model had a better performance in simulating maximum rather than minimum temperature and also compared to the LARS-WG model.

Concerning the status of precipitation, the conditions are slightly different; the SDSM model was to some extent more successful in simulating monthly precipitation in some stations (see Fig. 6) while simulating annual precipitation in the period of interest, the simulated values by the LARS-WG model approached the observed values and in all the stations, the amount of precipitation estimated by the SDSM model was more than the observed values. In fact, the LARS-WG model was more successful than the SDSM model (Fig. 7). Our results were in agreement by Khan et al. (2006), Goudarzi et al. (2015), Salahi et al. (2017) and Heydari Tasheh Kabood et al. (2020) that

obtained the high accuracy of these models in temperature and precipitation simulations.

Conclusion

This study presented the results of analysis related to the capabilities of two downscaling models of LARS-WG and SDSM in simulating temperature and precipitation changes in western Iran in the period 1989–2018. To assess the accuracy of the models, the MSE, RMSE, MAE, and R^2 were used. The obtained results showed that both models had an acceptable level of ability in simulating temperature and precipitation changes in the area under investigation though their accuracy was not similar across different stations and different climatic parameters. Both models had lower accuracy in simulating precipitation than temperature. This might be due to the complexity involved in the precipitation process and its nature. The findings revealed that the SDSM model had the lowest error in simulating the observed data. Although the LARG-WG model had a good ability in simulating the observed data for downscaling, its ability is not equal to that of the SDSM model. In the SDSM model, downscaling is done via creating a regressive relationship between the predictors and the predicted in one station, but in the LARS-WG model, atmospheric large-scale variables have no direct role in simulating the data and the model analyzes them, first, to determine the parameters and the statistical properties of the observed data related to them. Then, in line with the type of future changes in the large-scale
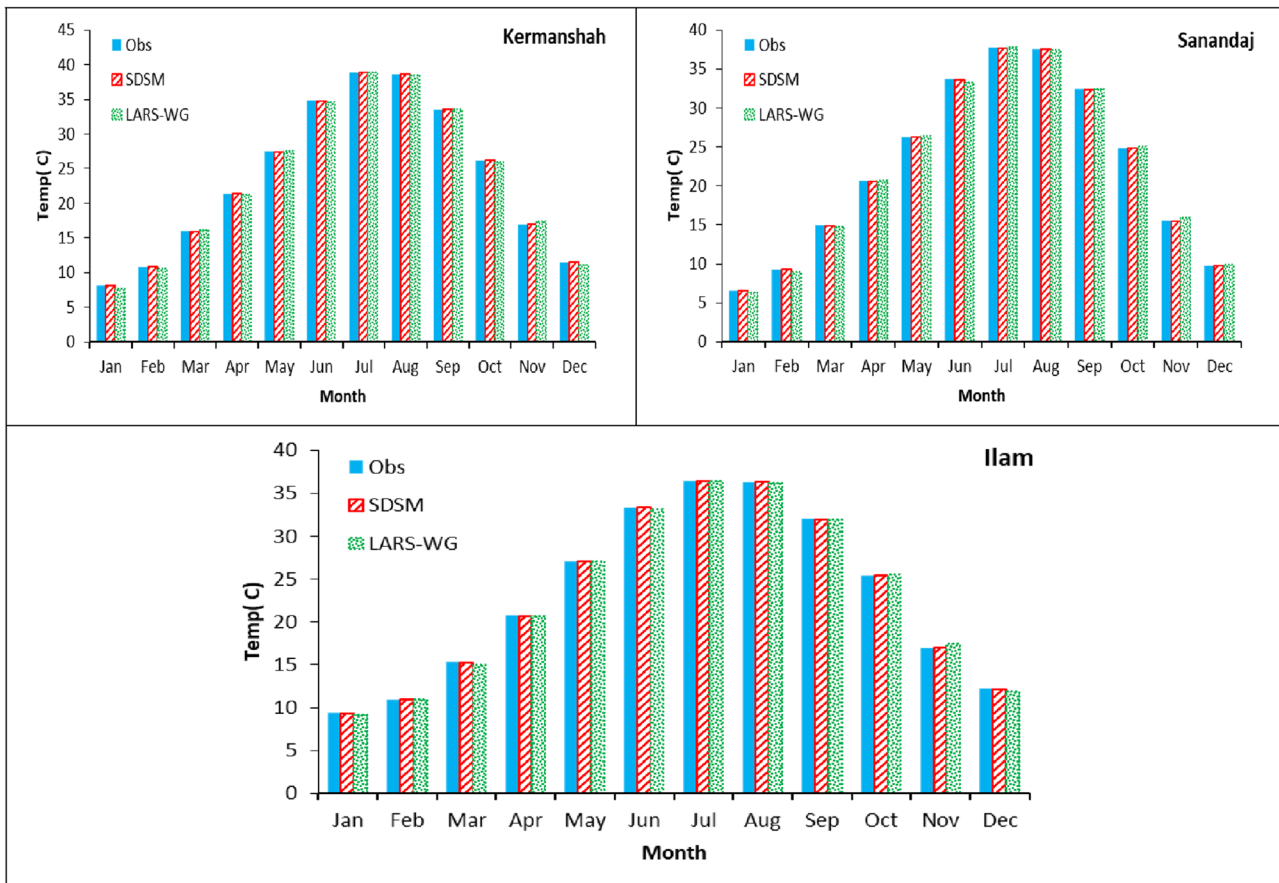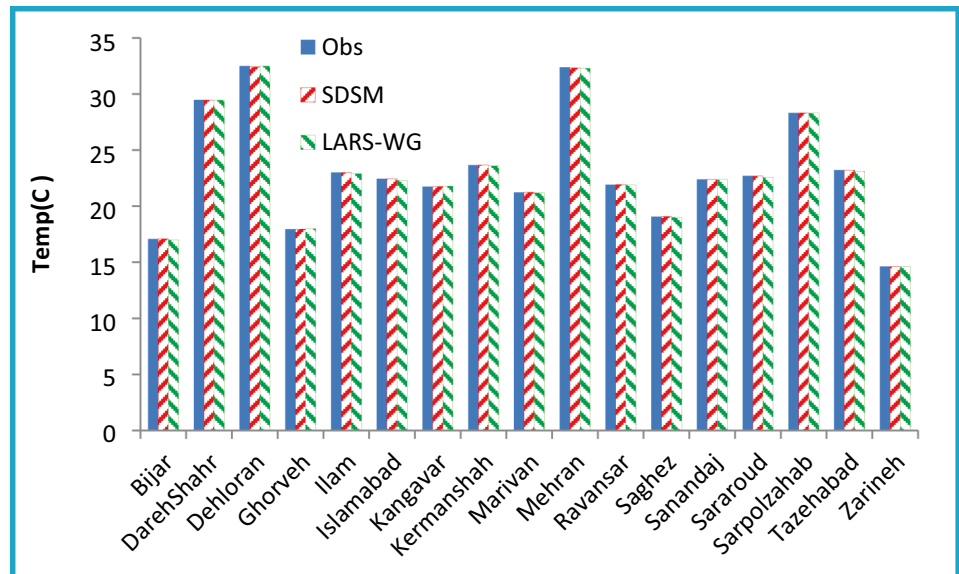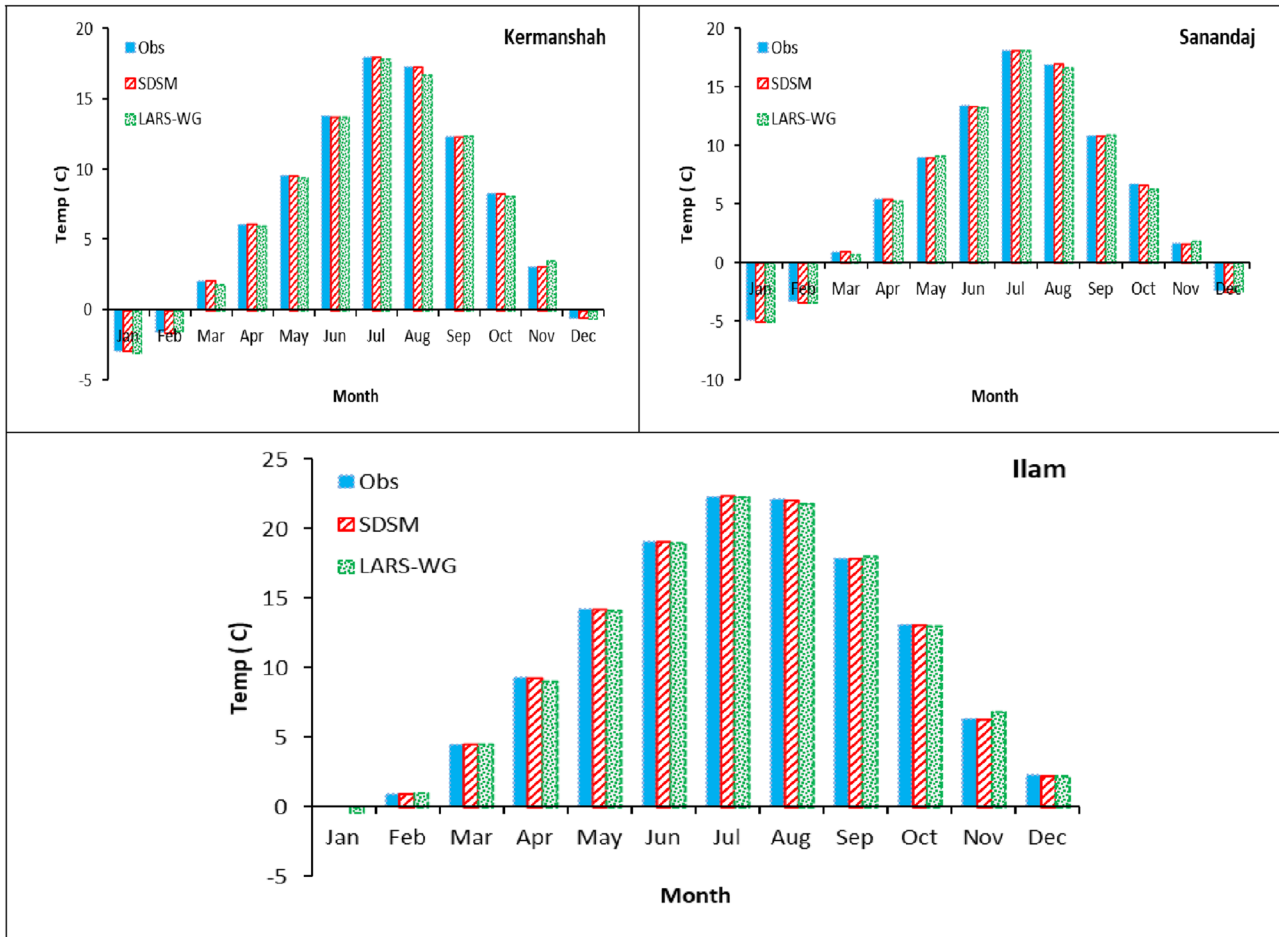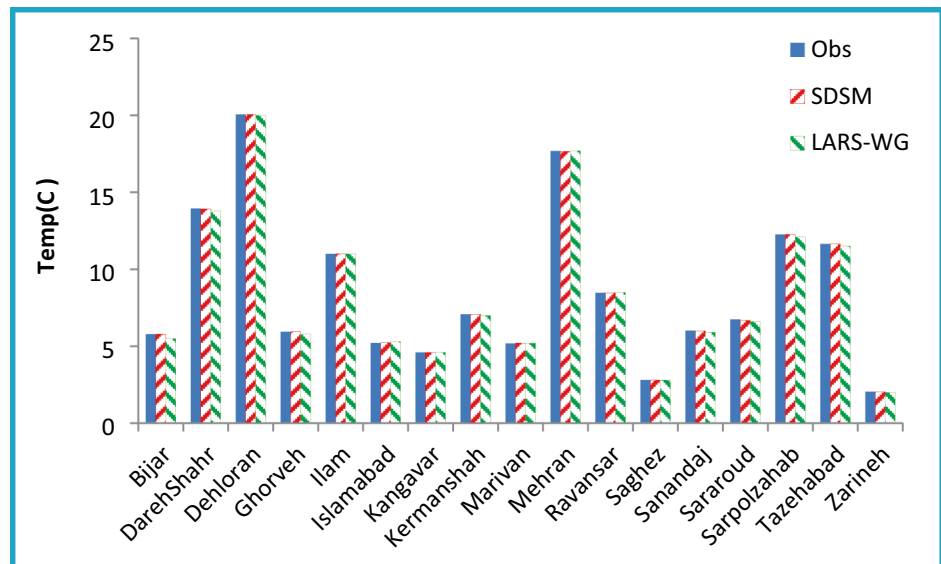
Fig. 2 Observed and simulated values related to monthly maximum temperature by SDSM and LARS-WG models

Fig. 3 Observed and simulated values related to annual maximum temperature by SDSM and LARS-WG models

climatic variables, it changes the statistical parameters of the observed data and recreates the data in the future periods. Based on the error matrixes and comparing the two models, one of them cannot be entirely preferred over the other because in analyzing the performance of the models in different areas and for different climatic parameters and also
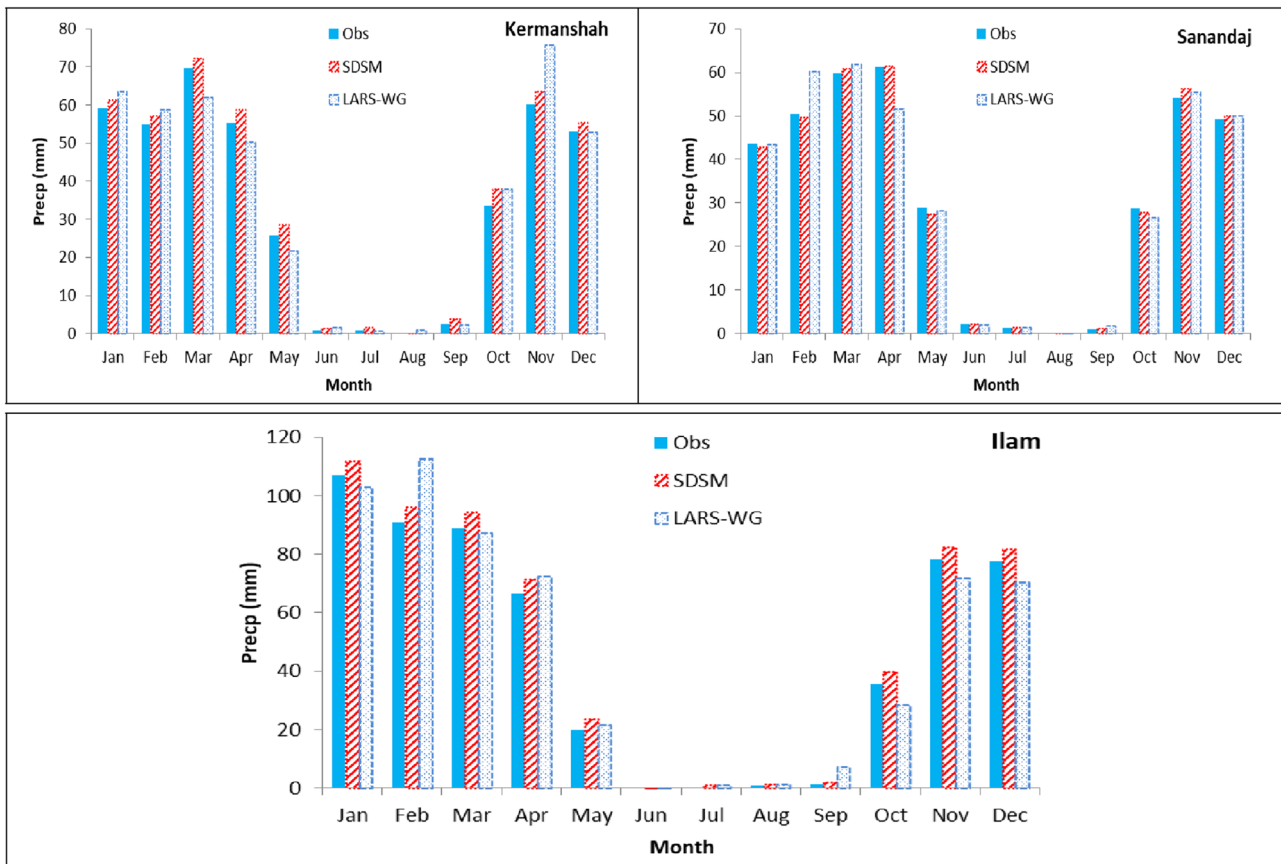
Fig. 4 Observed and simulated values related to monthly minimum temperature by SDSM and LARS-WG models

Fig. 5 Observed and simulated values related to annual minimum temperature by SDSM and LARS-WG models
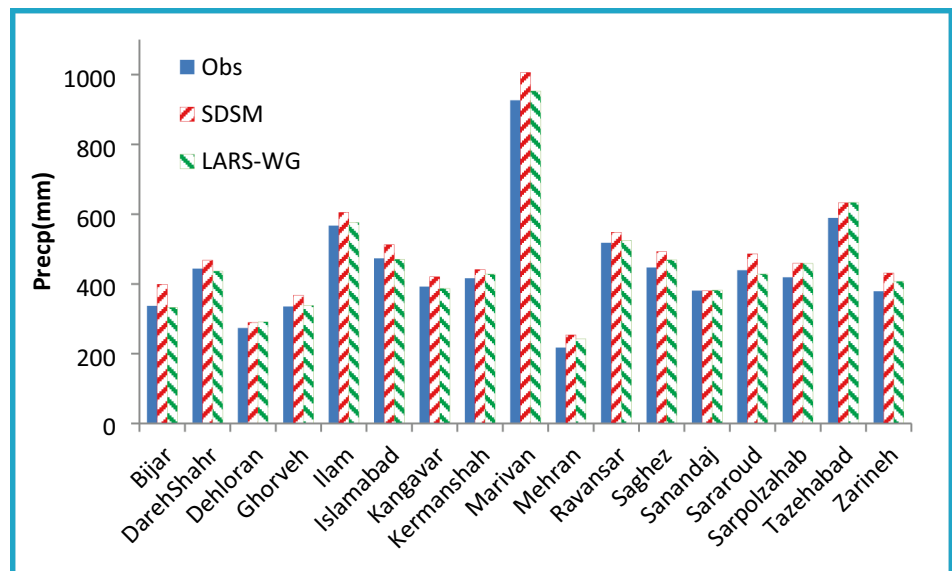
Fig. 6 Observed and simulated values related to monthly precipitation by the SDSM and LARS-WG models

Fig. 7 Observed and simulated values related to annual precipitation by the SDSM and LARS-WG models

the monthly and annual indices in the period under study, a difference was observed in the results and performance of the models. However, due to the type of simulation process and also the integrated structure of the SDSM model

in downscaling the data and direct use of GCM models and large-scale NCEP data, the SDSM model had higher accuracy in simulating the data in the area under study. On the other hand, the LARS-WG model is better and provides

users with more flexibility due to its simple mechanism, the input data for the model, the need for less skill, and its high-performance speed. The SDSM model, in contrast, has a relatively more complex process and needs more precision and specialization by the user. Besides meteorological parameters such as temperature, precipitation, sunny hours, and wind speed, this model can be applied to other hydrological and environmental variables including air quality, snow cover, evaporation and transpiration, wave height, etc. On the other hand, new climate change scenarios can be defined for the LARS-WG model, which can be useful in using these models in climate change discussions. It can be concluded that these models produce the statistical behavior of climate data in a weather station in terms of mean, standard deviation, etc. in a way that is similar to the statistical behavior of the observed data and none of the models has absolute superiority over the other. Because in any region before the executing of climate change models, testing their accuracy is essential (recommended by the Intergovernmental Panel on Climate Change (IPCC)). Also, according to the results of this study, it is possible to use the outputs of these models in climate change studies and predict the climatic parameters in the coming decades in different regions.

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