Future changes in maximum temperature using the statistical downscaling model (SDSM) at selected stations of Iran

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Abstract In the 21st century, climate change in the dry lands is considerate to be one of the greatest environmental threats to the world. This study presents the projection of future changes in maximum temperatures under A2, A1B and B1 SRES of the CGCM3 outputs using the statistical downscaling model (SDSM) in the 7 selected station over Iran during the two future periods (2041–70 and 2071–99). For this purpose, after examining the ability of SDSM in simulation of the basic period climate (1981–2010), the daily maximum temperature for future decades was downscaled by considering the uncertainty in 7 synoptic stations as climatic representatives of Iran. In uncertainties analysis related to model-scenarios, it was found that CGCM3 model under scenario B1 had the best performance in the simulation of future maximum temperatures among all of the scenarios. The findings showed that average maximum temperature at study stations over Iran will be increased between 0.3 and 3.5 °C. Also this maximum temperature changes will be more severe increased based on scenario A2 compared to other scenarios of the CGCM3 model.

Keywords Climate projection · Maximum temperature changes · Iran · Statistical downscaling model · SDSM

Introduction

In arid and semi arid regions, the observed climatic instability is an unpredictable and complex phenomenon mainly attributed to human activity and in particular to gas emissions, which seem to influence the global warming of the planet. The temperature variations in arid and humid climates have been observed in most regions of the planet. So that, temperature changes in the dry lands will accelerate the process of desertification. According to the 5th Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), global average temperature has shown a 0.85 °C increase over the period of 1800–2012 (IPCC 2013), and a 0.18–0.74 °C increase during the last 100 years (1906–2005) (IPCC 2007). Also, this trend in global warming is predicted to likely increase during the 21st century under all the representative concentration pathways (RCPs). This is probably due to the effects of industrialization that has increased greenhouse gas emissions. The intense interest in climate change has stimulated detailed studies of temperature records in many areas of the world. So far, extensive studies have been conducted in different countries with regarding to temperature trend during the current period. So that, these studies in the perspective of spatial scale, it can be grouped into three studies: regional (Kadioğlu et al. 2001; Toros 2012; Whan et al. 2014; Toros et al. 2015), hemispherical (Jones 1994; Stern and Kaufmann 2000; Jones and Moberg 2003) and planetary (Horton 1995; Rahmstorf and Ganopolski 1999). In all these studies have investigated the status quo of temperature parameters, while a few researches has been done regarding the impacts of climate change on the temperatures trend in the coming decades.

In order understanding of the global warming effects and climate change during the future periods, can be used the output of general circulation models (GCM). So that,

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average global temperature will be increased in terms of various models-scenarios outputs during the future periods due to emission of greenhouse gases. All of these models depend on the time and has a three-dimensional numerical simulation from atmospheric motions, heat exchanges and interactions among ice, ocean and land (Dracup and Vicuna 2005). Therefore, increasing global temperature in the most parts of the world due to climate change effects has provided various results and predictions of GCM outputs. In other words, according to GCM models, global temperatures till 2100 will be increased in a range from 2 to 4.5 °C (IPCC 2007). Since, temporal and spatial resolution of GCM models is coarse so that downscaling methods is necessary to convert the GCM outputs to local variables in scale of observation stations (Salon et al. 2008). For this purpose, dynamical and statistical methods can be used. Furthermore, dynamic models require to ultra-fast laboratory facilities that most countries are lacking, therefore researcher's attention are directed to statistical models. In this regard, the statistical downscaling model (SDSM) by Wilby et al. (2002) as its builders has been considered as a perfect tool for statistical downscaling as well as described the functionality of the SDSM model in predicting and producing the present and future climatic data. So far, extensive researches in the field of climate change and global warming have been used the SDSM model for downscaling process (Chu et al. 2010; Huang et al. 2011; Mahmood and Babel 2013). At a regional scale most studies seeking to detect the effects of climate change on climatic variables and temperature extreme are conducted in East and South-East Asia, China, India and Pakistan (Islam et al. 2009; Gu et al. 2012; Mahmood and Babel 2014). While, future changes in temperature extreme and extreme climatic phenomena is necessary in any regions due to have information about negative impacts on human society and the natural environment than the changes in mean climate. The report of Iran Meteorological Organization (IRIMO 2012) showing effects on mitigation and adaptation to climatic extremes indicated that there is an increase in extreme climate events in Iran, particularly temperature extremes. Therefore, in this study it has been tried to evaluate the maximum temperature changes under global warming in Iran during the near future (2041–70) and the far future (2071–99), by using of the statistical downscaling method (SDSM) on the output of CGCM3-T63 Model under existing scenarios (A2, A1B and B1).

Study area

Iran is geographically uneven located in the arid and semiarid area in the Middle East and the average height of sea level is around 1250 meters. There are high mountains

and diverse topography that has caused the temperature distribution in Iran has not followed the regular pattern. However, Iran temperature from North to South and from West to East is generally increasing due to the characteristics of mountains that there are in the North and West of the country. In this study, in order to gain a perspective of temperature changes has been studied 7 synoptic stations as representative of b climate zones over Iran (Fig. 1).

Materials and methods

Data analysis

To assess maximum temperature changes in the coming decades, the SDSM model has been used as a tool for handling statistical downscaling data on GCM outputs. Downscaling process is an agent that establishes relationship between climate variables on a local scale (predicted) and large-scale atmospheric variables (predictors) (Wilby and Dawson 2013). Therefore, to do this study and achieve a prospect of daily maximum temperature variations in station scales, two sets of data are needed: (1) daily maximum temperatures that prepared by Iran Meteorological Organization (via <http://www.irimo.ir>) at 7 synoptic stations in the range of Iran's climatic regions during the observational period 1981–2010. The accuracy of this data at the significance level of 95 % was approved based on data adequacy test, homogeneity of Run test and normality of Kolmogorov–Smirnov test. (2) Daily large-scale atmospheric variables as predictors that prepared from the National Center for Environmental Prediction (NCEP) during the observation periods and also outputs of CGCM3 model under existing scenarios in similar observation periods and in future periods (2041–70 and 2071–99) that extracted from the Canadian Climate Change Scenarios Network (CCCSN). Table 1 indicates that the nearest grid box numbers to the study stations for extracting the CGCM3 data regarding to the longitude and latitude of study area.

Then the large-scale predictors were normalized rather than average and standard deviations of the observation period (1981–2010). Table 2 summarizes the most important features of CGCM3 model as input of the SDSM software (IPCC 2007).

Statistical downscaling model (SDSM)

Statistical downscaling model has been developed by Wilby et al. (2002) as an appropriate tool for statistical downscaling and even producing meteorological data using a combination of stochastic weather generator (SWG) and multiple linear regression (MLR). It is the one of the best

Fig. 1 Topography map and distribution of the selected stations in Iran **Table 1** The latitude and longitude box numbering of CGCM3 model in study stations

GCM	Mashhad	Zahedan	Tehran	Esfahan	B-Abbas	Ahvaz	Tabriz
CGCM3 (T63)							
X number	21	22	18	18	20	17	16
Y number	45	43	45	44	42	44	44

Table 2 The characteristic of study GCM model as SDSM software input

GCM	IPCC	SRES	Resolution	Reference
CGCM3-T63	IPCC4	A2, B1, A1B	2.81° × 2.81°	AR4, Canadian Centre for Climate Modeling and Analysis (CCCma), Canada

models in the classification of various downscaling methods. The basis of this method is designing multiple regression models. So that in this method, in order to simulate climatic parameters for any time scale period (monthly, seasonally or annually), a multivariate linear regression model is developed between large-scale predictors (as independent variables) and predicted climatic variables at station scale (as dependent variable) and through following steps:

Monitoring and screen variables

In this step, since maximum temperature time series is normally distributed so it is considered an unconditional variable. Therefore, to select multivariate regression model in SDSM software, the directly relationship is considered

between observational maximum temperature as predicted variable and large scale predictors as independent variables. So, to identify and select suitable predictors with strongest significant correlation with observational temperature at each study station, correlation analysis are used between predictors and predicted that is including correlation matrix analysis, partial correlation, scatter plot as well as the percentage of variance explained among variables. Thus, in this study, the best predictors were selected based on the results of correlation analysis for selecting the best multiple regression models at each local stations.

Table 3 summarizes the results of partial correlation between selected predictor variables from CGCM3 model and maximum temperature variable at each station. Therefore, the predictors in following Table represent a compromise maximum overlap between NCEP and

Table 3 The partial correlations between the selected predictors of CGCM3 model and the maximum temperature at each station over the observation period

Predictor	Description	Station						
		Tehran	Tabriz	Esfahan	Ahvaz	Zahedan	Mashhad	B-Abbas
Mslp	Mean sea level pressure	−0.28	−0.28	−0.03	−0.05	−0.11	−0.23	–
P500	Geopotential height (500 hPa)	0.43	0.48	0.44	0.14	0.55	0.41	0.28
P850	Geopotential height (850 hPa)	–	–	−0.10	–	−0.03	–	–
P8_u	U Wind (850 hPa)	−0.28	0.13	–	–	–	−0.07	–
R850	Relative humidity (850 hPa)	−0.07	−0.06	−0.26	−0.36	−0.29	−0.28	−0.14
Shum	Near surface specific humidity	–	0.09	–	–	–	–	–
Temp	Mean temperature at 2 m	0.29	0.18	0.26	0.51	0.17	0.12	0.62

CGCM3 achieves, as well as a range of choice for downscaling.

Calibration and validation

To evaluate performance of multivariate regression models that is resulted from validation step of SDSM model, there are some measurement errors for calibration of predictions outputs. In this study, to evaluate accuracy and relative comparison have been done on the results of multivariate regression model of prediction at each station during the base period (1981–2010). So, in order to assess relative comparison in results of multivariate regression models with observation maximum temperature values at each station during the base period (1981–2010) have been used the spatial and temporal standard error (SE) of predictions, R square (R^2), mean absolute error (MAE) and mean bias error (MBE). Overall, results of different statistical measurement error showed that the final regression equations has acceptable accuracy to predict daily maximum temperature during future decades based on large-scale atmospheric variables as independent variables from each GCM models (Table 4). Also, statistical analysis of the t test in any time scale (monthly, seasonally and annually) showed that there is no significant difference in critical level of 0.05 between final prediction variables and observational values of maximum temperature at each study station during the observation period (1981–2010).

Climatic scenarios generation

Since climate change will be highly dependent on human activities in the future, IPCC considers about 40 emission scenarios issued from special report on emission scenarios (SRES) that is related to amount of greenhouse gases emissions, land use, technology development and other human activities. The number of emission scenarios is increasing with regard to the various consideration in future but the most important family in the emission

Table 4 Results of calibration and validation phase of SDSM model in observation period (1981–2010)

Station	SE	R^2	MAE	MBE
Tehran	2.25	0.62	1.84	0.04
Tabriz	2.53	0.61	2	0
Esfahan	2.20	0.55	2.45	0
Ahvaz	2.01	0.59	2.2	−0.002
Zahedan	2.20	0.61	1.7	−0.23
Mashhad	3.42	0.48	2.8	−0.004
B-Abbas	1.80	0.45	2	0.01

scenarios and their characteristics defined by IPCC are A1, A1F1, A1B, A1T, A2, B1, and B2 (IPCC 2007). Accordingly, also in SDSM software producing future climate scenarios about changes in local parameters will be based on various emission scenarios in the future decades. In this stage of the study, according to final regression equations and calibrated multivariate regression models between various predictors of large-scale variables with maximum temperature variable at study station scales in the observation period, the process of downscaling will be done on outputs of CGCM3 Model under various emissions scenarios during future periods. Thus, daily maximum temperature time series at station scale is simulated and produced for future period.

Uncertainty analysis

In climate change studies should be considered various uncertainties of modeling to achieve more reliable results (Semenov and Stratonovitch 2010). In assessing climate change, there are also many sources of uncertainty that is categorized into two main groups. The first case is related to dynamic structure of GCMs and their computational process that the contribution of this type of uncertainty gradually decreases with the passage of time due to increasing quality and accuracy of GCM models. The

second case is related to amount of greenhouse gas emissions (Covey et al. 2003). Generally in this study, to evaluate the uncertainty arising from using of various model-scenarios is used mean observed temperature method (Eq. 1) (for the more details refer to Hashemi-Ana et al. 2015).

$$W_{i,j} = \frac{\frac{1}{\Delta T_{i,j}}}{\sum_{j=1}^n (1/\Delta T_{i,j})} \quad (1)$$

In this equation, $W_{i,j}$ is the weight given to each model-scenarios (j), $\Delta T_{i,j}$ is difference between average of simulated maximum temperature in the feature periods from average of observational maximum temperature for each day (i) and n, is total number of model-scenarios.

Thus in this study, the probability weights that is related to ability of any used models-scenarios about simulation of maximum temperature was calculated. According to Table 5, it is clear that simulation of maximum temperature based on CGCM3 and under the emission scenarios B1 has better performance in all stations. In other words, the results of B1 scenario allocates the highest probability of occurrences than other model-scenarios.

Then, according to the range of uncertainty that is associated with output of all various model-scenarios, the Assemble Scenario with regard to the weight of each models-scenarios were produced to get a similar and comprehensive scenario of maximum temperature changes at local scale in Iran during future decades (Eq. 2).

$$SRE_{Assemble} = \sum_{j=1}^n (\Delta T_{i,j} \times W_{i,j}) \quad (2)$$

In this regard, the components of above equation are the same with Eq. 4.

Table 5 Probability occurrence of each scenario in the simulation of maximum temperature during the future periods

CGCM3 model	SRES					
	2041–70			2071–99		
	A2	B1	A1B	A2	B1	A1B
Tehran	0.29	0.42	0.30	0.23	0.45	0.32
Tabriz	0.27	0.42	0.31	0.22	0.46	0.32
Esfahan	0.26	0.48	0.26	0.19	0.48	0.33
Ahvaz	0.24	0.51	0.25	0.19	0.51	0.30
Zahedan	0.26	0.51	0.24	0.21	0.50	0.30
Mashhad	0.08	0.84	0.08	0.17	0.54	0.29
B-Abbas	0.28	0.47	0.25	0.22	0.44	0.34

Results and discussion

In this study after assessing ability of the SDSM, daily maximum temperature of future decades were downscaled based outputs of CGCM3 model at a station scale in Iran. Then, simulation results of daily maximum temperature were extracted based on each model-scenarios with regarding to uncertainty analysis in two future periods (2041–70 and 2071–99). Finally, maximum temperature changes based on each model-scenarios in future periods were compared than the observation period (1981–2010). It is worth noting that the obtained results based on each model-scenarios represent an increase in maximum temperature at all study stations during the future decades. However, this increasing in maximum temperature is different at each station and for each future period (Figs. 2 and 3).

After uncertainty analysis onto the outputs of all model-scenarios during the coming periods at station scale, it was found that the lowest increase in maximum temperature with the minimum range of uncertainty is observed at B-Abbas and Ahvaz stations which are located in the southern regions of Iran and vice versa, the greatest increase in maximum temperature with the maximum uncertainty range at Tabriz and Tehran stations which are located in the northern regions of Iran. In other words, by analyzing of the maximum temperature changes in the middle of current century (2041–70), it was found that the average maximum temperatures will be increased around 0.06 to 2.47 °C based on the all of scenarios in Iran. Also, the greatest increase in maximum temperature is observed based on scenario A2 and vice versa, the lowest increase in maximum temperature is observed based on scenario B1 as well as simulation results shown that the rising in

Fig. 2 The uncertainty of model- scenarios resulted from changes simulation of maximum temperature in the near future

Fig. 3 The uncertainty of model- scenarios resulted from changes simulation of maximum temperature in the Far future

maximum temperature based on scenario B1 is lower than scenario A2. In this respect, based on various scenarios of CGCM3 model, the greatest increase in maximum temperature is observed at Tabriz station which is located in the northwestern regions of Iran and vice versa, the lowest increase in maximum temperatures is observed in Mashhad and B-Abbas stations which are located in the central and southern regions of Iran.

In other hand, increasing the maximum temperature during the period of end-century (2071–99) has similar spatial distribution in relation to the period of mid-century (2041–70). So what are important in comparative evaluation of maximum temperature changes between the two future periods will be changes in the intensity values of maximum temperature. In other words, at the end of 21st century will be added intensity values of rising maximum temperature in compared to its middle period, so that this increase in maximum temperature will be between 0.42 and 4.42 °C. Also at the end of 21st century (2071–99), the greatest increase in maximum temperature based on scenario A2 is observed at Tabriz station which in the north-west of Iran and vice versa, the lowest increase in maximum temperature based on scenario B1 is observed at B-Abbas station in the southern regions of Iran. Therefore, based on simulation results of scenario A2 in compared to scenario B1, future trend of maximum temperature has been increased and under various study scenarios at study stations in Iran.

Conclusion

Climate change especially rising temperatures in arid and semi arid regions are one of the important environmental issues in human society that has allocated many studies in

recent years. Thus, in this study for necessity recognition and comparative evaluation about climate change effects on the occurrence of daily maximum temperatures during the two future periods (2041–70 and 2071–99), it has been tried that the data of CGCM3-T63 model under existing scenarios (A2, A1B, B1) are downscaled by using of the SDSM model. As simulation results about increasing of maximum temperatures in future decades showed that the future changes of maximum temperature will be more intensified based on scenario A2 rather than the all scenarios of CGCM3 model. So, after taking into uncertainty range that is related to outputs of all model-scenarios, the results of Assemble scenario showed that the average of rising maximum temperature variation will be increased between 0.15 and 2 °C for near future period (2041–70) and between 0.5 and 3 °C for far future period (2071–99) in Iran. In other words, based on simulation results of all model-scenarios in study stations, maximum temperature of Iran during the middle and the end of twenty-first century will be increased an average of between 0.3 and 3.5 °C compared to the base period (1981–2010). Also in terms of geographic distribution, the greatest increase in maximum temperature is observed at Tabriz station which is located in the northwestern mountainous of Iran and vice versa, the lowest increase is observed at B-Abbas station which is located in the southern coasts of Iran. In general, what can be obtained from the survey results of this study for all output of various scenarios is that the mountainous stations which is located in the more northern latitudes with drier climate will be more faced to risk of the rising maximum temperatures during the coming decades.

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