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Evaluation and comparison of performance of SDSM and CLIMGEN models in simulation of climatic variables in Qazvin plain

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Abstract

Climate change is found to be the most important global issue in the 21st century, so to monitor its trend is of great importance. Atmospheric General Circulation Models because of their large scale computational grid are not able to predict climatic parameters on a point scale, so small scale methods should be adapted. Among downscaling methods, statistical methods are used as they are easy to run. Two famous models, ClimGen and SDSM, were studied for daily total precipitation and temperature data in Qazvin station. For this purpose, three steps of models calibration, verification and simulation, in Qazvin station were performed and model performances in terms of similarities in produced data with those using parameters such as root mean square error (RMSE), coefficient of determination (R2) and Nash coefficient (NSE) were assessed. The results in climatic range showed that Climgen outperform in rainfall data generation while SDSM outperforms in simulating average temperatures. However, both models have high potential to simulate temperature and precipitation.

Keywords: Rainfall; Average temperature; Climate change; SDSM model; Climgen model; Qazvin plain

1. Introduction

Climate change is a change in the climatic parameters compared with the long term average, or a variation in the climatic characteristics of a region that persists for a long time. This phenomenon may occur over decades as a result of the natural factors or human activities (IPCC, 2007). Climate change is one of the greatest challenges facing humanity in the twenty-first century, since it can have severe effects on water resources, agriculture, energy, tourism and human living condition. Therefore, prediction of changes in the amount and trend of the climatic variables is a must for strategic planning in the country, particularly in relation to the disaster risk management (Abbasi *et al*., 2010). Climate models have provided new tools in the last 30 years. In any climate model it has been attempted to simulate the processes that affect climate, and subsequently forecast the climate for the upcoming years. As the exact prediction of the future climatic conditions is not possible, different scenarios with different possibilities have emerged as an alternative solution. Nowadays, the most reliable tool to produce these scenarios, are the atmospheric general circulation models or GCMs (Mehdizadeh, 2011). GCM data can be measured in a network with the dimension of 150 to 300 kilometers. One of the main limitations of these models is the lack of accurate spatial resolution which makes them unsuitable for the prediction of climatic parameters at the local and regional scales. To overcome this problem, the output of these models has to be downscaled before any utilization (Samadi, 2013; Etemadi, 2014). Various methods have been used to produce regional-scale climatic scenarios, called downscaling techniques (Goyal, 2012). SDSM model is one of the downscaling techniques

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employed today (Samadi *et al*., 2013). The SDSM is an exponential statistical downscaling model developed by Wilby *et al* (2007) as a tool to downscale the atmosphere general circulation models. The basis of this model is the incorporation of multivariate regression analysis to predict long-term climatic parameters such as precipitation and temperature with respect to the large-scale climatic signals. Numerous studies, at the global or national level have been conducted in this field, and a few cases are reviewed below:

In a study using neural network and SDSM models, rainfall was predicted. The results showed that artificial neural network model had better performance (Harpham and Wilby, 2005). Researchers, using LARS-WG model, have examined the climate of the country for the 2020s and concluded that the country is going to face 9% decrease in precipitation and 0.5°C increase in temperature (Babaian *et al*., 2009).

Uncertainty of SDSM multiple linear model in North Karoun basin was studied by (Farzaneh, 2010). The results showed high accuracy in the simulation of climatic variables in the base period. In another study in southern Iceland, LARS-WG and SDSM models were compared for the simulation and downscaling of extreme rainfalls for next 5, 10, 20, 40, 50 and 100 years. The results showed that both models have matching ability for the simulation of climate variables and can be used with sufficient reliability in the assessment of the impacts of climate change on watersheds (Hashmi *et al*., 2011). Castellvi and Stöckle (2001) compared the performance of WGEN and ClimGen in the generation of long-term series of weather data using seven sites representing a wide range of climates. The authors observed that comparison of actual and generated cumulative distribution functions of maximum and minimum temperature, solar radiation, and evapotranspiration from WGEN and ClimGen showed that both programs were unable to replicate the actual distribution over the entire range of values. However, WGEN better replicated the monthly mean temperature and ClimGen's simulations were better for daily temperature and solar radiation. McKague *et al* (2005) evaluated the weather generator ClimGen for generation of daily precipitation, air temperature, solar radiation, wind speed, and relative humidity for southern Ontario conditions. The comparison of simulated weather data with 30 years of weather data for six stations indicated that ClimGen performed with reasonable accuracy with some limitations in generating rainfall intensities and solar radiation, particularly for the winter months. Also ClimGen performance is similar to or better than WGEN in simulating the range of monthly average precipitation and temperature values for the test stations.

Bazrafshan *et al* (2009) studied two models including ClimGen and LARS-WG for total precipitation, minimum and maximum temperatures of air and solar radiation in fifteen climatic regions of Iran. Results showed that LARS-WG outperforms in generating rainfall data and ClimGen has great potential to simulate minimum and maximum temperatures. However, both models failed in long term simulation of solar radiation data. Dehghanpoor *et al*. (2011) has used SDSM model for downscaling precipitation, temperature and evaporation data. The results suggested an acceptable downscaling performance. SDSM accuracy in simulating minimum and maximum temperatures and precipitation was studied by Goodarzi *et al*. (2011). The results showed that the model was able to estimate the minimum and maximum average temperature; however precipitation was slightly underestimated than the observational values. SDSM models and support vector machine were used for downscaling rainfall in the Hanjyang river basin. SDSM models showed a better performance in comparison with support vector machine (Chen *et al*., 2012). In a study, SDSM downscaling model was incorporated to predict temperature in the Shikoku basin. The results showed that in the period of 2099 to 2071, compared to the baseline period, temperature increases under most scenarios (Tatsumi *et al*., 2013).

In another study, variables of temperature and precipitation in the Bar watershed in Neishabur was predicted using SDSM model. The results showed that in the coming period, average minimum, maximum, and average annual temperature along with precipitation will increase compared to the baseline period (Taei Semiromi *et al*., 2014).

Kabiri *et al*. (2015) evaluated the effects of climate change on runoff process using SDSM and HEC-HMS model. Based on their findings, SDSM, as a statistical downscaling model, is an efficient method to predict the climate variables. Hajarpoor *et al*. (2014) evaluated performance of three models CLIMGEN, LARS-WG and WeatherMan in fine-scale prediction and in weather stations scale for climate variables including maximum temperature, minimum temperature, precipitation and solar radiation for the years 2000-2009 in three areas Gorgan, Mashhad and Gonbad. The present research aims to assess models CLIMGEN and SDSM. This study was conducted to evaluate potentials of these two methods for fine-scale forecasting and in weather stations for climatic variables and models performances were evaluated in simulation of data in a given statistical period.in other words, to overcome low spatial resolution of Atmospheric General Circulation Models which is identified as a weak point of CCM in regional studies, here exponential downscaling method was used.

2. Materials and Methods

2.1. Study area

The study area is located at the Qazvin administrative boundary, which is 150 km north west of Tehran. It lies between 49° 10′ to 50° 40′ E and 35° 20′ to 36° 30′ N (Fig. 1). The elevation of the study area ranges between 2971 and 1100m AMSL. Regarding the administrative watershed division boundaries of Iran, this area is limited from the north to the Shahroud watershed, from the west to the River Abharroud, from the south to the River Shourchai’s watershed, Gharahbolagh and Gharachai, and form the east to the River Kordan and Karaj.

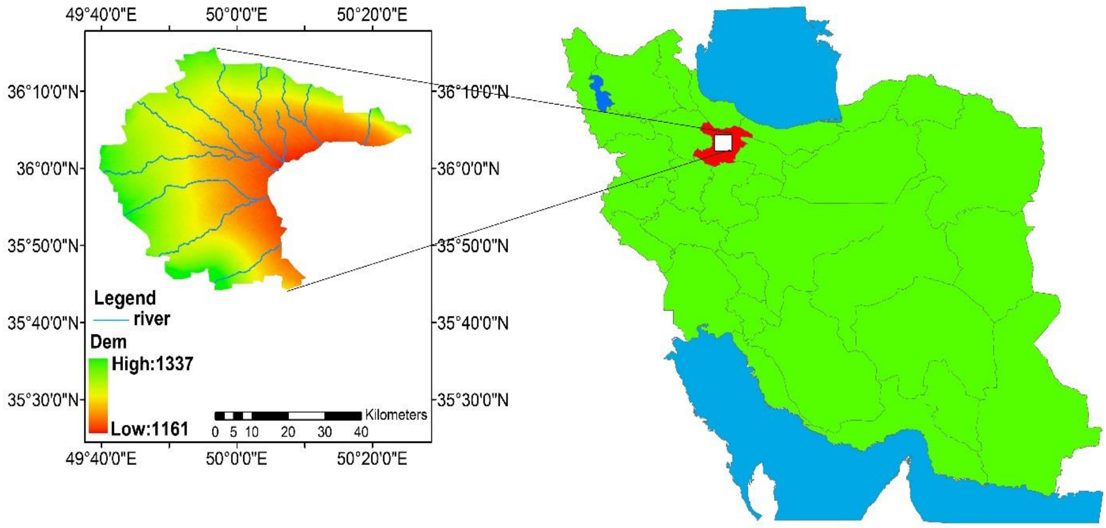

Fig. 1. Geographical location of Qazvin Plain

2.2. Research Methodology

SDSM model

In this research, observation data at the Qazvin synoptic station was acquired from the National Weather Service and its quality was controlled. Then statistical downscaling model of SDSM 5.1 was employed to simulate the temperature and precipitation data in the base and future periods under the influence of climate change. In the case of the SDSM, after the preparation and quality control of observational data, statistical downscaling was performed using daily observed data (predictor), observational predictors (National Centers for Environmental Prediction (NCEP)), and also large scale predictands from the general circulation of the atmosphere (HadCM3). In the next step, after selecting the best predictor variables of the NCEP, model calibration and validation was performed (respectively, 1961-1988 and 1989-2001) and eventually climate scenarios were simulated using observed predictors. Figure 2 shows the SDSM framework.

To evaluate the performance of different models and to draw a comparison, graphical techniques and commonly used evaluation indices including Nash-Sutcliffe efficiency (NSE), Root mean square error (RMSE) and Returns the square (R^2) were used. These indices are calculated using formula 1 to 3 as follows.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(o_i - s_i)^2}{\sum_{i=1}^{n}\left(o_i - \bar{o}\right)^2} \qquad (1)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(s_i - o_i)^2\right]^{1/2} \qquad (2)$$

$$R^2 = \left[\frac{\frac{1}{n}\sum_{i=1}^{n}\left(s_i - \bar{s}\right)\left(o_i - \bar{o}\right)}{\sigma_s \times \sigma_o} \right]^2 \quad (3)$$

Where oi is the observed data, si is the modeled data, and ō and $\bar{s}$ are the average of observed and modeled data and σ_o and σ_s are the standard deviation of observed and modeled data. RMSE is used to evaluate the predictive power of different models. An efficiency of one corresponds to a perfect match of modeled parameters to the observed data. An efficiency of 0 (RMSE = 0) indicates that the model predictions are as accurate as the mean of the observed data. R^2 indicates the relationship between the observed and modeled data. This parameter ranges between zero and one, and an R^2 of 1 indicates strong relationship between the two groups of data.

Table 1 shows the selected predictors for the downscaling of daily temperature and precipitation data at the Qazvin station.

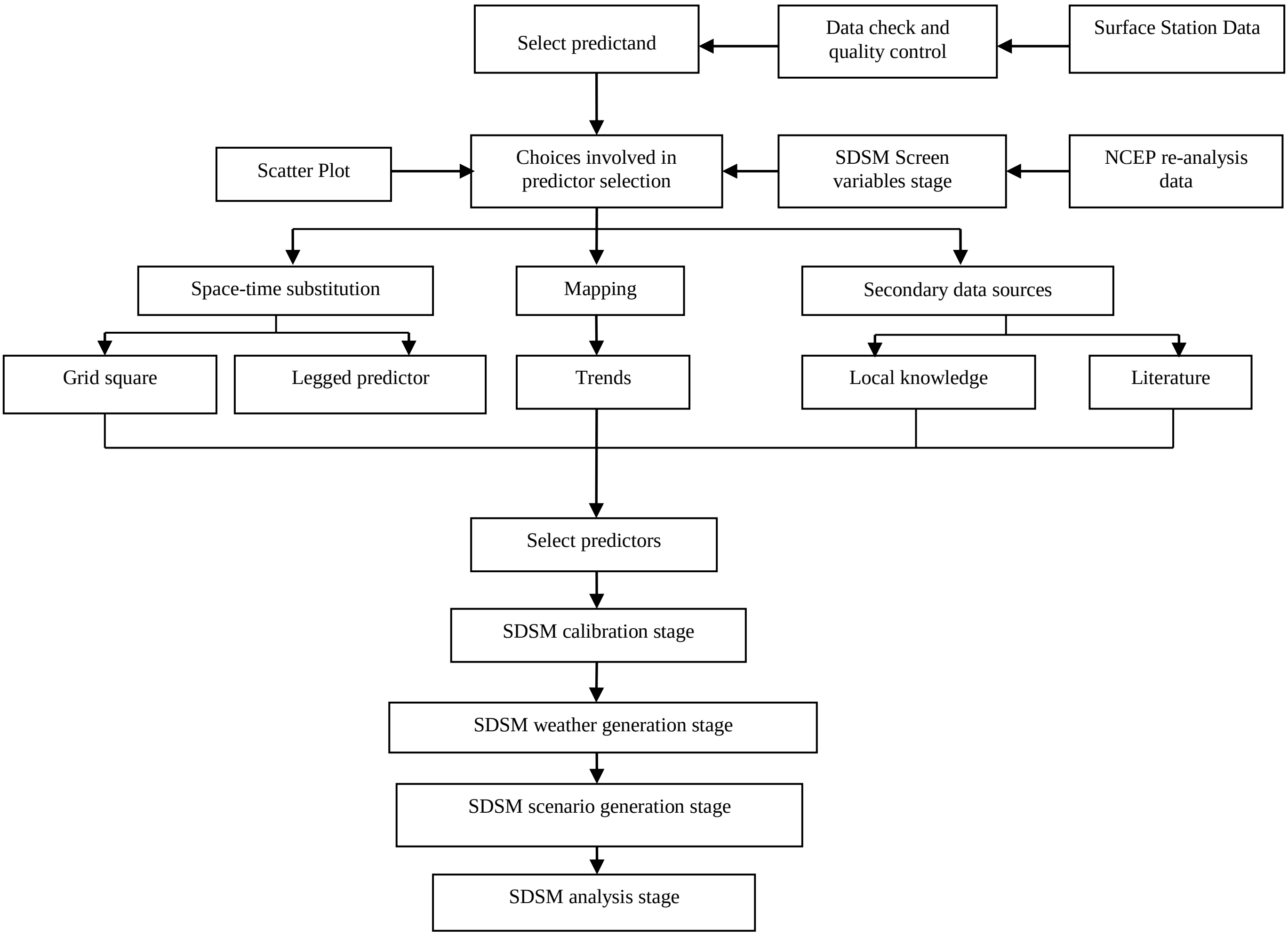

Fig. 2. SDSM model's framework

Table 1. Selected Predictors for downscaling daily temperature and precipitation data

Variables	Selected predictors	Partial regression
Mean temperature	Mean Sea Level Pressure	0.46
	Surface zonal velocity	0.31
	500hpa Geopotential	0.52
	Mean Temperature at 2m	0.64
Rainfall	500 hpa meridional velocity	0.12
	relative humidity in 500 hpa surface	0.2
	relative humidity in 850 hpa surface	0.4

2.3. Climgen model

Since it is impossible to access long term climatic data (in particular daily data) in most weather stations, weather generators and simulator can be used to prolong data series of weather parameters. The main purpose of weather generators is to generate data statistically similar to observed data. CLIMGEN as a generator of random whether data has potential to estimate parameters rainfall, temperature, solar radiation, dew point, relative humidity and wind speed for a given geographical location(Zhang, 2003). Initially, this model was developed as a part of the Water Erosion Prediction Project (WEPP). CLIMGEN model was tested in many places of the world, for example, America, Africa and Australia (Kou *et al,* 2007). CLIMGEN models simulates daily rainfall events using Markov chain and it was based on dry and wet periods (McKague et al., 2003).in the present research CLIMGEN model version 4/05/06 was used. Finally, model calibration and validation was performed for calibration and validation (respectively, 1961-1988 and 1989-2001) and climatic data simulated for future.

3. Results

The results of the evaluation of the models indicate that the NCEP and scenarios have had relatively good efficiency and accuracy in estimating the average temperature and precipitation at the synoptic station of Qazvin. The results show a satisfactory performance for the model in Qazvin Plain as a semi-arid area. According to the values of RMSE and NSE in Tables 2 and 3, it was determined that by comparison, temperature is more correlated to observed data. This is explained by the fact that precipitation is a conditional parameter and is influenced by many factors. Yet temperature as an unconditional and continuous variable is less affected by climatic anomalies and other factors, which is in agreement with the findings of Zilkarnain *et al*. (2014).

Table 2. Performance evaluation indicators of SDSM and Climgen models at Qazvin station

Step			Climatic variable	RMSE	NSE	R^2
SDSM	NCEP	Calibration	Precipitation	3.87	0.76	0.83
			Average temperature	2.35	0.85	0.88
		Validation	Precipitation	4.84	0.68	0.72
			Average temperature	3.54	0.79	0.84
	HadCM3	Validation	Precipitation	4.32	0.69	0.76
			Average temperature	2.36	0.78	0.82
Climgen		Calibration	Precipitation	1.24	0.86	0.92
			Average temperature	4.98	0.72	0.8
		Validation	Precipitation	2.32	0.83	0.89
			Average temperature	6.34	0.61	0.75

The produced variance inflation for the downscaling of precipitation and temperature has been respectively 14 and 6 for the NCEP's predictors, while 1 and 19 for the HadCM3's predictors. Figure 3 and 4 illustrate the observed and modeled precipitation at the Qazvin station for two models of Climgen and SDSM during 1961-1988 in the calibration step. The results showed that SDSM has higher accuracy in temperature simulation and Climgen has higher accuracy in precipitation simulation in calibration and validation phase.

Figures 5 and 6 show the observed and modeled temperature and precipitation data at the Qazvin station for two models of SDSM and Climgen in the validation phase (1989-2001).

The results for the observed and modeled data by two models of SDSM and Climgen in the future period show a decrease in the average annual precipitation and an increase in average annual temperature relative to the base period. Based on the result, in 2015-2040 (2020s) compare to the base period, average annual precipitation is expected to respectively decrease 19.8% and 10.2% while for average annual temperature changes into 0.9 and 1.25 °C (Fig. 7 and 8).

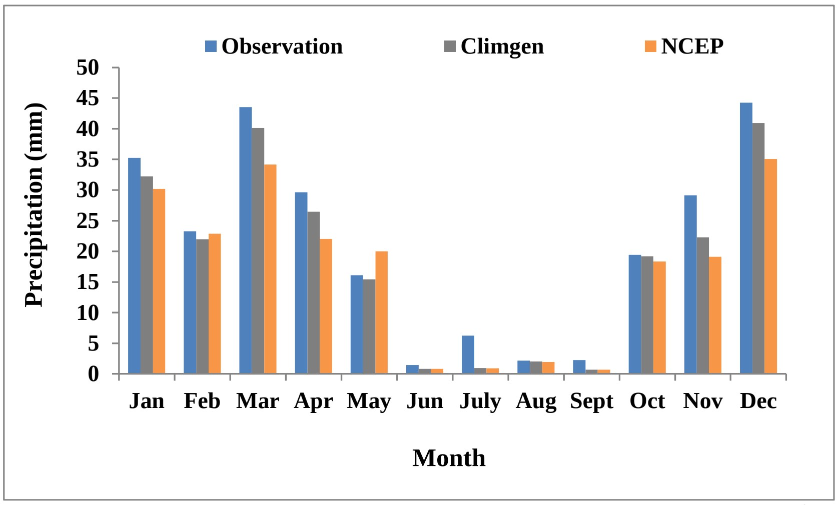

Fig. 3. Comparison between the average observed and synthesized monthly precipitation data by two models of Climgen and SDSM in the calibration phase (1961-1988)

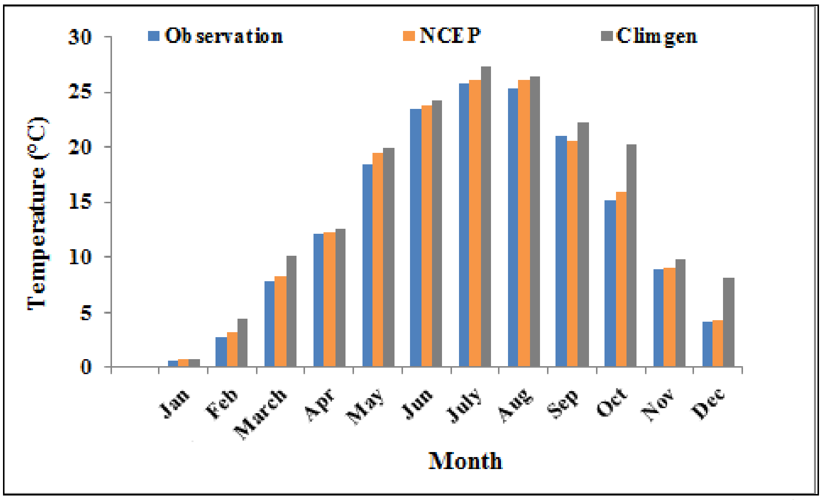

Fig. 4. Comparison between the average observed and synthesized monthly temperature data by two models of Climgen and SDSM in the calibration phase (1961-1988)

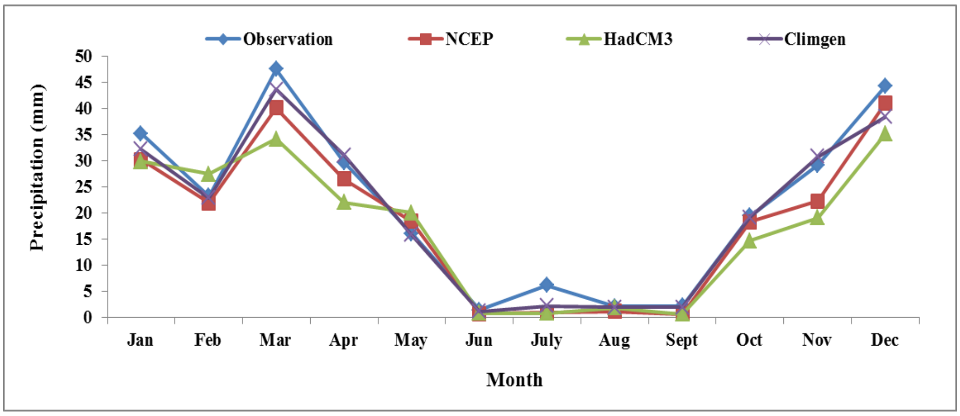

Fig. 5. Comparison between the average observed and synthesized monthly precipitation data by two models of Climgen and SDSM in the validation phase (1989-2001)

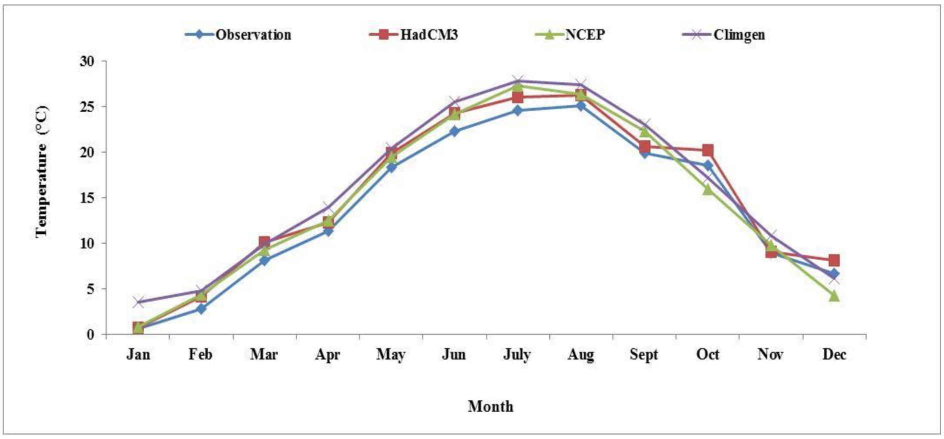

Fig. 6. Comparison between the average observed and synthesized monthly temperature data by two models of Climgen and SDSM in the validation phase (1989-2001)

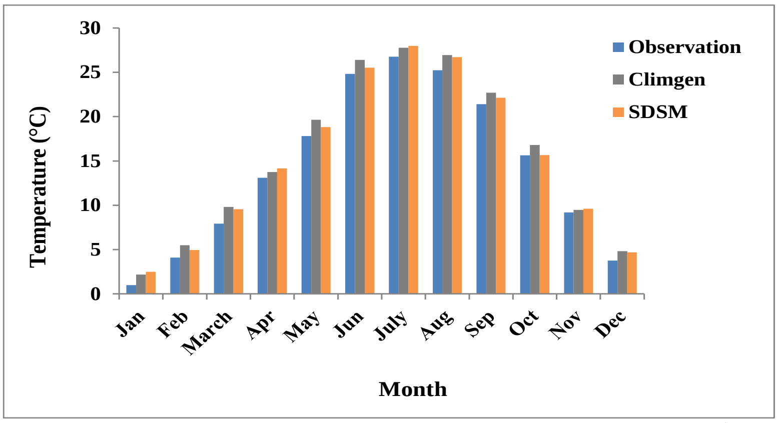

Fig. 7. Changes in average monthly temperature in the base and simulated periods by two models of Climgen and SDSM

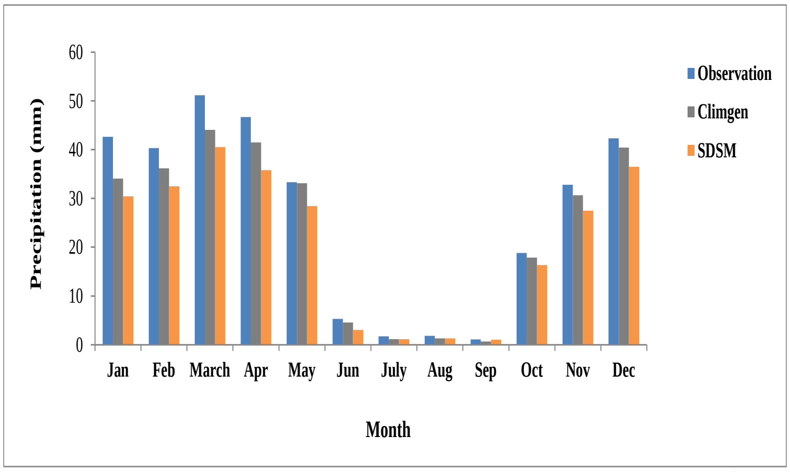

Fig. 8. Changes in average monthly precipitation in the base and simulated periods by two models of Climgen and SDSM

Figures 9 and 10 show the simulated climate variables in two models of SDSM and CLIMGEN in future periods compared to the base period. After the prediction of the temperature and precipitation in the period of 2015-2040, simulated values were compared with the baseline values. The average monthly temperature will increase while average monthly precipitation will decrease in all months.

The results show that the average yearly temperature increases in Climgen and SDSM models, respectively 1.25 and 0.95 °C and the average yearly rainfall is going to reduce in Climgen and SDSM models respectively 10.2 and 19.8 %.

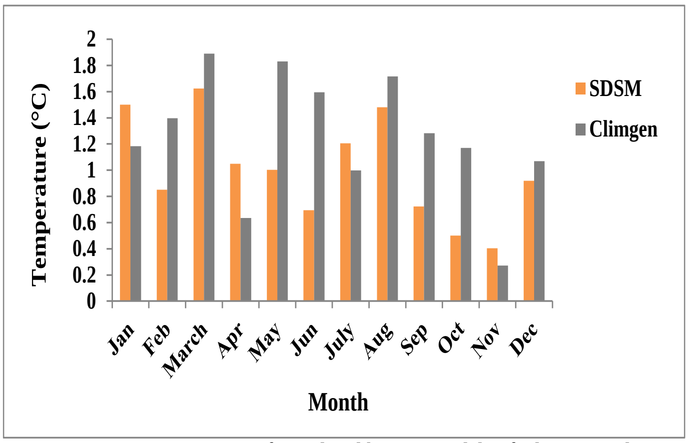

Fig. 9. Changes in average temperature of simulated by two models of Climgen and SDSM in future

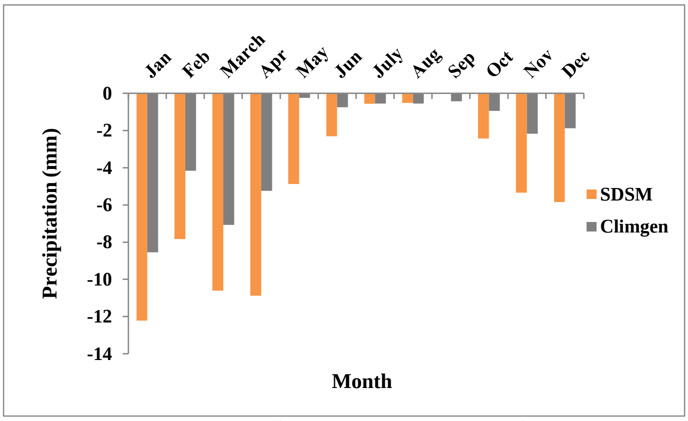

Fig. 10. Changes in average precipitation of simulated by two models of Climgen and SDSM in future

Table 5. Future changes of annual rainfall and average temperature according to baseline period (1961-2001) based on two models of CLIMGEN and SDSM

	2020s
	Annual Rainfall (%)
SDSM B2	-19.8
Climgen	-10.2
	b Tmean (◦C)
SDSM B2	0.95
Climgen	1.25

4. Discussion and Conclusion

The results showed that SDSM has higher accuracy in temperature simulation and Climgen has higher accuracy in precipitation simulation in calibration and validation phase. Overall the results of the models evaluation based on relevant statistics showed that SDSM and Climgen models have reasonable accuracy in the simulation of climatic parameters which is consistent with the results of Wilby *et al.* (2003), Samadi *et al.* (2013) McKague *et al.* (2005). The results of the study showed that the temperature increases in Climgen and SDSM models, respectively 1.25 and 0.95 °C which is in accordance with the study results of Holden *et al* (2003), Zhang and Niring (2005), Yano *et al*. (2007), Rezai *et al* (2014) and Abkar et al (2014). The rainfall is going to reduce in Climgen and SDSM models respectively 10.2 and 19.8 %. This would be due to the increased greenhouse gases and rising temperatures that are consistent with the results of the research conducted by (Semiromi *et al*., 2014). In the overall analysis of the changes in temperature and precipitation, it was shown that the climate is changing, and a decrease in precipitation and increases in temperature and thus a relative warming is expected. It is therefore imperative that provincial officials and planners in agriculture and water resources sectors consider mitigation and adaptation strategies to new climatic conditions.

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